Renewable Energy, Oil Prices, and Economic Activity: A Granger-causality in Quantiles Analysis

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Abstract: This paper analyzes the causal relationship between renewable energy consumption, oil prices, and economic activity in the United States from July 1989 to July 2016, considering all quantiles of the distribution. Although the concept of Granger-causality is defined for the conditional distribution, the majority of papers have tested Granger-causality using conditional mean regression models in which the causal relations are linear. We apply a Granger-causality in quantiles analysis that evaluates causal relations in each quantile of the distribution. Under this approach, we can discriminate between causality affecting the median and the tails of the conditional distribution. We find evidence of bi-directional causality between changes in renewable energy consumption and economic growth at the lowest tail of the distribution; besides, changes in renewable energy consumption lead economic growth at the highest tail of the distribution. Our results also support the unidirectional causality from fluctuations in oil prices to economic growth at the extreme quantiles of the distribution. Finally, we find evidence of lower-tail dependence from changes in oil prices to changes in renewable energy consumption. Our findings call for government policies aimed at developing renewable energy markets, to increase energy efficiency in the U.S.

Keywords: Granger-causality; Quantile Regression; Oil Prices; Renewable Energy Consumption; Economic Growth.

JEL Classification: C22; Q41; Q43

1. Introduction

The relationship between energy consumption and economic growth is the subject of intense debate. If there is causality from energy consumption to economic growth, then reductions in energy availability have significant welfare implications. As reported by the International Energy Outlook 2016 (IEO2016), economic growth, along with accompanying structural changes, strongly influences world energy consumption. As countries develop and living standards improve, energy demand grows rapidly. Renewable energy consumption has emerged as an energy source that may alleviate the growing concerns over greenhouse gas emission, high and volatile energy prices, and the dependency on foreign energy sources. As reported by the IEO2016, with the Clean Power Plan (CPP) regulations in the United States, U.S. renewable energy use in 2020 may be 7% higher than in the Reference case, and in 2040 it may be 37% higher than in the Reference case.

According to the U.S. Energy Information Administration in 2018, renewable energy sources accounted for about 10% of total U.S. energy consumption in 2016. The three most promising renewable markets (United States, China, and India) will account for two thirds of global renewable expansion up to 2022. Due to recent concerns about air pollution, China alone is responsible for over 40% of global renewable capacity growth. However, the recent uncertainty on energy policies could have implications for renewable energy consumption and production. Thus, the development of a sustainable energy pattern has brought renewable energy to the forefront of policy discussions. Based on country-specific studies, Sari and Soytas (2004), Ewing et al. (2007), Sari et al. (2008), Payne (2009; 2011), and Bowden and Payne (2010), among others, have found mixed results on the causality between renewable energy consumption and economic growth. On the other hand, Sadorsky (2009), Apergis and Payne (2010a,b), Apergis and Payne (2011), among others, have obtained a bi-directional causal relationship between the variables, using multi-country panel approaches.

The oil market is a strategic raw commodity market, as periods of high oil prices (oil shocks) are usually associated with recessions and inflationary pressures. Many research papers suggest a negative relationship between oil prices and economic growth (see e.g., Hamilton, 1983, 1996, 2003; Hooker, 1996, 2002; Huntington, 1998; Kim and Loungani, 1992; Mork, 1989, 1994; Timilsina, 2015). However, there is no consensus about the causal relationship between oil prices and economic growth. First, some studies rejected the effects of oil price shocks on economic growth in the U.S. due to a restrictive monetary policy (Bohi, 1991; Bernanke et al., 1997; Barsky and Kilian, 2001). Besides, oil prices have a different impact on each of the countries because of their use of alternative energy sources, their relative position as oil importer or exporter, and their tax structure. Finally, the recent literature displays a negative relationship between oil prices and economic growth decreasing over time due to governmental measures against oil price shocks (see e.g., Doroodian and Boyd, 2003; Jbir and Zouari-Ghorbel, 2009). The oil market also affects the profitability of the substitution of exhaustible energy resources with renewable energy resources (Kumar et al. 2012). It is important to study the relationship between oil prices and renewable energy consumption for evaluating investments in renewable energy resources during periods of high or low oil prices. Besides, understanding how oil prices affect renewable energy consumption allow policy makers to reduce public expenditures on finite fossil fuels when oil prices dynamics provide the necessary supply- or demand-side incentives to invest in renewable energy industry (Reboredo, 2015). Therefore, the dynamics between oil prices and renewable energy consumption has relevant policy implications for investors and governments. These dynamics between renewable energy consumption, oil prices, and economic growth motivate researchers to know exactly the relationship between these variables. The Granger-causality definition proposed by Granger (1969) is the fundamental concept for studying dynamic relationships between economic variables. Although the concept of Granger-causality is defined for the conditional distribution, the majority of papers have tested Granger-causality using conditional mean regression models in which the causal relations are linear. As a result, a conditional mean regression model cannot assess a tail causal relation or nonlinear causalities.

This paper analyzes the causal relationship between renewable energy consumption, oil prices, and economic activity in the United States from July 1989 to July 2016, considering all quantiles of the distribution. We apply the Granger-causality in quantiles test proposed by Troster (2016) that evaluates causal relations in all conditional quantiles of the distribution. Our main goal is to evaluate such a relation on each quantile of the distribution. Under this approach, we can discriminate between causality affecting the median and the tails of the conditional distribution. Besides, it provides a sufficient condition for Granger-causality when all quantiles are considered. The quantile regression approach provides a more detailed analysis of the entire conditional distribution than the conditional mean-regression analysis, which focuses only on a single part of the conditional distribution. In addition, a quantile causal relation may contrast with causality in the mean of the conditional distribution. While a relationship with mean-causality shifts at least a non-negligible number of quantiles, a tail causal relation does not necessarily imply causality in the mean. For example, Lee and Yang (2012) show that money-income Granger-causality in the conditional mean is weak and unstable, while it is significant in tail quantiles in most data sets. Rather than checking a necessary condition for Granger-causality, we analyze a continuum of quantile functions that fully characterizes the concept of Granger-causality in distribution. Then, our proposed empirical analysis provides a more complete description of the causal relation between the variables. This paper contributes to the existing literature by considering a detailed analysis of the relationship energy-growth nexus. The quantile regression approach allows us to determine whether extremely low or high changes in energy consumption or prices lead economic growth. Besides, we are able to analyze whether this relationship is asymmetric across the quantiles of the distribution. A detailed pattern of causality clarifies how to establish sustainable renewable energy policies.

To test for Granger-causality in quantiles between economic variables, some studies applied the Sup-Wald test proposed by Koenker and Machado (1999) on the coefficients of a quantile regression model (see e.g., Chuang et al., 2009; Bastianin et al., 2014; Sim and Zhou, 2015). However, the method of Troster (2016) requires only a model for the marginal quantile regression (under the null hypothesis that there is no Granger-causality), and then it searches for rejections of the null hypothesis in every direction; on the other hand, the Sup-Wald test requires a particular model specification for the quantile regression under the alternative hypothesis of Granger-causality. In addition, the method of Troster (2016) is consistent over a range of quantiles, and it allows for nonlinear specifications of the quantile regression model. Our empirical analysis reveals no Granger-causality between variations in oil prices, economic activity, and renewable energy consumption considering all quantiles of the distribution. However, we find evidence of bi-directional causality between changes in renewable energy consumption and economic growth at the lowest quantiles of the distribution; besides, there is also unidirectional causality running from changes in renewable energy consumption to economic growth at the highest quantiles of the distribution. Our findings also support the unidirectional causality from changes in oil prices to economic growth at the extreme quantiles of the distribution. Finally, we report evidence of lower-tail causality running from oil price changes to changes in renewable energy consumption.

Our results suggest that negative shocks in oil prices affect the consumption of renewable energy resources, but the oil price behavior provides inadequate incentives to affect renewable energy consumption when oil prices are high. We also found evidence of lower-tail causality from large decreases in economic activity to changes in renewable energy consumption. Thus, economic growth provides asymmetric incentives to develop renewable energy consumption in the U.S. During periods of recessions, renewable energy consumption can increase without the need of energy policies. However, our results call for green energy policies during economic expansions periods. Therefore, policy makers need to consider the asymmetric causality from changes in oil prices and economic activity to renewable energy consumption changes to develop a sustainable energy system. Our results also provide the direction of causality from renewable and nonrenewable energy consumption to economic activity in the United States at different quantile levels. This implies that the sources of energy consumption including renewable versus non-renewable energy consumption are sensitive to economic activity in the United States. The results of this paper are important because energy conservation policies may affect economic activity. The tail dependence from changes in renewable energy consumption to economic growth suggests that energy policies such as tax credits for energy production, renewable energy portfolio standards, and installation of renewable energy systems affect economic growth. However, this relationship is asymmetric. Large decreases in renewable energy consumption (at the lowest quantile of the distribution) reduce economic growth. On the other hand, large increases in renewable energy consumption (at the highest quantile of the distribution) contribute to economic growth. Thus, policy makers need to consider this asymmetric effect to implement sustainable energy policies.

The rest of the paper is organized as follows. In Section 2, we provide a literature review on the panel and time series analyses on the renewable energy-economic growth nexus. We also present a review of the literature on the causal relation between oil prices and economic growth. In Section 3, we describe the econometric methodology. Section 4 discusses the empirical analysis, and Section 5 concludes the paper.

2. Related Literature Review

2.1. Panel Analysis on the Renewable Energy-Economic Growth Nexus

Existing literature on renewable energy consumption-economic growth causality is inconclusive across sample periods, sample sizes, and model specifications. Yu and Choi (1985) found no causal relationship between energy consumption and gross domestic product (GDP) for the U.K., the U.S., and Poland. However, there is Granger-causality from energy consumption to GDP for the Philippines, and from GDP to energy consumption for South Korea. Erol and Yu (1987) found mixed results for six industrialized countries over the period 1952-1982. Masih and Masih (1996) also found mixed results for the Granger-causality between total energy consumption and real income of six Asian economies, from 1955 to 1990.

Soytas and Sari (2003) reconsidered the causal relationship between energy consumption and GDP in the top 10 emerging markets (excluding China due to lack of data) and G-7 countries, from 1950 to 1992. They observed bi-directional causality in Argentina, causality running from GDP to energy consumption in Italy and Korea, and from energy consumption to GDP in Turkey, France, Germany, and Japan. Lee (2005) employed data on 18 developing countries from 1975 to 2001. His evidence suggests that there is unidirectional Granger causality from energy consumption to GDP. Using the Toda and Yamamoto (1995) Granger causality test in the G-11 countries, Lee (2006) found bi-directional causality in the United States and unidirectional running from energy consumption to GDP in Canada, Belgium, the Netherlands, and Switzerland.

Lee and Chang (2007) and Mahadevan and Asafu-Adjaye (2007) also found evidence of bi-directional causality between economic growth and energy consumption for a set of developed countries over the period 1971-2002. Using panel data of energy consumption and GDP for 82 countries from 1972 to 2002, Huang et al. (2008) found unidirectional Granger-causality from economic growth to energy consumption for middle- and high-income countries. Narayan and Smyth (2008) also found the same pattern of causality in a panel of G-7 countries from 1972 to 2002. However, Lee et al. (2008) found bi-directional causal linkages between energy consumption and economic growth for a set of 22 countries of the Organization for Economic Co-operation and Development (OECD) using annual data covering the period 1960-2001.

Sadorsky (2009) explored the relationship between renewable energy consumption using data of 18 emerging countries over the period 1994-2003. He applied ordinary least squares (OLS), fully modified least squares (FMOLS), dynamic ordinary least squares (DOLS), and Granger-causality approaches within a bivariate framework. The empirical results indicate that renewable energy consumption is positively linked with income; however, there is causality running from income to renewable energy consumption in the short-run. Similarly, Apergis and Payne (2010a) examined the relationship between renewable energy consumption and economic growth for a panel of twenty OECD countries over the period 1985-2005 using panel cointegration and error-correction model. Their results show a long-run equilibrium relationship and bidirectional causality between renewable energy consumption and economic growth. Using bootstrap Granger non-causality tests for G-7 countries over the period 1960-2006, Balcilar et al. (2010) found that there is predictive power from energy consumption to economic growth only for Canada; however, the results from the bootstrap rolling window estimation showed no causality between the series under consideration. Apergis and Payne (2010b) used an augmented production function by incorporating renewable energy consumption for 13 countries within Eurasia over the period 1992-2007. They found bidirectional causality between renewable energy consumption and economic growth. Apergis and Payne (2011) also found evidence of bidirectional causality between renewable energy consumption and economic growth in a panel of six Central American countries over the period 1980-2006.

Menegaki (2011) examined the causal relationship between economic growth and renewable energy for 27 European countries over the period 1997-2007; his results rejected causality between renewable energy consumption and GDP, although panel causality tests unfolded a short-run relation between renewable energy consumption, greenhouse gas emissions, and employment. Apergis and Payne (2012) applied a multivariate panel approach including 80 countries over the period 1990-2007; they found bidirectional causality between renewable energy consumption and economic growth in both short and long run. Marques and Fuinhas (2012) analyzed the role of different energy sources in economic growth for a set of 24 European countries (1990–2007). Their results suggest that the negative effect of the use of renewable energy supplants the positive effect of creating income, and thus economic growth does not appear to improve with the change towards renewable energy. Using panel data for upper middle income, lower middle-income, and high-income countries, Al-Mulali et al. (2013) found a bi-directional long-run relationship between renewable energy consumption and economic growth via the FMOLS. They concluded that 79% of the countries have a positive bi-directional long-run relationship between renewable energy consumption and economic growth whereas 19% of the countries have neutral effect between the variables. Ohler and Fetters (2014) considered the electricity generation from different sources of renewable energy (biomass, geothermal, hydroelectric, solar, waste, and wind) for a set of 20 OECD countries, over 1990 to 2008, via a panel error-correction model. They found a bidirectional relationship between aggregate renewable generation and real GDP. Aïssa et al. (2014) collected data for 11 African countries to examine association between renewable energy consumption and economic growth by applying a panel Granger causality test. They found that economic growth Granger-causes renewable energy consumption. Al-mulali et al. (2014) applied the Pedroni cointegration test (Pedroni, 1999, 2004) and the Vector Error-Correction (VEC) causality test for a set of Latin American countries, to examine linkages between renewable energy consumption and economic growth. They noted that renewable electricity consumption is more significant than non-renewable electricity consumption in promoting economic growth in the investigated countries in the long and short run. Their empirical analysis also indicated the presence of bidirectional causal relationship between renewable energy consumption and economic growth.

Using a multivariate panel vector error correction model for 1990-2010 data for a set of 31 OECD countries and 49 non-OECD countries, Cho et al. (2015) showed that the hypothesis of unidirectional causality running from economic growth to renewable energy consumption is valid in the long run for OECD countries, and the bidirectional causality, for non-OECD countries. Jebli and Youssef (2015) investigated the association between renewable energy consumption and economic growth for a set of 69 developing countries over the period 1980-2010. Their empirical results indicated that renewable energy consumption plays a vital role in stimulating economic output. Chang et al. (2015) examined the causal relationship between renewable energy consumption and economic growth across G-7 countries using annual data for the period of 1990-2011. Their results support the existence of a bi-directional causal relationship between economic growth and renewable energy for the overall panel. However, country specific results are inconclusive. Bhattacharya et al. (2016) found that renewable energy consumption has a significant and positive impact on economic output for 57% of 38 top renewable energy-consuming countries from 1991 to 2012. Cetin (2016) also observed a positive impact of renewable energy consumption on economic growth in E-7 (Emerging Seven) countries over the period 1992-2012. Destek (2016) applied an asymmetric causality test to examine relationship between renewable energy consumption and economic growth in newly industrialized countries from 1971 to 2011. They noted that a negative shock in renewable energy consumption leads to a positive (negative) shock in real GDP for South Africa and Mexico (India), but a neutral effect also exists for Brazil and Malaysia. Kahia et al. (2016) examined the impact of renewable (non-renewable) energy consumption on economic growth in net oil exporting countries in the Middle East and North Africa (MENA) region by applying a FMOLS method. They found that renewable (nonrenewable) energy consumption adds in economic growth. Tugcu and Tiwari (2016) used Total Factor Productivity (TFP) as a measure of economic activity to examine the association between economic growth and renewable energy consumption; they used data of Brazil, Russia, India, China, and South-Africa (BRICS) from 1992 to 2012. Their results show that no remarkable causal link exists between renewable energy consumption and TFP growth in the BRICS.

Recently, Koçak and Sarkgünesi (2017) collected data for Black Sea and Balkan countries (1990-2012) to explore the link between renewable energy consumption and economic growth.

For this purpose, they applied the Pedroni panel cointegration test (Pedroni, 1999, 2004) and the Dumitrescu and Hurlin (2012) heterogeneous panel causality test. They concluded that there is a long-run cointegration relationship between the variables, and renewable energy consumption has a positive impact on economic growth. The heterogeneous causality analysis supports unidirectional causality running from renewable energy consumption to economic growth in Bulgaria, Greece, Macedonia, Russia, and Ukraine. They also found bidirectional causality between both variables in Albania, Georgia, and Romania. Furthermore, Narayan and Doytch (2017) found no evidence that residential renewable energy is a driver of economic growth or vice versa for income panels over the period 1971 to 2011. Only renewable totals in low and lower middle income countries are found to drive economic growth. Liu et al. (2017) investigated the impact of renewable energy on output with a sample of 15 Asia-Pacific countries for the period of 1994-2014. Long-run causality tests report the evidence of bidirectional causality between output and renewable energy consumption.

2.2. Time Series Analysis on the Renewable Energy-Economic Growth Nexus

Existing papers on renewable energy consumption-economic growth nexus also found mixed results using time series for specific country studies. Using linear and non-linear Granger causality tests for yearly data from 1954 to 2006, Chiou-Wei et al. (2008) found no causality between energy consumption and economic growth for the U.S., Thailand, and South Korea, although they found unidirectional causality from economic growth to energy consumption for the Philippines and Singapore. Pao and Fu (2013) used multivariate production function to investigate the association between renewable energy, non-renewable energy consumption, and economic growth in Brazil (1980-2010) by applying Johansen's cointegration test. They found that cointegration exists between the variables and feedback exists between renewable (non-renewable) energy consumption and economic growth. Lin and Moubarak (2014) applied the Autoregressive Distributed Lag (ARDL) approach to cointegration in China for the period 1977-2011. They found that there is bi-directional long-term causality between renewable energy consumption and economic growth in China. Marques et al. (2014) concluded that there is no evidence of causal relationships from renewable electricity consumption to economic growth, either in the short- or long-run, in Greece from August 2004 to October 2013. Shahbaz et al.

(2015) tested the role of renewable energy consumption in promoting economic growth by incorporating capital and labor as potential determinants of production function in Pakistan (1972–2011). They found bidirectional causality between renewable energy consumption and economic growth. These empirical findings are similar to Shahbaz et al. (2012), who investigated the relationship between renewable energy consumption and economic growth in Pakistan (1972–2011) using the ARDL bounds testing and Gregory and Hansen (1996) structural break cointegration approaches.

Ibrahiem (2015) used the ARDL bound testing approach to assess the linkage between renewable electricity consumption and economic growth in Egypt over the period from 1980 to 2011. His empirical findings show that the variables are cointegrated and there is bidirectional causality between renewable electricity consumption and economic growth. Rafindadi and Ozturk (2017) investigated the impacts of renewable energy consumption on the German economic growth (1971-2013) by applying different cointegration tests. They noted that renewable energy consumption increases economic growth and feedback effect exists between both variables. Shakouri and Khoshnevis Yazdi (2017) examined the causal link between economic growth, renewable energy consumption, energy consumption, capital fixed formation, and trade openness in South Africa over the period 1971-2015. Their empirical findings show that there exists bidirectional causality between renewable energy consumption and economic growth.

2.3. The Renewable Energy-Economic Growth Nexus in the USA

Existing studies investigating the association between renewable energy consumption and economic growth for the U.S. economy are handful but with mixed findings. The seminal paper of Kraft and Kraft (1978) demonstrated the existence of Granger-causality running from real GDP to energy consumption in the U.S. for the postwar period from 1947 through 1974. On the other hand, Akarca and Long (1979) support the unidirectional causality running from energy consumption to economic growth in the U.S. covering the period January 1973-March 1978. However, Akarca and Long (1980) found no causality between energy consumption and economic growth in the U.S. Yu and Hwang (1984), Yu and Jin (1992), and Cheng (1995) also found no causality between GDP and energy consumption in the U.S. for the periods 1947-1979, 1974-1990, and 1947-1990, respectively. On the other hand, Abosedra and Baghestani (1989) found evidence of unidirectional causality from GDP to energy consumption in the U.S., for the period 1947-1987. Ewing et al. (2007) investigated the effect of disaggregate energy consumption on industrial output in the U.S. They noted that unexpected shocks to coal, natural gas, and fossil fuel energy sources have the highest impacts on the variation of output, while other renewable sources are significant to output as well.

Bowden and Payne (2009) examined the relationship between energy consumption and real GDP in the U.S. from 1949 to 2006 using a disaggregated analysis. They found bidirectional Granger-causality between commercial and residential primary energy consumption and real GDP; however, Granger-causality is absent between total and transportation primary energy consumption and real GDP. Payne (2009) re-examined the causal relationship between renewable (and non-renewable) energy consumption and real GDP in the U.S. for annual data from 1949 to 2006 applying Toda and Yamamoto (1995) Granger causality tests. His results reveal the absence of Granger-causality between renewable or non-renewable energy consumption and real GDP. Payne and Taylor (2010) analyzed the relationship between nuclear energy consumption growth and real GDP growth within a neoclassical production function framework for the U.S. using annual data from 1957 to 2006. The Toda and Yamamoto (1995) test for long-run Granger-causality reveals the absence of Granger-causality between nuclear energy consumption growth and real GDP growth. Gross (2012) investigated the causality between energy consumption and economic growth in the U.S. for the period from 1970 to 2007 for three sectors, industry, commercial sector, transport, as well as on the macro level. Using the ARDL bounds testing approach, he found evidence for unidirectional long-run Granger causality in the commercial sector from growth to energy, as well as evidence for bi-directional long-run Granger causality in the transport sector. Hatemi-J and Uddin (2012) re-examined the causal nexus of energy use and GDP per capita in the U.S. for the period from 1960 to 2007 using an asymmetric causality test. Their empirical results reveal that negative energy consumption shocks cause negative shocks in output per capita.

Tiwari (2014) analyzed the relationship between energy consumption and economic growth for the U.S. economy (1973-2011) using an asymmetric Granger-causality test. He found evidence of bidirectional Granger-causality between renewable energy consumption and economic growth. Recently, Carmona et al. (2017) reconsidered the energy-growth nexus in the U.S. over the period 1973-2015. Their Granger-causality tests reveal that energy consumption cycles cause output cycles and vice versa. Dogan and Ozturk (2017) investigated the impact of real income, renewable energy consumption, and non-renewable energy consumption on carbon emissions for the US over the period of 1980-2014. Their results suggest that increases in renewable energy consumption leads economic growth and mitigate environmental degradation in the US. Using U.S. state-level data for 2010, Squalli (2017) explored the causal links between renewable energy production and carbon emissions. The empirical results reveal that a 10% increase in the share of renewable energy could decrease carbon emissions by 0.26% after controlling for other sources of emissions. Shahbaz et al. (2017b) showed that economic growth causes biomass energy consumption and similar is true from opposite side.

2.4. Oil Prices and Economic Growth

Many research papers suggest that oil price shocks affect output and inflation (see e.g., Hamilton, 1983, 1996, 2003; Hooker, 1996, 2002; Huntington, 1998; Kim and Loungani, 1992; Mork, 1989, 1994). However, there is no consensus about the causal relationship between oil prices and economic growth. Darby (1982) found no significant relationship between oil prices and real GDP, in the U.S. and other developed countries over the period 1957-1976; however, when the effects of exports, exchange rates, and money are considered, there is a significant relationship between oil prices and GDP. Hamilton (1983) observed a causal relationship between oil price changes and economic growth using post-war data in the U.S. Burbidge and Harrison (1984) and Gisser and Goodwin (1986) confirmed the findings of Hamilton (1983) in the U.S. over the period 1961-1982, although the results for other countries are diverse. Mork (1989) verified that the causality between oil prices and economic growth breaks down (1949-1988) if the analysis includes data from the oil price decline of 1986. He showed that the coefficients on oil price increases are negative and statistically significant, whereas the coefficients on oil price declines are positive, but small and not statistically significant. However, Lee et al. (1995) and Hamilton (1996) suggested that this breakdown of oil prices-economic growth relationship displays a nonlinear relation between these variables. They proposed different nonlinear specifications of this relationship.

Mory (1993) also presented evidence of an asymmetric effect of oil prices spikes in the U.S. economy over the period 1951-1990. Mork et al. (1994) investigated the relation between oil-prices movements and GDP fluctuations for the U.S., Canada, Japan, Germany, France, the U.K., and Norway over the period 1967-1992. They found that the U.S. and other five OECD countries experienced a negative relationship between oil prices increases and economic growth. His results show that oil prices increases may generate reductions in economic activities. Hooker (1996) found strong evidence that oil prices do not Granger-cause economic growth in the U.S. after 1973. Nevertheless, Hamilton (1996) restored a significant relationship between oil prices and economic growth (1948-1994) by introducing the concept of net oil prices increase in a VAR model for the U.S. economy.

Other studies rejected the effects of oil prices shocks on economic growth in the U.S. due to a restrictive monetary policy. Bohi (1991) found no statistical relationship between oil prices shocks on the business cycle of four countries (Germany, Japan, the U.K., and the U.S.) over the period 1966-1986. He argues that the restrictive monetary policy is responsible for much of the decline in GDP in the years following an oil price shock. Bernanke et al. (1997) supported these results, using a VAR model in the U.S. over the period 1965-1995. Barsky and Kilian (2001) also suggest that the economic crisis observed in the 1970s was mainly a monetary phenomenon. However, Balke et al. (2002), and Hamilton and Herrera (2004) showed that the monetary policy alone cannot account for the real effects of oil prices declines in the U.S. from 1970 to 2000. Other papers analyzed the relationship between oil prices and economic growth using advanced non-linear econometric methods. Raymond and Rich (1997), Clements and Krolzig (2002), Holmes and Wang (2003), and Cologni and Manera (2009) applied the Markov-switching approach to evaluate the impact of oil shocks on GDP in the U.S. and G-7 countries. Huang et al. (2005) used a multivariate threshold model to investigate the impacts of an oil price change and its volatility on economic activities for monthly data of the U.S., Canada, and Japan from 1970 to 2002.

Other studies analyzed the relationship between oil prices and economic growth for other countries than the U.S. Cuñado and Pérez de Gracia (2003) showed that oil prices have permanent effects on inflation and asymmetric effects on production growth rates for a set of European countries using quarterly data for the period 1960-1990. Jiménez-Rodríguez and Sánchez (2005) and Cologni and Manera (2008) performed multivariate VAR analyses for some OECD countries and for the G-7 countries, respectively. Jiménez-Rodríguez and Sánchez (2005) found evidence of a non-linear impact of oil prices on real GDP for the period 1972-2001; Cologni and Manera (2008) found a negative relationship between oil prices and economic growth (1980-2003) taking into account the reaction of monetary variables to external shocks. Lardic and Mignon (2006) analyzed the long-term relationship between oil prices and GDP in 12 European countries for 1970-2003. Their results provide evidence for asymmetric cointegration between oil prices and GDP in the majority of the considered European countries while standard cointegration is rejected. Kilian (2008) showed that there is no evidence that the 1973-1974 and 2002-2003 oil supply shocks had a substantial impact on real growth in any G-7 country; on the other hand, the 1978-1979, 1980, and 1990-1991 shocks contributed to lower growth in at least some G-7 countries. Mehrara (2008) and Jayaraman and Choong (2009) examined the relationship between oil prices and economic growth for oil-exporting and oil-importing economies, respectively. They found that output growth is adversely affected by negative oil shocks. Özlale and Pekkurnaz (2010) and Tang et al. (2010) also found that oil prices shocks negatively affect economic growth for the Turkish and Chinese economy, respectively.

Timilsina (2015) and Ftiti et al. (2016) reexamined the relationship between oil prices and economic growth for 25 economies and selected OPEC countries, respectively. They found that oil price increases strengthen the economy of oil-exporting countries while there is a significant negative effect of oil price on GDP for oil-importing economies. Sarwar et al. (2017) used panel data of 210 countries over the period 1960-2014 to analyze the empirical relationship between economic growth and oil prices. The results of full panel confirm a bidirectional relationship between oil prices and GDP. Finally, Shahbaz et al. (2017a) employed data from 157 countries from 1960 to 2014 to analyze the relationship between economic growth and oil prices. The empirical results indicate the presence of cointegration between the variables; moreover, there is bidirectional causality between oil prices and economic growth.

3. Econometric Methodology

We apply the following methods in our analysis. First, we test if the variables follow a unit process through different procedures. Then, we test whether the quantiles of the distribution follow a unit root process using the quantile autoregression unit root test proposed by Koenker and Xiao (2004) and Galvao (2009). Once the null hypothesis of a unit root is not rejected, we apply the linear cointegration test of Johansen (1991, 1995) to verify whether there is a cointegration relationship between the variables. We also test the null hypothesis of constant cointegrating coefficients by applying the quantile cointegration test proposed by Xiao (2009). Finally, we apply the test for Granger-causality in quantiles proposed by Troster (2016).

3.1. Unit Root Tests and Cointegration: Linear and Nonlinear Analysis

We apply the Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979), the Zivot and Andrews (1992) test (ZA), and the Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS) test of Elliott et al. (1996), to verify whether the series have a unit root. The ADF-GLS test is an efficient version of the ADF test statistic; we select the optimal lag order of the endogenous variable that minimizes the Modified Akaike Information Criterion (MAIC) of Ng and Perron (2001). The ZA unit root test allows for the possibility of an endogenous structural break. Besides, we also test whether the series are stationary through the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test of Kwiatkowski et al. (1992).

We also apply quantile autoregression unit root tests to verify the stationarity of each series not only on the conditional mean, but also at each quantile of the conditional distribution. Koenker and Xiao (2004) proposed the quantile auto-regressive (QAR) unit root tests; Galvao (2009) generalized their method by including covariates and a linear time trend into the QAR model. Let $\mathrm{Y_t}$ be a strictly stationary time series process with a past information set $\mathrm{I_t^Y} \coloneqq (\mathrm{Y_{t-1}}, \dots, \mathrm{Y_{t-s}})' \in \mathbb{R}^s$, where A' denotes the transpose matrix of A. Let $F_Y(\cdot\,|\mathrm{I_t^Y})$ be the conditional distribution function of $\mathrm{Y_t}$ given $\mathrm{I_t^Y}$. We perform the quantile autoregressive unit root test based on the following quantile linear regression model:

$$Q_\tau^Y(Y_t|I_t^Y) = \mu_1(\tau) + \mu_2(\tau)t + \alpha(\tau)Y_{t-1} + \sum_{j=1}^{p} \alpha_j(\tau)\Delta Y_{t-j} + F_u^{-1}(\tau), \quad (1)$$

where $Q_\tau^Y(\cdot\,|I_t^Y)$ is the τ-quantile of $F_Y(\cdot\,|I_t^Y)$, $\mu_1(\tau)$ is a drift term, t is a linear trend, $\alpha(\tau)$ is the persistence parameter, and F_u^{-1} is the inverse conditional distribution of the errors, for each quantile $\tau \in \mathcal{T} \subset [0,1]$. Thus, we estimate a different persistence parameter ($\hat{\alpha}$) for each quantile of the conditional distribution of $\mathrm{Y_t}$. We test the null hypothesis H_0: $\alpha(\tau) = 1$ by applying the *t*-statistic proposed by Koenker and Xiao (2004) and Galvao (2009) at different quantiles $\tau \in \mathcal{T}$.

Recently, Li and Park (2016) combined the nonlinear unit root test of Kapetanios et al. (2003) with the quantile unit root test of Koenker and Xiao (2004) to enable nonlinearity and asymmetric mean reversion at different quantiles. Bahmani-Oskooee et al. (2018) applied the nonlinear quantile unit root test of Li and Park (2016) for testing the purchasing power parity hypothesis across 29 African countries. We could also consider applying the nonlinear quantile unit root test of Li and Park (2016), but unreported results show that our findings remain unchanged. Thus, to save space, we omit the results of the nonlinear quantile unit root tests. We further apply the linear cointegration test of Johansen (1991, 1995), to verify whether the series are cointegrated. This method tests the cointegration between each pair of series through a vector error-correction model (VECM) as follows:

$$\mathrm{Y_t} = \alpha + \beta Z_t + \sum_{j=1}^{p} \Pi_j\, Y_{t-j} + \sum_{j=1}^{q} \gamma_j\, Z_{t-j} + u_t,$$

where $\mathrm{Y_t}$ and $\mathrm{Z_t}$ are integrated of order 1, and u_t is stationary in level. We select the lag lengths of the VECMs that minimize the Akaike information criteria (AIC) allowing for a maximum lag length of 18 months.

Many empirical applications in finance and economics suggest that the cointegrating vector changes over the distribution; thus, we apply the quantile cointegration test proposed by Xiao (2009). The quantile cointegration model can capture systematic influences of conditioning variables on the location, scale, and shape of the conditional distribution of the response variable. Following Saikkonen (1991), Xiao (2009) decomposes the errors of the cointegrating equation into lead-lag terms and a pure innovation component, to deal with the endogeneity in standard cointegration models. Thus, the quantile cointegration model includes the traditional cointegration model of Engle and Granger (1987) as special case where $\beta(\tau)$ is a vector of constants. In this special case, we have:

$$Y_t = \alpha + \beta' Z_t + \sum_{j=-K}^{K} \Delta Z'_{t-j} \Pi_j + u_t,$$

and

$$Q_\tau^Y(Y_t | I_t^Y, I_t^Z) = \alpha(\tau) + \beta(\tau)' Z_t + \sum_{j=-K}^{K} \Delta Z'_{t-j} \Pi_j + F_u^{-1}(\tau). \quad (2)$$

We also include a quadratic term of the regressor in the quantile cointegration model as follows:

$$Q_\tau^Y(Y_t | I_t^Y, I_t^Z) = \alpha(\tau) + \beta(\tau)' Z_t + \gamma(\tau)' Z_t^2 + \sum_{j=-K}^{K} \Delta Z'_{t-j} \Pi_j + \sum_{j=-K}^{K} \Delta Z^{2\prime}_{t-j} \Gamma_j + F_u^{-1}(\tau). \quad (3)$$

Xiao (2009) derived a test of the stability of the cointegrating coefficients in equation (3). Under the null hypothesis that H_0: $\beta(\tau) = \beta$ over all quantiles τ, he proposed a supremum norm of the absolute value of the difference $\widehat{V_n}(\tau) = \left(\hat{\beta}(\tau) - \hat{\beta}\right)$ as a test statistic. Thus, we apply the test statistic $\sup_\tau \left|\widehat{V_n}(\tau)\right|$ over all quantiles of the distribution. Following Xiao (2009), we perform 1,000 Monte Carlo simulations to calculate the critical values of the test statistic $\sup_\tau \left|\widehat{V_n}(\tau)\right|$.

3.2. Granger-Causality in Mean and in Quantiles

According to Granger (1969), a series Z_t does not Granger-cause another series Y_t if past Z_t does not help to predict future Y_t, given the past Y_t. Suppose there is an explanatory vector $I_t \equiv (I_t^Y, I_t^Z)' \in \mathbb{R}^d$, $d = s + q$, where I_t^Z is the past information set of Z_t, $I_t^Z :=$

$\left(\mathrm{Z}_{t-1},\ldots,\mathrm{Z}_{t-q}\right)' \in \mathbb{R}^{q}$. We define the null hypothesis of Granger non-causality from $\mathrm{Z_t}$ to $\mathrm{Y_t}$ as follows:

$$H_0^{Z\nrightarrow Y}: F_Y(y\left|I_t^Y, I_t^Z\right) = F_Y(y|I_t^Y), \text{ for all } y \in \mathbb{R}, \tag{4}$$

where $F_Y(\cdot\left|\mathrm{I}_t^Y, \mathrm{I}_t^Z\right)$ is the conditional distribution function of Y_t given $(\mathrm{I}_t^Y, \mathrm{I}_t^Z)$. We denote the null hypothesis of equation (4) as Granger non-causality in distribution. Since the estimation of the conditional distribution may be complicated, many papers have proposed tests for Granger non-causality in mean, which is only a necessary condition for equation (4). In this case, $\mathrm{Z_t}$ does not Granger cause $\mathrm{Y_t}$ in mean if

$$\mathrm{E}(Y_t\left|I_t^Y, I_t^Z\right) = \mathrm{E}(Y_t|I_t^Y), \text{ a.s.}, \tag{5}$$

where $\mathrm{E}(Y_t\left|I_t^Y, I_t^Z\right)$ and $\mathrm{E}(Y_t|I_t^Y)$ are the means of $F_Y(\cdot\left|I_t^Y, I_t^Z\right)$ and $F_Y(\cdot|I_t^Y)$, respectively. Granger non-causality in mean of equation (5) can be easily extended to higher order moments (see e.g. Cheung and Ng, 1996). However, causality in mean (or in higher moments) ignores the possibly dependence in the conditional tails of the distribution. On the other hand, the null hypothesis of Granger non-causality distribution of equation (4) does not inform us about the level of the causality if equation (4) is rejected. Thus, we test for Granger non-causality in conditional quantiles, since it determines the pattern of causality and provides a sufficient condition for testing the null hypothesis in equation (4), as the quantiles fully characterize a distribution. Let $Q_\tau^{Y,Z}(\cdot\,|I_t^Y, I_t^Z)$ be the τ-quantile of $F_Y(\cdot\left|I_t^Y, I_t^Z\right)$, we can rewrite equation (4) as follows:

$$H_0^{QC:Z\nrightarrow Y}: Q_\tau^{Y,Z}(Y_t\left|I_t^Y, I_t^Z\right) = Q_\tau^{Y}(Y_t|I_t^Y), \text{ a.s. for all } \tau \in \mathcal{T}, \tag{6}$$

where $\mathcal{T}$ is a compact set such that $\mathcal{T} \subset [0,1]$, and the conditional τ-quantiles of $\mathrm{Y_t}$ satisfy the following restrictions:

$$\Pr\{\mathrm{Y_t} \le Q_\tau^Y(Y_t|I_t^Y)|I_t^Y\} := \tau, \text{ a.s. for all } \tau \in \mathcal{T},$$

$$\Pr\{\mathrm{Y_t} \le Q_\tau^{Y,Z}(Y_t|I_t^Y, I_t^Z)|I_t^Y, I_t^Z\} := \tau, \text{ a.s. for all } \tau \in \mathcal{T}. \quad \textbf{(7)}$$

Given an explanatory vector I_t, then $\Pr\{\mathrm{Y_t} \le Q_\tau(Y_t|I_t)|I_t\} = E\{1[\mathrm{Y_t} \le Q_\tau(Y_t|I_t)]|I_t\}$, where $1[\mathrm{Y_t} \le \mathrm{y}]$ is an indicator function of the event that $\mathrm{Y_t}$ is less than or equal to *y*. Thus, the null hypothesis of Granger non-causality in equation (6) is equivalent to:

$$E\{1[\mathrm{Y_t} \le Q_\tau^{Y,Z}(Y_t|I_t^Y, I_t^Z)]|I_t^Y, I_t^Z\} = E\{1[\mathrm{Y_t} \le Q_\tau^Y(Y_t|I_t^Y)]|I_t^Y\}, \text{ a.s. for all } \tau \in \mathcal{T}, \quad \textbf{(8)}$$

where the left-hand side of equation (8) is equal to the τ-quantile of $F_Y(\cdot\,|I_t^Y, I_t^Z)$ by definition. Following Troster (2016), we apply a parametric model to estimate the τ-th quantile of $F_Y(\cdot\,|I_t)$. We assume that $Q_\tau(\cdot\,|I_t)$ is correctly specified by a parametric quantile model $m(\cdot, \theta(\tau))$ belonging to a family of functions $\mathcal{M} = \{m(\cdot, \theta(\tau))|\theta(\cdot): \tau \mapsto \theta(\tau) \in \Theta \subset \mathbb{R}^p, \text{ for } \tau \in \mathcal{T} \subset [0,1]\}$. Then, under the null hypothesis in equation (8), the τ-conditional quantile, $Q_\tau^Y(\cdot\,|I_t^Y)$, is correctly specified by a parametric quantile model $m(I_t^Y, \theta_0(\tau))$ that uses only the restricted information set I_t^Y. We can rewrite the null hypothesis of non-Granger-causality in equation (8) as follows:

$$H_0^{Z \nrightarrow Y}: E\{1[\mathrm{Y_t} \le m(I_t^Y, \theta_0(\tau))]|I_t^Y, I_t^Z\} = \tau, \text{ a.s. for all } \tau \in \mathcal{T}, \quad \textbf{(9)}$$

versus

$$H_A^{Z \nrightarrow Y}: E\{1[\mathrm{Y_t} \le m(I_t^Y, \theta_0(\tau))]|I_t^Y, I_t^Z\} \ne \tau, \text{ a.s. for some } \tau \in \mathcal{T}, \quad \textbf{(10)}$$

where $m(I_t^Y, \theta_0(\tau))$ correctly specifies the true conditional quantile $Q_\tau^Y(\cdot\,|I_t^Y)$, for all $\tau \in \mathcal{T}$. We can rewrite equation (9) as $H_0^{Z \nrightarrow Y}: E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \le 0) - \tau]|I_t^Y, I_t^Z\} = 0$ almost surely, for all $\tau \in \mathcal{T}$. Then, we can characterize the null hypothesis equation (9) by a sequence of unconditional moment restrictions:

$$E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \le 0) - \tau]\exp(i\boldsymbol{\omega}' I_t)\} = 0, \text{ for all } \tau \in \mathcal{T}, \quad \textbf{(11)}$$

where $\exp(i\boldsymbol{\omega}' I_t) := \exp[i(\omega_1 (Y_{t-1}, Z_{t-1})' + \cdots + \omega_r (Y_{t-r}, Z_{t-r})')]$ is a weighting function, for all $\boldsymbol{\omega} \in \mathbb{R}^r$ with $r \leq d$, and $i = \sqrt{-1}$ is the imaginary root. The test statistic is a sample analog of $E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau] \exp(i\boldsymbol{\omega}' I_t)\}$:

$$v_T(\boldsymbol{\omega}, \tau) := \frac{1}{\sqrt{T}} \sum_{t=1}^{T} [1(Y_t - m(I_t^Y, \theta_T(\tau)) \leq 0) - \tau] \exp(i\boldsymbol{\omega}' I_t), \tag{12}$$

where θ_T is a $\sqrt{T}$-consistent estimator of $\theta_0(\tau)$, for all $\tau \in \mathcal{T}$. Then, we apply the test statistic proposed by Troster (2016):

$$S_T := \int_{\mathcal{T}} \int_{W} |v_T(\boldsymbol{\omega}, \tau)|^2 dF_{\boldsymbol{\omega}}(\boldsymbol{\omega}) dF_{\tau}(\tau), \tag{13}$$

where $F_{\boldsymbol{\omega}}(\cdot)$ is the conditional distribution function of a d-variate standard normal random vector, $F_{\boldsymbol{\tau}}(\cdot)$ follows a uniform discrete distribution over a grid of $\mathcal{T}$ in n equally spaced points, $\mathcal{T}_n = \{\tau_j\}_{j=1}^{n}$, and the vector of weights $\boldsymbol{\omega} \in \mathbb{R}^d$ is drawn from a standard normal distribution. The test statistic in equation (13) can be estimated using its sample analog. Let Ψ be a $T \times n$ matrix with elements $\psi_{i,j} = \Psi_{\tau_j}\left(Y_i - m\left(I_i^Y, \theta_T(\tau_j)\right)\right)$, where $\Psi_{\tau_j}(\cdot)$ is the function $\Psi_{\tau_j}(\varepsilon) := 1(\varepsilon \leq 0) - \tau_j$. Then, we apply the following test statistic:

$$S_T = \frac{1}{Tn} \sum_{j=1}^{n} |\psi'_{\cdot j} \boldsymbol{W} \psi_{\cdot j}|, \tag{14}$$

where $\boldsymbol{W}$ is the $T \times T$ matrix with elements $\boldsymbol{w}_{t,s} = \exp[-0.5(I_t - I_s)^2]$, and $\psi'_{\cdot j}$ denotes the j-th column of Ψ. We reject the null hypothesis of Granger non-causality in distribution (9) whenever we observe large values of S_T in equation (14). We use the subsampling procedure of Troster (2016) to calculate critical values for S_T in equation (14). Given our series $\{X_t = (\mathrm{Y_t}, \mathrm{Z_t})\}$ of sample size T, we generate $B = T - b + 1$ subsamples of size b (taken without replacement from the original data) of the form $\{X_i, \dots, X_{i+b-1}\}$. Then, the test statistic S_T in equation (14) is calculated for each subsample; we obtain p-values by averaging the subsample test statistics over the B subsamples. Following Sakov and Bickel (2000), we choose a subsample of size $b = [kT^{2/5}]$, where $[\cdot]$ is the integer part of a number, and k is a constant parameter.

To apply the S_T test in equation (14), we specify three different QAR models $m(\cdot)$, for all $\tau \in \mathcal{T} \subset [0,1]$, under the null hypothesis of non-Granger-causality in equation (9) as follows:

$$\begin{aligned}
&\text{QAR}(1)\text{: } m^1\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t\Phi_u^{-1}(\tau),\\
&\text{QAR}(2)\text{: } m^2\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \sigma_t\Phi_u^{-1}(\tau),\\
&\text{QAR}(3)\text{: } m^3\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \sigma_t\Phi_u^{-1}(\tau),
\end{aligned} \quad \textbf{(15)}$$

where the parameters $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_t)'$ are estimated by maximum likelihood in an equally spaced grid of quantiles, and $\Phi_u^{-1}(\cdot)$ is the inverse of a standard normal distribution function. To verify the sign of the causal relationship between the variables, we estimate the quantile autoregressive models in equation (15) including lagged variables of another variable. For simplicity, we present the results using only a QAR(3) model with the lagged values of the other variable as follows:

$$Q_\tau^Y(Y_t | I_t^Y, I_t^Z) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \beta(\tau)Z_{t-1} + \sigma_t\Phi_u^{-1}(\tau). \quad \textbf{(16)}$$

4. Empirical Analysis

We analyze the causal relationship between renewable energy consumption, oil prices, and economic activity in the U.S. economy. Our data consist of 331 monthly observations on oil prices (OP), U.S. industrial production index (IPI) measure of economic activity, and renewable energy consumption (R) over the period from January 1989 to July 2016. We obtained all series from Datastream.

Table 1 displays summary statistics and correlations of oil prices, economic activity, and renewable energy consumption. All correlations between the variables are positive and higher than 0.49. Besides, Jarque-Bera normality tests (Jarque and Bera, 1980) reject the null hypothesis of normality for each one of the series at the 1% significance level. This illustrates the applicability of the quantile regression analysis that is robust to non-normal skewness in estimation. Table 2 shows the results of the unit root tests for oil prices, economic activity, and renewable energy consumption. All series are nonstationary at the 1% significance level or higher. Besides, these results are robust to a possible endogenous structural break, as we apply the ZA unit root test. Thus, we perform our analysis on the log-difference of the series.

Table 1. Summary Statistics and Pairwise Correlations

	OP_t	IPI_t	R_t
Mean	45.73	88.90	583.91
Median	30.75	93.97	548.21
Std. Dev.	30.57	14.11	117.71
Skewness	0.83	-0.65	0.94
Kurtosis	2.37	1.96	2.95
Minimum	11.35	62.71	395.80
Maximum	133.88	106.69	922.07
Jarque-Bera	43.84	37.74	49.30
Probability	0.00	0.00	0.00
		Correlation Matrix	
OP_t	1.00	-	-
IPI_t	0.66	1.00	-
R_t	0.61	0.49	1.00

Note: The data consist of 331 monthly observations on oil prices (OP), U.S. industrial production index (IPI) measure of economic activity, and renewable energy consumption (R) from January 1989 to July 2016. We obtained all series from Datastream.

Table 2. Traditional Unit Root Analysis

	OP_t	IPI_t	R_t
ADF Test: Level	-2.72	-0.75	-1.54
ADF Test: 1st Diff.	**-10.68**	**-8.85**	**-15.48**
ZA Test: Level	-3.98	-3.43	-4.78
ZA Test: 1st Diff.	**-11.02**	**-6.66**	**-6.75**
ADF-GLS Test: Level	-2.68	-1.51	-0.90
ADF-GLS Test: 1st Diff.	**-9.34**	**-3.77**	**-16.87**
KPSS Test: Level	**0.47**	**1.12**	**0.98**
KPSS Test: 1st Diff.	0.07	0.11	0.02

Note: The oil prices, economic activity, and renewable energy consumption series are taken in natural logarithms. The null hypothesis is that the series has a unit root in the ADF (Dickey and Fuller, 1979), ZA (Zivot and Andrews, 1992), and ADF-GLS (Elliott et al., 1996) tests, whereas the series is stationary under the null hypothesis of the KPSS test (Kwiatkowski et al., 1992). Bold values denote rejection of the null hypothesis at the 1% significance level.

Table 3 displays the results of the quantile unit root test. It shows the persistence estimates and the t-statistics of the null hypothesis that $H_0: \alpha(\tau) = 1$ in equation (1) for the grid of 19 quantiles $\mathcal{T}$ = [0.05; 0.95]. We included 10 lags of the difference of the dependent variable to avoid serial correlation of the residuals. Oil prices and economic activity are non-stationary at the 5% significance level for all the quantiles of the conditional distribution. These results are in line with the results of the unit root tests in Table 2. The renewable energy consumption is also nonstationary at the lowest quantiles of the distribution. However, we reject the null hypothesis of unit root for the renewable energy consumption at the median and higher quantiles of the conditional distribution at the 5% significance level. We further apply the linear cointegration test of Johansen (1991, 1995), to verify whether the series are cointegrated. Table 4 shows that there is no linear cointegration between oil prices, renewable energy consumption, and economic activity at the 5% significance level.

Table 3. Quantile Autoregression Unit Root Analysis

τ	OP_t		IPI_t		R_t	
	$\hat{\alpha}$	t-statistic	$\hat{\alpha}$	t-statistic	$\hat{\alpha}$	t-statistic
0.05	0.996	-0.096	1.011	0.369	0.930	-1.108
0.10	0.988	-0.320	1.008	0.790	0.945	-0.978
0.15	0.994	-0.275	1.005	0.609	0.891	-1.960
0.20	0.991	-0.393	0.998	-0.274	0.891	-2.042
0.25	0.994	-0.288	0.996	-0.672	0.902	-1.953
0.30	1.007	0.381	0.994	-1.082	0.875	**-2.760**
0.35	0.981	-1.050	0.999	-0.144	0.848	**-3.517**
0.40	0.982	-1.081	0.995	-1.003	0.845	**-3.670**
0.45	0.976	-1.503	0.994	-1.231	0.855	**-3.560**
0.50	0.972	-1.879	0.994	-1.321	0.861	**-3.478**
0.55	0.973	-1.821	0.993	-1.574	0.847	**-3.939**
0.60	0.964	-2.565	0.996	-0.893	0.840	**-3.955**
0.65	0.961	-2.619	0.997	-0.516	0.839	**-3.848**
0.70	0.965	-2.266	0.994	-1.052	0.819	**-4.483**
0.75	0.980	-1.163	0.993	-1.231	0.821	**-4.188**
0.80	0.975	-1.528	0.996	-0.737	0.804	**-4.705**
0.85	0.960	-2.514	0.996	-0.720	0.795	**-4.808**
0.90	0.966	-1.678	0.994	-1.095	0.770	**-5.624**
0.95	0.938	-1.375	0.995	-0.460	0.757	**-3.975**

Note: This table displays the persistence estimates ($\hat{\alpha}$) and t-statistics of the quantile unit root test proposed by Koenker and Xiao (2004) and Galvao (2009). Bold values of t-statistics denote rejection of the null hypothesis $H_0: \alpha(\tau) = 1$ at the 5% significance level.

Table 4. Johansen Linear Cointegration Test

	Trace statistic H_0: rank=0 (15.41)	Max. eigenvalue statistic H_0: rank=0 (14.07)
OP_t vs. IPI_t	7.47	4.88
OP_t vs. R_t	8.09	5.32
IPI_t vs. R_t	4.70	4.37

Note: This table reports the linear cointegration test of Johansen (1991, 1995) for the logarithm of the oil price, economic activity, and renewable energy consumption. We selected the lag lengths of vector autoregressive models that minimize the AIC, allowing for a maximum lag length of 18 months. Numbers in parentheses next to H_0: rank = 0 represent the 5% critical values of the corresponding test statistic.

We apply the quantile cointegration test proposed by Xiao (2009) to verify whether the cointegration relationship between the variables changes over the distribution. As the renewable energy consumption series is stationary at the 5% level for all quantiles higher than τ = 0.25, we use an equally spaced grid of the five lowest quantiles, $\mathcal{T}$ = [0.05; 0.25], for the quantile cointegration analysis between renewable energy consumption and oil prices or economic activity. We include two lags and two leads of $(\Delta Z_t, \Delta Z_t^2)$ in the quantile cointegrating model in (3). Table 5 presents the results of the stability test of the coefficients of the quantile cointegration model in equation (3). In contrast to the results of the linear cointegration test in Table 4, we find evidence of a statistically non-linear cointegration relationship between the quantiles of oil prices, renewable energy consumption, and economic activity at the 1% significance level.

Table 5. Quantile Cointegration Test

Model	Coefficient	$\sup_\tau\left\|\widehat{V_n}(\tau)\right\|$	CV1	CV5	CV10
OP_t vs. IPI_t	β	**32630.50**	10286.49	8361.47	7094.76
	γ	**3685.03**	1041.44	685.60	516.65
OP_t vs. R_t	β	**17653.73**	2104.60	1368.62	1075.01
	γ	**1367.67**	159.27	91.10	66.97
IPI_t vs. R_t	β	**4500.36**	494.68	317.36	6.08
	γ	**338.10**	37.67	23.09	17.09

Note: This table presents the results of the quantile cointegration test of Xiao (2009) for the logarithm of the oil price (OP), economic activity (IPI), and renewable energy consumption (R). We test the stability of the coefficients β and γ in the quantile cointegration model (3). CV1, CV5, and CV10 are the critical values of statistical significance at 1%, 5%, and 10%, respectively. We use 1,000 Monte Carlo simulations to generate the critical values. We use an equally spaced grid of 19 quantiles, [0.05; 0.95], to calculate the test statistic of the quantile cointegration model between oil prices (OP) and economic activity (IPI). We use an equally spaced grid of 5 tail quantiles, [0.05; 0.25], to calculate the test statistic between renewable energy consumption (R) and oil prices (OP) or economic activity (IPI). Bold values denote rejection of the null hypothesis at the 1% significance level.

Table 6 reports the estimated cointegrating coefficients $\hat{\beta}(\tau)$ and $\hat{\gamma}(\tau)$ of the quantile cointegrating model in (3). The estimated coefficients of the model between oil prices and economic activity are negative and statistically significant at the 1% level for all quantiles below or equal to $\tau = 0.80$. Besides, the estimated coefficients increase with the quantiles of the distribution. Table 6 also suggests a non-linear cointegrating relationship between oil prices and renewable energy consumption; all the estimated coefficients are negative for all quantiles of the distribution. However, the coefficients of the cointegrating model between economic activity and renewable energy consumption are not significant at the 1% level, for all quantiles lower or equal to $\tau = 0.25$.

Table 6. Quantile Cointegration Model: Estimated Coefficients

τ	OP_t vs. IPI_t		OP_t vs. R_t		IPI_t vs. R_t	
	$\beta(\tau)$	$\gamma(\tau)$	$\beta(\tau)$	$\gamma(\tau)$	$\beta(\tau)$	$\gamma(\tau)$
0.05	-131.09***	15.06***	-42.06*	3.37*	1.72	-0.06
0.10	-119.16***	13.72***	-50.08***	4.00***	5.86*	-0.38
0.15	-114.04***	13.16***	-50.10***	4.02***	4.63	-0.29
0.20	-101.03***	11.69***	-49.97***	4.02***	5.06	-0.33
0.25	-104.25***	12.07***	-52.38***	4.23***	3.41	-0.20
0.30	-107.95***	12.50***	-	-	-	-
0.35	-108.28***	12.55***	-	-	-	-
0.40	-106.19***	12.32***	-	-	-	-
0.45	-103.64***	12.05***	-	-	-	-
0.50	-104.12***	12.11***	-	-	-	-
0.55	-102.69***	11.96***	-	-	-	-
0.60	-103.53***	12.07***	-	-	-	-
0.65	-94.86***	11.10***	-	-	-	-
0.70	-99.29***	11.63***	-	-	-	-
0.75	-98.65***	11.58***	-	-	-	-
0.80	-89.49***	10.55***	-	-	-	-
0.85	-27.45	3.49	-	-	-	-
0.90	-13.52	1.90	-	-	-	-
0.95	2.20	0.11	-	-	-	-

Note: This table displays the estimated coefficients of the quantile cointegration model (3), where ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively.

We further apply the S_T test in equation (14) for Granger-causality in quantiles. We estimate three different QAR specifications in equation (15) under the null hypothesis of Granger non-causality in quantiles in equation (9). Tables 7-9 report the p-values of the S_T test for the logarithm of the three series. We implement test the S_T test in equation (14) over an equally spaced grid of 19 quantiles $\mathcal{T} = [0.05; 0.95]$. Following Sakov and Bickel (2000), we apply a subsample size $b = \left[kT^{2/5}\right]$, where $[\cdot]$ is the integer part of a number, $k = 5$ is a constant parameter, and $T = 331$. The resulting subsample size is $b = 51$, but unreported p-values show that our results are robust to other choices of subsample sizes. Table 7 reports the p-values of the test for Granger-causality in quantiles to ΔOP_t. Considering all quantiles, changes in economic activity (economic growth) or changes in renewable energy consumption do not Granger-cause variations in oil prices at the 1% significance level. These results are robust to different specifications of the quantile auto-regressive model under the null hypothesis of Granger non-causality. Besides, there is no evidence of Granger-causality from economic growth or changes in renewable energy consumption to changes in oil prices, for each quantile of the distribution.

Table 7. Granger-causality to ΔOP_t: Subsampling p-values

τ	ΔIPI_t to ΔOP_t			ΔR_t to ΔOP_t		
	$I_t^{\Delta OP_t} = 1$	$I_t^{\Delta OP_t} = 2$	$I_t^{\Delta OP_t} = 3$	$I_t^{\Delta OP_t} = 1$	$I_t^{\Delta OP_t} = 2$	$I_t^{\Delta OP_t} = 3$
[0.05; 0.95]	0.486	0.550	0.507	0.482	0.554	0.507
0.05	0.367	0.482	1.000	0.317	0.475	1.000
0.10	0.162	0.295	0.723	0.162	0.295	0.723
0.15	0.115	0.083	0.165	0.115	0.083	0.205
0.20	0.324	0.155	0.137	0.360	0.165	0.158
0.25	0.788	0.701	0.863	0.799	0.705	0.921
0.30	0.356	0.683	0.227	0.302	0.565	0.227
0.35	0.072	0.173	0.317	0.072	0.173	0.317
0.40	0.162	0.036	0.122	0.162	0.036	0.126
0.45	0.371	0.363	0.817	0.371	0.374	0.914
0.50	0.597	0.615	0.342	0.597	0.615	0.342
0.55	0.863	0.896	0.820	0.863	0.899	0.820
0.60	0.727	0.712	0.665	0.727	0.712	0.665
0.65	0.579	0.594	0.752	0.608	0.615	0.752
0.70	0.554	0.594	0.428	0.554	0.594	0.439
0.75	0.604	0.669	0.773	0.604	0.669	0.773
0.80	0.493	0.568	0.424	0.493	0.568	0.424
0.85	0.162	0.227	0.065	0.162	0.227	0.065
0.90	0.543	0.583	0.270	0.547	0.633	0.270
0.95	0.442	0.252	0.320	0.442	0.252	0.320

Note: This table presents the subsampling p-values of the S_T test in (14). ΔOP_t is the log-difference of oil prices, ΔIPI_t is the log-difference of IPI, and ΔR_t is the log-difference of renewable energy consumption. $I_t^{\Delta OP_t}$ is the number of lags of the dependent variable, ΔOP_t, under the null hypothesis of non-Granger-causality in (9). The subsample size is $b = 51$ for a sample of T = 331 observations.

Table 8 shows that fluctuations in oil prices or changes in renewable energy consumption do not Granger-cause economic growth at the 1% significance level, considering all quantiles of the distribution. However, we find evidence of Granger-causality at the extreme tails of the distribution. If we consider only the extreme tails of the conditional distribution, $\tau = \{0.05, 0.10, 0.15\}$ or $\tau = \{0.85, 0.90, 0.95\}$, there is Granger-causality running from ΔOP_t or ΔR_t to ΔIPI_t at the 1% significance level. Besides, these results are robust to different specifications of the quantile auto-regressive model. Therefore, large positive or negative fluctuations in oil prices or in renewable energy consumption lead extreme changes in economic activity. Finally, Table 9 illustrates that there is no causality running from changes in oil prices or economic growth to changes in renewable energy consumption at the 1% significance level, considering all quantiles of the distribution. However, there is Granger-causality running from ΔOP_t or ΔIPI_t to ΔR_t at the lowest quantiles of the distribution, for $\tau = \{0.05, 0.10\}$, at the 1% significance level. These results suggest that only the lowest negative variations in oil prices or in economic activity Granger-cause variations in renewable energy consumption.

Table 8. Granger-causality to ΔIPI_t: Subsampling *p*-values

τ	ΔOP_t to ΔIPI_t			ΔR_t to ΔIPI_t		
	$I_t^{\Delta IPI_t} = 1$	$I_t^{\Delta IPI_t} = 2$	$I_t^{\Delta IPI_t} = 3$	$I_t^{\Delta IPI_t} = 1$	$I_t^{\Delta IPI_t} = 2$	$I_t^{\Delta IPI_t} = 3$
[0.05; 0.95]	0.065	0.086	0.072	0.065	0.086	0.072
0.05	**0.007**	**0.007**	**0.004**	0.115	**0.007**	**0.004**
0.10	**0.004**	**0.004**	**0.004**	**0.004**	**0.004**	**0.004**
0.15	**0.004**	**0.004**	**0.004**	**0.004**	**0.004**	**0.004**
0.20	**0.004**	**0.004**	0.119	**0.004**	**0.004**	0.119
0.25	0.014	0.180	0.054	0.014	0.180	0.054
0.30	0.194	0.194	0.241	0.194	0.194	0.241
0.35	0.194	0.349	0.338	0.194	0.349	0.338
0.40	0.209	0.281	0.629	0.209	0.281	0.629
0.45	0.723	0.809	0.374	0.781	0.802	0.374
0.50	0.147	0.281	0.151	0.147	0.281	0.129
0.55	0.122	0.353	0.086	0.122	0.353	0.086
0.60	1.000	1.000	0.050	1.000	1.000	0.050
0.65	0.173	0.986	0.018	0.173	0.903	0.018
0.70	0.090	0.165	0.025	0.090	0.165	0.025
0.75	0.248	0.022	0.191	0.248	0.022	0.191
0.80	0.108	**0.004**	0.241	0.108	**0.004**	0.241
0.85	**0.004**	**0.004**	**0.007**	**0.004**	**0.004**	**0.007**
0.90	**0.004**	0.068	**0.004**	**0.004**	0.068	**0.004**

0.95	**0.004**	**0.004**	0.313	**0.004**	**0.004**	0.313

Note: This table presents the subsampling p-values of the S_T test in (14). ΔOP_t is the log-difference of oil prices, ΔIPI_t is the log-difference of IPI, and ΔR_t is the log-difference of renewable energy consumption. $I_t^{\Delta IPI_t}$ is the number of lags of the dependent variable, ΔIPI_t, under the null hypothesis non-Granger-causality in (9). The subsample size is $b = 51$ for a sample of T = 331 observations. Bold p-values denote rejection of the null hypothesis at the 1% significance level.

Table 9. Granger-causality to ΔR_t: Subsampling p-values

τ	ΔOP_t to ΔR_t			ΔIPI_t to ΔR_t		
	$I_t^{\Delta R_t} = 1$	$I_t^{\Delta R_t} = 2$	$I_t^{\Delta R_t} = 3$	$I_t^{\Delta R_t} = 1$	$I_t^{\Delta R_t} = 2$	$I_t^{\Delta R_t} = 3$
[0.05; 0.95]	0.119	0.032	0.072	0.119	0.032	0.061
0.05	0.108	**0.004**	0.022	0.108	**0.004**	0.022
0.10	0.237	**0.007**	**0.007**	0.237	**0.007**	**0.007**
0.15	0.043	0.043	0.147	0.043	0.043	0.147
0.20	0.291	0.248	0.691	0.209	0.183	0.691
0.25	0.741	0.691	0.716	0.737	0.687	0.691
0.30	0.709	0.824	0.482	0.615	0.817	0.482
0.35	0.277	0.306	0.295	0.277	0.266	0.295
0.40	0.086	0.047	0.011	0.086	0.047	0.011
0.45	0.004	0.014	0.842	0.004	0.014	0.842
0.50	0.144	0.094	0.730	0.144	0.094	0.730
0.55	0.165	0.626	0.989	0.155	0.626	0.971
0.60	0.547	0.766	0.363	0.547	0.766	0.335
0.65	0.212	0.504	0.367	0.212	0.504	0.367
0.70	0.392	0.421	0.187	0.392	0.421	0.187
0.75	0.173	0.065	0.151	0.144	0.079	0.151
0.80	0.083	0.076	0.180	0.083	0.076	0.180
0.85	0.022	0.036	0.065	0.022	0.036	0.065
0.90	0.730	0.511	0.432	0.730	0.561	0.558
0.95	0.227	0.169	0.112	0.227	0.169	0.112

Note: This table presents the subsampling p-values of the S_T test in (14). ΔOP_t is the log-difference of oil prices, ΔIPI_t is the log-difference of IPI, and ΔR_t is the log-difference of renewable energy consumption. $I_t^{\Delta R_t}$ is the number of lags of the dependent variable, ΔR_t, under the null hypothesis non-Granger-causality in (9). The subsample size is $b = 51$ for a sample of T = 331 observations. Bold p-values denote rejection of the null hypothesis at the 1% significance level.

We further estimate a QAR(3) model with the lagged values of the other variable as described in equation (16) to verify the sign of the Granger-causality between the variables. Table 10 displays the estimated coefficients $\beta(\tau)$ in the quantile regression model (16) for all the quantiles of the distribution. Regarding the analysis from ΔOP_t to ΔIPI_t, large negative variations in oil prices have a positive sign, whereas large positive fluctuations in oil prices have a negative sign (column 3 of Table 10). In line with the results of Table 8, there is Granger-causality at the extreme tails from ΔOP_t to ΔIPI_t, with opposite signs. We find the same pattern of signs for the causality running from ΔR_t to ΔIPI_t, except for the lowest quantile of the distribution $\tau = 0.05$

(column 4 of Table 10). For the Granger-causality analysis from ΔOP_t or ΔIPI_t to ΔR_t, the estimated coefficients have positive signs at the lowest quantiles of the distribution, except for $\tau = 0.05$ for the relationship from ΔOP_t to ΔR_t (column 6 of Table 10). Thus, large oil shocks negatively affect economic growth, but there is no clear pattern of signs of the causal relationship from changes in renewable energy consumption to economic growth.

Table 10. Quantile Regression Estimated Coefficients

τ	ΔIPI_t to ΔOP_t	ΔR_t to ΔOP_t	ΔOP_t to ΔIPI_t	ΔR_t to ΔIPI_t	ΔOP_t to ΔR_t	ΔIPI_t to ΔR_t
0.05	3.304	-0.255	0.008	-0.005	-0.008	1.102
0.10	1.349	-0.043	0.008	0.001	0.027	0.903
0.15	1.814	0.046	0.002	0.000	0.044	-0.069
0.20	1.799	0.102	0.002	0.001	-0.003	-0.034
0.25	1.609	0.099	0.003	0.001	0.036	0.356
0.30	1.999	0.151	0.003	0.003	0.022	0.329
0.35	1.460	0.138	0.004	0.005	-0.004	-0.032
0.40	1.341	0.083	0.002	0.007	-0.003	0.396
0.45	1.674	0.042	0.001	0.006	-0.015	0.422
0.50	1.676	0.046	0.000	0.004	-0.036	0.701
0.55	1.216	0.032	0.000	0.004	-0.011	0.302
0.60	0.734	0.038	-0.001	0.004	0.001	1.398
0.65	-0.223	0.021	-0.001	0.002	0.002	0.797
0.70	-0.632	0.055	-0.001	0.001	-0.015	1.087
0.75	-0.182	0.036	-0.004	-0.001	-0.071	0.523
0.80	-1.460	0.025	-0.007	-0.004	-0.037	0.566
0.85	-1.724	0.064	-0.002	-0.001	-0.027	0.687
0.90	-2.231	-0.028	-0.005	-0.006	-0.053	-0.049
0.95	-2.915	0.077	-0.011	0.001	-0.056	-0.075

Note: This table presents the estimated coefficients $\beta(\tau)$ of the quantile autoregressive model in (16).

Our findings are consistent with Hamilton (1983, 1996, 2003), Hooker (1996, 2002), Kilian (2008), and Timilsina (2015), among others, who support the causality running from changes in oil prices to economic growth in the U.S., via standard causality approaches. Besides, we found lower-tail dependence between changes in oil prices and renewable energy consumption; these results are consistent with Reboredo (2015), who reported evidence of tail dependence between oil prices and a set of global renewable energy indices. Our findings are also in line with Akarca and Long (1979), Lee (2005, 2006), Soytas and Sari (2006), Mahadevan and Asafu-Adjaye (2007), Sari et al. (2008), and Cho et al. (2015), who found evidence of Granger-causality from changes in energy consumption to economic growth in the U.S.

In contrast to the papers of Huang et al. (2008), Sadorsky (2009), Apergis and Payne (2010a,b), Apergis and Payne (2011), Lin and Moubarak (2014), Sebri and Ben-Salha (2014), and Tiwari (2014), we found a bi-directional causal relationship between economic growth and renewable energy consumption only at the lowest tail of the conditional distribution. Besides, our results contradict the previous literature for the United States such as Akarca and Long (1980), Yu and Hwang (1984), Yu and Jin (1992), Cheng (1995), Chiou-Wei et al. (2008), Payne (2009), Payne and Taylor (2010), Balcilar et al. (2010), Tugcu et al. (2012), and Narayan and Doytch (2017), who found no causality between renewable energy consumption and economic activity in the U.S.

The empirical results of dependence between changes in renewable energy consumption, oil prices, and economic activity have important policy implications. Our results report evidence of lower-tail causality running from oil prices changes to changes in renewable energy consumption. Our quantile-based analysis suggests that negative shocks in oil prices affect the consumption of renewable energy resources. However, oil prices behavior provides inadequate incentives to affect renewable energy consumption when oil prices are high. We also found evidence of lower-tail causality from large decreases in economic activity to changes in renewable energy consumption. Thus, economic growth provides asymmetric incentives to develop renewable energy consumption in the U.S. During periods of recessions, renewable energy consumption can increase without the need of energy policies. However, our results call for green energy policies during economic expansions periods. Therefore, governments should consider the asymmetric causality from changes in oil prices and economic activity to renewable energy consumption changes to develop a sustainable energy system. In line with Reboredo (2015), our results call for the implementation of policies that support the profitability of clean energy companies only during periods of large negative shocks in oil prices. Governments could help mitigate the downside risk stemming from oil price declines by implementing subsidization policies that depend on oil price changes (Rausser et al. 2010). Thus, our results allow policy makers to identify the kind of downside risk to subsidize. Besides, governments should take into account the asymmetric effect of economic growth to renewable energy consumption to implement sustainable energy policies during economic growth periods.

The tail dependence from changes in renewable energy consumption to economic growth suggests that energy policies such as tax credits for energy production, renewable energy portfolio standards, and installation of renewable energy systems affect economic growth. However, this relationship is asymmetric. Large decreases in renewable energy consumption (at the lowest quantile of the distribution) reduce economic growth. On the other hand, large increases in renewable energy consumption (at the highest quantile of the distribution) contribute to economic growth. Thus, policy makers need to take into account this asymmetric effect to implement sustainable energy policies. We found causality from changes in oil prices to economic growth at the tails of the distribution. In line with Kilian and Vigfusson (2011), there is an asymmetric effect of oil shocks to economic growth in the U.S. economy. Our results suggest a decline in economic growth in response to increases in oil prices, yet an increase in economic growth in response to negative oil shocks. Therefore, our analysis calls for the development of renewable energy markets in the U.S. to reduce their dependence on oil, allowing the U.S. economy to become less sensitive to positive shocks in oil prices.

5. Conclusions

Many important economic and financial analyses are investigated through testing for Granger-causality between the variables. However, most of the results in the literature were obtained in the context of Granger-causality in mean. In this paper, we analyze the causal relationship between renewable energy consumption, oil prices, and economic activity for the United States from July 1989 to July 2016, considering all quantiles of the distribution. Rather than focusing on a single part of the conditional distribution, we evaluate possible causal relations in all conditional quantiles. Under this approach, we can discriminate between causality affecting the median and the tails of the conditional distribution, providing a sufficient condition for Granger-causality when all quantiles are considered.

We find that there is no Granger-causality between variations in oil prices, economic activity, and renewable energy consumption, when all quantiles are taken into account. However, we find evidence of bi-directional causality between changes in renewable energy consumption and economic growth at the lowest quantiles of the distribution; besides, there is also unidirectional causality running from changes in renewable energy consumption to economic growth at the highest tail of the distribution. Our findings also support unidirectional causality from changes in oil prices to economic growth at the extreme quantiles of the distribution. Finally, we found lower-tail dependence from changes in oil prices to renewable energy consumption changes.

Our results provide the direction of causality between renewable energy consumption and economic activity in the United States at different quantile levels. This implies that changes in renewable energy consumption are sensitive to economic growth in the United States at the lowest quantiles of the distribution. The results of this paper are important because energy conservation policies may affect the economic activity. Our findings suggest that policy makers should not only focus on the non-renewable energy consumption (crude oil price), but also on the contribution to the overall renewable energy mix in the production process. In contrast to the papers of Sadorsky (2009), Apergis and Payne (2010a,b), Apergis and Payne (2011), Lin and Moubarak (2014), Sebri and Ben-Salha (2014), and Tiwari (2014), we found a bi-directional causal relationship between economic growth and renewable energy consumption only at the lowest tail of the conditional distribution.

As an aftermath of the 21st meeting of the Conference of the Parties (COP21)-Paris agreement and the current geo-political tension in crude oil market, the causal relationship between renewable energy consumption and economic growth highlights the importance of promoting renewable energy consumption in the U.S. Our quantile-based analysis suggests that negative shocks in oil prices affect the consumption of renewable energy resources. We also found evidence of lower-tail causality from large decreases in economic activity to changes in renewable energy consumption. Therefore, our results call for the implementation of policies that support the profitability of clean energy companies only during periods of large negative shocks in oil prices. Governments could help mitigate the downside risk stemming from oil prices decreases by implementing subsidization policies that depend on oil prices changes (Rausser et al. 2010).

The bidirectional causality between changes in renewable energy consumption and economic growth, at the lowest tail of the distribution, calls for government policies aimed at developing renewable energy markets, to increase energy efficiency in the U.S. These policies include, for instance, the creation of tax incentives for the production and consumption of renewable energy, the establishment of partnerships between the public and private sector, and the implementation of renewable energy portfolio standards. As suggested by Kaygusuz (2007), Hirschl (2009), and Apergis and Payne (2010a, 2011), the development of markets for tradable renewable energy certificates together with the exchange of information on technologies across countries should foster the renewable energy sector. Moreover, the development of renewable energy markets in the U.S. contribute to reduce their dependence on oil, allowing the U.S. economy to become less sensitive to positive shocks in oil prices.

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