ENERGY CONSUMPTION-ECONOMIC GROWTH NEXUS: AN EMPIRICAL STUDY OF CHINA

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ENERGY CONSUMPTION-ECONOMIC GROWTH NEXUS: AN EMPIRICAL STUDY OF CHINA

ABSTRACT

Research on the nexus between energy consumption and economic growth provide important insights that the government needs to design proper policies for the country. However, the existing literature present mixed findings. Therefore more research that is able to produce more reliable and consistent results are still needed. This study aims to examine the energy consumption and economic growth in China by focusing on the aspects that are usually neglected in the literature such as multiscale causality relationship, nonlinear causality relationship and Asymmetric causality relationship. In order to achieve these objectives, different new research methods will be adopted. The newly proposed linear causality test, nonlinear causality test and asymmetric causality test are applied on the national data. The first two methods fail to capture causality in any direction while the third method identifies causality between positive and/or negative energy and growth shocks. Then the wavelet decomposition technique is combined with these three tests respectively. The result shows that the wavelet decomposition does help reveal the dynamics of the time series in different time horizon, i.e. short, medium and long run. Furthermore, the combination of wavelet decomposition and the asymmetric causality test proves to be able to provide more accurate information on the energy-growth nexus than the other two methods. The newly proposed causality test that uses the bootstrapping method to tackle the small sample issues is applied on the individual regions in China. The test helps identify the characteristics of the energy-growth nexus for individual regions with robust results. Since the development of renewable energy is a growing trend not only in China but also all over the world, the causal relationship between renewable energy consumption and economic growth is examined lastly. Other than contributing in terms of

methodology improvement, with all of the empirical results derived from the tests conducted above, this study manages to provide policy recommendations for the Chinese central government in different time horizons and the local governments. In addition, it also sheds light on the renewable energy policy in China.

ENERGY CONSUMPTION-ECONOMIC GROWTH NEXUS: AN EMPIRICAL STUDY OF CHINA

ABSTRAK

Kajian terhadap neksus antara penggunaan tenaga dan pertumbuhan ekonomi memberikan maklumat mendalam tentang betapa perlunya pihak kerajaan memastikan polisi yang terbaik untuk sesebuah negara. Bagaimanapun, kajian-kajian terdahulu membuktikan terdapatnya keputusan kajian yang pelbagai dan kurang tepat. Untuk itu, lebih banyak kajian yang mampu memberikan keputusan yang boleh dipercayai dan konsisten masih perlu dikenal pasti. Tujuan kajian yang dijalankan oleh penyelidik ini adalah untuk mengkaji penggunaan tenaga dan pertumbuhan ekonomi di negara China dengan memfokuskan aspek-aspek yang selalunya tidak diguna pakai dalam kajian terdahulu seperti perkaitan hubungan pelbagai skil, perkaitan hubungan tidak linear dan perkaitan hubungan tidak simetri. Untuk mencapai objektif ini, kaedah baru telah diguna pakai iaitu ujian perkaitan linear, ujian perkaitan tidak linear dan perkaitan tidak simetri dengan menggunakan data yang diperoleh pada peringkat nasional. Dua kaedah pertama didapati tidak berjaya untuk mendapatkan hasil hubung kait berkenaan. Sementara itu, kaedah ketiga pula hanya dapat mengenal pasti perkaitan antara penggunaan tenaga yang positif atau negatif dan kejutan pertumbuhan. Kemudian teknik '*wavelet decomposition*' digunakan bersama untuk melihat siri perubahan dalam jangka masa pendek, sederhana dan jangka masa panjang. Hasil kajian menunjukkan teknik ini membantu mengenal pasti perubahan dalam tempoh masa berkaitan. Seterusnya, kombinasi antara teknik '*wavelet decomposition*' dan ujian perkaitan tidak linear memberikan hasil kajian yang lebih tepat terhadap perkaitan antara penggunaan tenaga dan pertumbuhan ekonomi berbanding dua kaedah sebelumnya. Ujian terbaru yang dicadangkan ini menggunakan kaedah '*bootstraping*' ke atas sample bersaiz kecil dan dilaksanakan di wilayah berlainan di negara China. Ujian ini membantu mengenal

pasti ciri-ciri hubung kait sumber tenaga dan pertumbuhan negara dengan keputusan yang lebih tepat. Sejak pembangunan sumber tenaga boleh diperbaharui berkembang dengan pesat bukan sahaja di negara China, tetapi juga di seluruh dunia, perhubungan antara penggunaan sumber tenaga boleh diperbaharui dan pertumbuhan ekonomi akhirnya dapat dikaji. Selain penambahbaikan kaedah kajian serta keputusan impirikal yang diperoleh daripada ujian-ujian yang telah dijalankan, hasil kajian ini berupaya mencadangkan penambahbaikan polisi kepada kerajaan China yang berbeza tempoh masa dan juga kerajaan tempatan. Selain daripada itu, kajian ini juga membuka lebih peluang kepada penambahbaikan polisi tenaga boleh diperbaharui di negara China.

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LIST OF SYMBOLS AND ABBREVIATIONS

$\nRightarrow$	:	Does not Granger cause
Δ	:	Operator for first differencing
ADB	:	Asian Development Bank
ADF	:	Augmented Dickey-Fuller
AIC	:	Akaike's Information Criterion
ARCH	:	Autoregressive conditional heteroskedasticity
ARDL	:	Autoregressive Distributed lags
BRICS	:	Brazil, Russia, India, China and South Africa
CO2	:	Carbon dioxide
CPI	:	Consumer price index
CWT	:	Continuous wavelet transforms
DT	:	Dummy variables for a shift in the trend
DU	:	Dummy variables for a break in the intercept
DWT	:	Discrete wavelet transforms
EC	:	Energy consumption per capita
GDP	:	Gross domestic product
GNP	:	Gross national product
GHGs	:	Greenhouse-gas

GPC	:	Real GDP per capita
HJC	:	Hatemi-J information criteria
HQC	:	Hannan and Quinn information criterion
ISC	:	Industrial sector consumption
J-J	:	Johasen and Juselius
K	:	Real capital stock per capita
KPSS	:	Kwiatkowski, Phillips, Schmidt, and Shin
L	:	Average labour population
LA	:	Daubechies Least Asymmetric wavelet with length of 8
MODWT	:	Maximal Overlap DWT
MWALD	:	Modified Wald
MW	:	Million watts
OECD	:	Organization for Economic Co-operation and Development
PP	:	Phillips and Perron
PV	:	Photovoltaic
RSC	:	Residential sector consumption
SIC	:	Schwarz Bayesian information criteria
TB	:	Time of the structural break
TEC	:	Total electricity consumption

T-Y	:	Toda-Yamamoto
UHV	:	Ultra-high voltage
USA	:	united States of America
VAR	:	Vector autoregressive
ZA	:	Zivot-Andrew

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Over the past few decades (1990 to 2014), although world Gross Domestic Product (GDP) has increased almost 2.5 times from USD22.547 trillion to USD77.869 trillion (World bank, 2015), CO_2 (Carbon dioxide) emission, which is a major component of the greenhouse-gas (GHGs) emission, has grown over 50% (International Energy Agency, 2015). Without immediate actions with full commitment, the climate change resulted from the GHGs emission will irreversibly and severely affect the world, as concluded by the International Panel on Climate Change (International Energy Agency, 2015). Therefore, all the countries are urged to contribute to reducing GHGs emission. China, as the world's largest GHGs emitter (Buckley, 2010), has been facing both international and domestic pressure to pledge in taking immediate and effective actions to reduce emission. In response to the call to pledge actions to mitigate GHGs emissions in 2009, China, among other countries, has made the plan to reduce the carbon intensity of GDP by 40 to 45% by 2020 compared to 2005 levels (Su, 2015). In 2015, China aimed to reduce such carbon intensity further by 60% to 65% by 2030 compared to 2005 levels (Su, 2015).

The key to achieving such goals seems to reduce energy consumption, especially the use of fossil energy since most of the emission is energy-related, e.g. GHGs emissions generated by the energy sector accounts for approximately 70% of the total anthropogenic GHGs emissions whereby CO_2 caused by fossil-fuel combustion represents more than 90% of energy-related emission (International Energy Agency, 2015). The composition of Chinese energy consumption is well-known for its high percentage of fossil energy. As shown in Figure 1, Chinese economy relies heavily on fossil energy. In the year 2000, coal, oil and gas accounted for 69%, 22% and 2% respectively of the total energy consumption. Such composition has not changed drastically until 2012, whereby the three fossil energy consumptions represented 67%, 19% and 5% respectively while other clean energy such as hydro and wind energy accounted for quite a small share of the country's total primary energy consumption. Therefore, in order to solve pollution problem, the government has made plans to reduce fossil energy consumption, e.g. limit the use of coal to 62% by 2020 (U.S. Energy Information Administration, 2015).

However, such reduction in energy consumption may hamper its economic development if energy consumption has a positive impact on economic growth. As shown in Figure 2, industry sector and service sector constantly accounted for more than 70% and 14% of the total energy consumption respectively from 2000 to 2013. During the same time period, the two sectors contributed greatly and almost exclusively to economic growth (Figure 3). Therefore, it is reasonable for the government to be cautious on the potential impact of energy conservation policy on its economic growth.

Figure 4 illustrates the growth of GDP and GDP per capita growth of China from 1980 to 2013. It is clear that the growth rate of GDP per capita closely tracked the growth rate of GDP. And the two growth rates have not been stable along the way. Many factors may have caused such fluctuations. More importantly, it is noticed that since the year 2010, when the 12^{th} Five-year plan (2011 to 2015) that aimed at reducing both energy intensity (16% by 2020) and total energy consumption (limiting to 4.8 billion tons of standard coal equivalent per year) was initiated, the growth rate of GDP has been declining from 11% to 7% while the growth rate of GDP per capita also showed the same trend with a decrease from 10% to 7%. These phenomena may imply that reducing energy consumption does have a negative impact on economic growth in

China. Such impact is of great concern for the policy makers. The GDP per capita of China is still low, ranked 77th in the world as compared to that of USA (United States of America) rank 11th (Schwab, 2013). Due to its large and increasing population, achieving rapid growth of GDP per capita seems a rather difficult task. However, the government has set the targets in the 13th Five-Year Plan (2016 to 2020) to maintain "medium to high growth" so that the dream of building "a moderately prosperous society in all aspects" can be achieved (The State Council of China, 2015). This requires both the GDP and GDP per capita to be doubled by 2020 as compared to 2010 level which can be reached only if an average annual growth of 6.5% is maintained during next five years (The State Council of China, 2015). Given such circumstances, there is no room for the country to slow down the economic development. Therefore, it is very urgent to understand whether the drop in economic growth observed during 12th Five-Year Plan was caused by a reduction in energy consumption or vice versa.

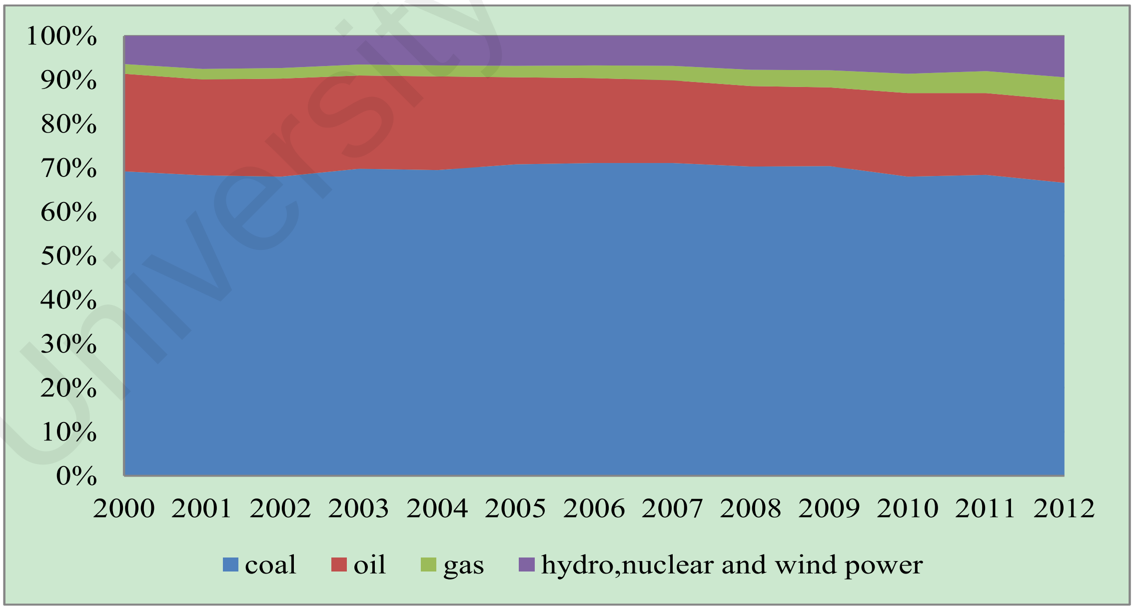

Figure 1: Energy consumption by type (2000 to 2012)
Source: based on data from China Energy Yearbook (2013)

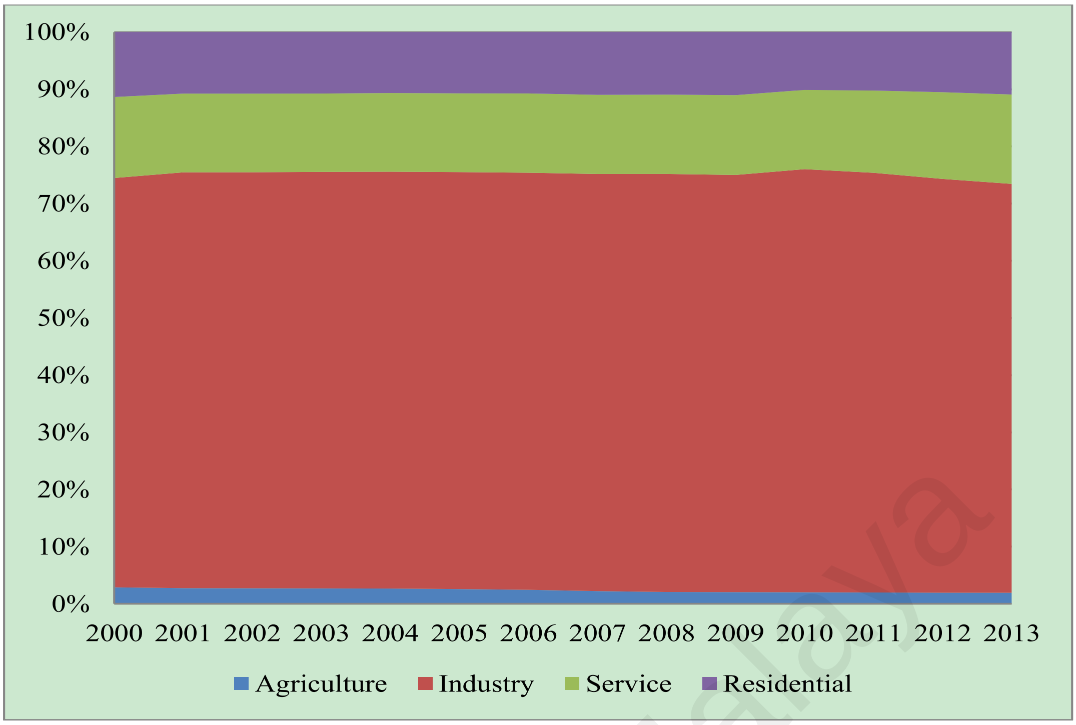

Figure 2: Energy consumption by sector (2000 to 2013)
Source: based on data from National Bureau of Statistics of China

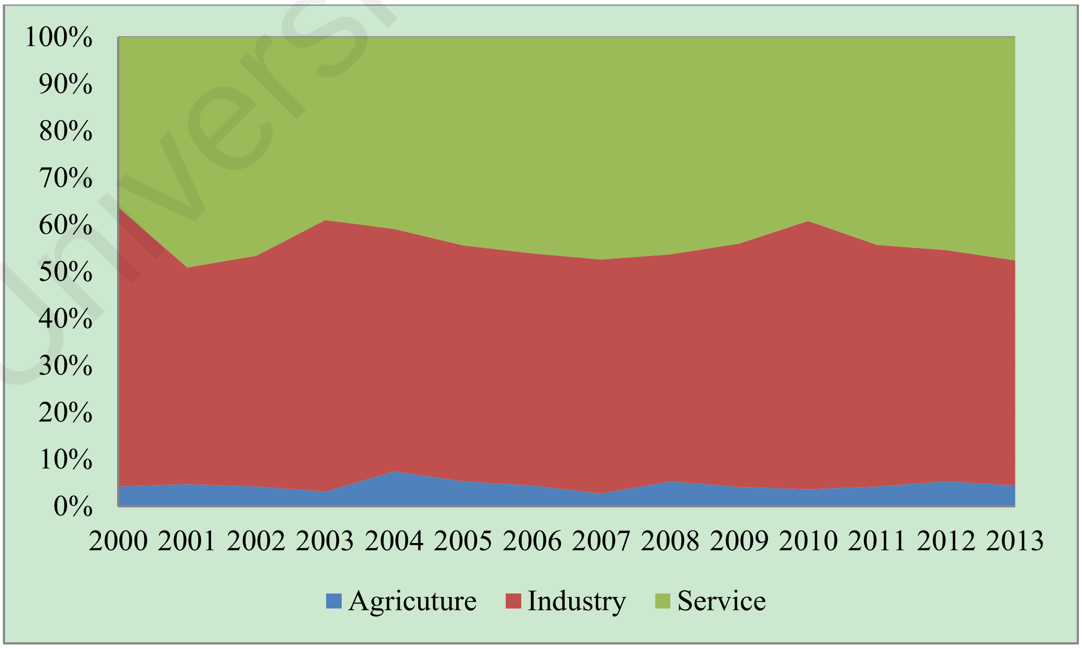

Figure 3: Contribution to GDP by sector (2000 to 2013)
Source: based on data from National Bureau of Statistics of China

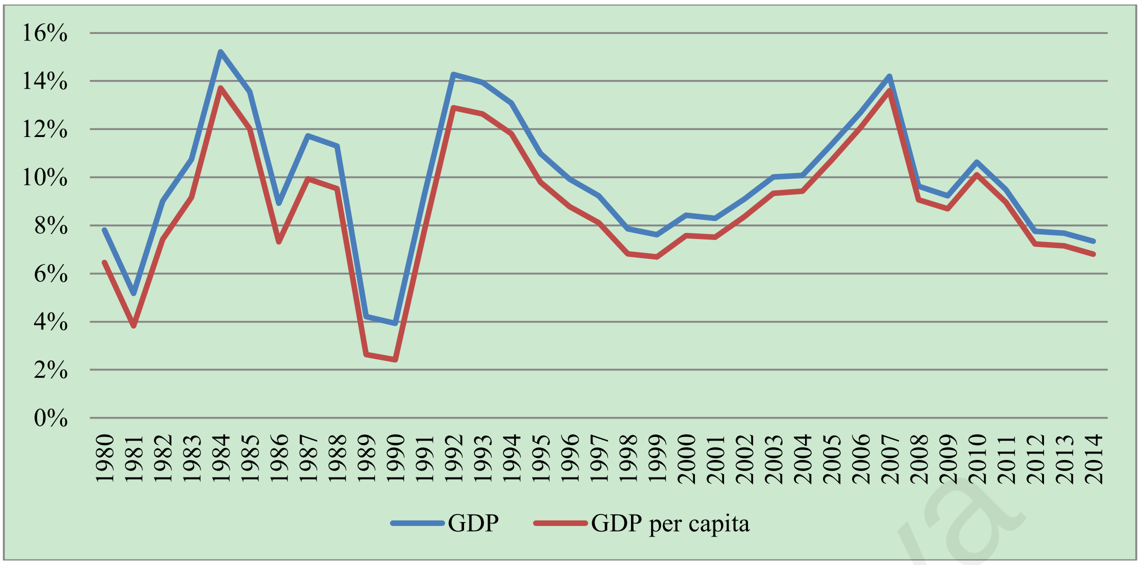

Figure 4: GDP and GDP per capita growth rate (1980 to 2014)
Source: based on data from World Development Indicator of World Bank

Overall, given the special conditions and characteristics of the Chinese energy economy, there is dire need to identify the accurate interactive nexus between economic growth and energy consumption in order to help Chinese government design proper and prudent energy policies that can help the country meet its own expected economic targets while solving problems such as GHGs emission.

However, the existing energy economy literature has produced rather contradicting results on the energy-growth nexus. At the national level, Ma et al. (2010) conducted a thorough review of the existing literature regarding Chinese economy. They found that there are three types of results: economic growth causes energy consumption, energy consumption causes economic growth and bidirectional causality between the two, using two major categories of methods. The possible reasons that caused the mixed findings include differences in the methods used, study periods, data sources and coverage of independent variables. On the other hand, at the international level, Payne (2010b) and Ozturk (2010) conducted comprehensive literature reviews on the studies conducted in the past three decades on the relationship between Energy consumption and Economic growth. They found that the international literature also produced mixed findings.

Realizing the need to have more reliable and conclusive findings, Karanfil (2009) advised the energy economists to think about new direction, new perspective and adopt new techniques after reviewing the conventional technique used in the empirical studies on the nexus between Energy consumption and Economic growth and the issues arisen from the increasing contradicting empirical results. He was of the view that applications of the same traditional techniques on different data sets or time periods will only add more confusion to the literature. This was supported by Payne (2010b) and Ozturk (2010) who reviewed the empirical studies conducted in the past three decades. They concluded similarly that new approaches and new methods should be applied to study the energy-growth nexus. In addition, Yalta (2011) and Yalta and Cakar (2012) proposed a maximum entropy (Meboot) framework, which was applied to the data of Turkey and China, in order to overcome the drawbacks of conventional tests. Their findings further supported Karanfil (2009), Payne (2010b) and Ozturk (2010). And Yalta and Cakar (2012) suggested that the future studies should adopt the "state of the art econometric methods" and be "more focused and detailed" in identifying reliable information on the energy-growth nexus with robust test results(p. 675).

In line with these suggestions, the current research focused on improvement of the econometric techniques applied by considering the aspects that are usually ignored in the field of energy-growth nexus study.

1.2 Statement of the problem

Within the context of the global climate problem, it is vital for policy makers to acquire accurate information on the causal relationship between energy consumption and economic growth. Although numerous studies have been conducted in providing empirical evidence on such energy-growth nexus, more reliable and conclusive results are still demanded.

One of the major reasons contributing to the existing mixed findings is that some important research aspects have been overlooked by the empirical studies.

The first aspect is multiscale analysis. Granger (1969, 1980) suggested that rather than testing the causality over a single period a more meaningful causality test should be conducted across different periods using a spectral-density approach. Studies have produced evidence for such necessity. For example, Ramsey and Lampart (1998) examined the relationships between economic variables such as consumption, income using wavelet decomposition. They identified the importance of time scale decomposition in investigating the relationships and its ability to interpret the anomalies that are found in the previous literature. In addition, Ma and Oxley (2012) also suggested the need of studying energy-growth nexus in China at different shorter periods rather than long time periods in order to differentiate the potential different causality information at different stages of economic development. In the case of China, such approach is necessary. Jian (2011) discussed the domestic energy shortage issue of China and its solutions. The author found that on one hand, Chinese enterprises imported oil from abroad to meet the short-term demand, on the other hand, to ensure the long-term energy supplies, they also chose to put direct investment in foreign companies. He further suggested that the government should design short-, medium- and long-run plans to meet different economic and energy targets. In fact, governments design energy policies and plans and implement them across different time periods. Chinese government implements a grand economic plan every five years. Each five-year plan has its own targets to meet while the country also has some long term targets to aim. The report of KPMG China (2011) provided some details about the long term and short term targets or plans of the Chinese government in the energy sector. For example:

(a) 5-year target or plan: from 2011 to 2015, it was planning to reduce the energy use per unit of GDP by 16% and CO2 emissions per unit of GDP by 17%.

(b) 10-year target or plan: during the next 10 years (from 2011 to 2020), more than RMB 11 trillion of investment will be put into the power industry. Within the same time period, the ratio of non-fossil fuel consumption to total energy consumption is planned to be reduced to 15%.

As examples shown above, it is reasonable that the relationship between economic growth and energy consumption is influenced by the government's energy policies or plans, therefore should vary across time scales. Hence multiscale analysis is useful as it may help reveal the hidden information on the energy-growth nexus in different time horizon, i.e. short, medium and long run.

The second aspect is the potential nonlinear causal relationship between energy consumption and economic growth. Literature has shown that energy consumption and macroeconomic variables may have some nonlinear causal relationships (Balke et al., 2002; Hamilton, 1996, 2003; Mork et al., 1994; Seifritz and Hodgkin, 1991). Lee and Chang (2005) suggested that nonlinear nature should be considered when studying energy consumption data based on the previous literature that provided evidence that structural changes in energy consumption may be caused by economic events, environmental changes, energy price fluctuations and energy policy changes (Hamilton, 2003; Hooker, 2002; Moral-Carcedo and Vicens-Otero, 2005). China has experienced many structural changes since 1953. Cheremukhin et al. (2015) studied the economic development of China from 1953 to 2012 and described the period of 1953 to 1978 as "one of the largest economic policy experiments and development programs in modern history" (p. 2). Similarly, Valli and Saccone (2009) compared the important structural change of the economic development between China and India from 1978 to 2008 and found that stronger structural change occurred in China mainly due to its "economic reforms and the growth of the internal market in the 1980s" and "a very rapid penetration of its industrial products in the world market" in the mid-1990s (p. 101). Moreover, from the Long-run perspective, Gupta et al. (1995) considered the Chinese economy as one that has been affected by enormous shocks due to sharp changes in policy and other factors. Given such unique characteristics of the Chinese economy, it is necessary to adopt research technique that is able to detect the possible nonlinear causality relationship between energy consumption and economic growth in China. This is also in line with Payne (2010b) who argued that the information captured by linear causality test may not be adequate to reveal the energy-growth nexus.

The third aspect is the possibility that asymmetric causality relationship may exist between energy consumption and economic growth. Most of the studies assumed the causal relationship between energy consumption and economic growth to be symmetric. However, Hatemi-J and Uddin (2012) pointed out that it is important to examine the asymmetric causality since different economic agents normally have more response towards negative shocks than to positive shocks in absolute terms. In a country, such as China, where stabilizing the economy and improving living standard has been set as a top priority, it is reasonable to expect that negative shocks should have more impact than positive shocks. If this is true, then different policy implications will have to be derived as compared to the studies that assume linear or symmetric causality between economic growth and energy consumption.

Fourthly, to gain more comprehensive information on energy-growth nexus in China, it may be helpful to integrate the discussed three aspects by combining the related research techniques.

Fifthly, as China consists of more than 30 administrative regions, in order to achieve its national economic and energy target, it will depend on the success of each region's implementation of the economic and energy plans. However, disparities exist among different regions. For example, Li et al. (2014) identified regional differences in energy use of 30 provinces in China and derived regional policy implications on energy conservation for different regions with "different scales, structures and intensities of energy consumption" (p. 426). Therefore, it is necessary to conduct regional analysis on energy-growth nexus for policy implications across China, which is in line with the suggestions of Ma and Oxley (2012) and Smyth and Narayan (2014). To date, some previous studies have discussed China's regional disparities on the nexus between China's energy consumption and economic growth (Akkemik et al., 2012; Fei et al., 2011; Herrerias et al., 2013; Wang et al., 2011a; Zhang and Xu, 2012). All of these studies adopted panel technique. Although panel test approach may help improve the power and size properties of statistical tests, Chandran et al. (2010) suggest that it tends to neglect the country-specific effects, i.e. causality information on the individual sample. Similarly, Smyth and Narayan (2014) also pointed out that panel data analysis is not suitable if the study focuses on deriving policy implications for individual samples. Both gave such suggestion implicitly based on the assumption that the panel data are not homogeneous. In fact, the findings of these previous panel studies have shown us the possible heterogeneity on energy-growth nexus at the provincial or regional level in China. For example, for the eastern regions of China, Yang and Yang (2010) found a bidirectional causal relationship between energy consumption and economic growth while a unidirectional causal relationship from economic growth to energy consumption was found. Therefore, we should take into account the possible heterogeneity when we conduct energy-growth nexus in China. Most of the previous studies on China tried to tackle this issue by grouping the regions by geographic location, e.g. the provinces are divided into Eastern Region, Central Region and Western region (Zhang and Xu, 2012). It is also possible to group them by their energy intensity and per capita GDP (Li et al., 2014). However, this kind of grouping may cause the pre-selection bias, i.e. provinces may be arbitrarily or sometimes wrongly categorized therefore categorizing by different criteria may provide us different results on the energy-growth nexus. Hence, it may be better not to categorize in such way but try to investigate the individual regions separately. In addition, Akkemik et al. (2012) pointed out that there may be a heterogeneity bias as the previous panel causality studies have implicitly assumed that the panel is homogeneous when it is in fact heterogeneous. The authors then took this issue into consideration by adopting a heterogeneous panel causality test that is able to provide individual heterogeneous non-causality test results for each province. The current study also aims to tackle the pre-selection and heterogeneity bias with an alternative approach, i.e. examining energy-growth nexus for each region using more robust econometric techniques that are able to provide reliable results on the regional data with small sample size.

Lastly, the development of renewable energy has drawn more and more attention from the policy makers in recent years. This is especially vital for countries like China, as according to the environmental Kuznet's curve, they are facing worse environmental problems given their current stage of economic development. Hence, Shahbaz et al. (2016) cited the study of Tahvonen and Salo (2001) which suggested that "largely, the emphasis on adoption of renewable energy sources is an outcome of environmental externality and climate change" (p. 1443). In other words, the main concern of adopting renewable energy is to tackle the environmental issues. It assumes that development of the renewable energy will benefit the world both environmentally and economically. Yet, whether this assumption is valid or not requires careful statistical information. Dai et al. (2016) measure the impacts of the development of renewable energy on the economy and environment of China by using dynamic computable general equilibrium model toward 2050. According to the scenarios constructed, they found that if renewable energy is developed in a large-scale, it will boost the economic growth and create a considerable number of jobs while reducing substantial amount of emissions. On the other hand, Shahbaz et al. (2016) are of the view that how the renewable energy consumption will affect the economic growth depends on “the modernization of technique under practice for the utilization of renewable energy sources” (p. 1443). Hence, efforts should be made on identifying the causal relationship between renewable energy consumption and economic growth. For China, the obstacle facing the researchers is that the data series are either not available or short in length. Nevertheless, a few studies tried to link renewable energy consumption to economic growth in China. The findings are mixed that supported different hypotheses, e.g. conservation hypothesis (Salim and Rafiq, 2012) and feedback hypothesis (Lin and Moubarak, 2014). In addition, Shahbaz et al. (2016) investigated the causal relationship between biomass energy consumption and economic growth in the BRICS (Brazil, Russia, India, China and South Africa) countries by using panel technique and quarterly data from 1991 to 2015. They found that both in the long run and short run there is a bidirectional causal relationship between biomass energy consumption and economic growth in the BRIC countries. The study, however, failed to provide any information on the individual sample countries. Therefore, this study aims to conduct a single sample study on China to investigate the causal relationship between renewable energy consumption and economic growth from both aggregate and disaggregated viewpoint by adopting a more robust econometric technique that is able to tackle finite sample issue.

1.3 Research questions

This study has three main research questions. They are as follows:

(a) Is there nonlinear and asymmetric causal relationship between economic growth and (renewable) energy consumption?

(b) Apart from the time domain that is commonly examined, will the inclusion of the frequency domain in the analysis reveal hidden information on the causal relationship between economic growth and energy consumption?

(c) Is the energy-growth nexus different across regions?

1.4 Objectives of the study

To find answers to the research questions, this study has three specific objectives:

(a) To investigate the existence of linear, nonlinear and asymmetric causality between energy consumption and economic growth;

(b) To uncover the causal relationship between energy consumption and economic growth at multiscale levels in both the time and frequency domains;

(c) To examine the causal relationship between energy consumption and economic growth at the regional level.

1.5 Significance of the study

For the Chinese government to design proper and prudent energy policies that can help the country meets its own economic targets while solving environmental problems, e.g. emission, accurate information on the causal relationship between energy consumption and economic growth are demanded. Therefore, this study aims to re-examine energy-growth nexus in China by contributing in the following way.

Methodologically, this study contributes by adopting new perspectives, namely, multiscale, nonlinear and asymmetric causality analysis. The original time series will be decomposed into different series on a scale-by-scale basis, i.e. at different time horizons. This approach will be able to unveil the structure at short, medium and long run. More importantly, the multivariate Granger causality tests (including linear, nonlinear and asymmetric tests) between two time series at different time horizons enable us to observe how the nexus between them varies as a function of time horizons. The richer results of such tests will reveal the important information that may be hidden using other methods. Above all, this study provides an alternative analytical framework by incorporating wavelet multiscale analysis, nonlinear and asymmetric causality tests that may be adopted for future causality studies on time series.

Empirically, this study provides detailed evidence on energy-growth nexus in China, including linear, nonlinear and asymmetric causality at the original level and different time scales, i.e. short, medium and long run. Moreover, the causality relationships between energy consumption and economic growth across China (29 regions) are identified. Lastly, this study also provides information on the causal relationship between economic growth and renewable energy consumption in China. Government officials in China may use these detailed findings of this research to have a deeper understanding of its energy-growth nexus, which may enable them to re-evaluate their current energy policy and design a more comprehensive and appropriate plan.

1.6 Scope of the study

This study focuses on investigating the causal relationship between economic growth and energy consumption in China at national and regional level. The sample of China does not include Hong Kong, Macao and Taiwan. In other words, only the mainland of People's Republic of China and its 29 administrative regions are studied on. These regions are: 4 municipalities, Beijing, Chongqing, Shanghai and Tianjin; 25 provinces, Anhui, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Xinjiang, Yunnan and Zhejiang.

The data used in this study includes yearly values of real GDP per capita, energy consumption per capita, capital stock per capita and average labour population for the whole nation and for the aforementioned 29 administrative regions. Due to the availability of data, the sample period spans from 1953 to 2013 for the whole nation while for the different regions, the length of sample periods vary.

All the data are collected from the National Bureau of Statistics of China, the Statistics Yearbooks and the Energy Statistics Yearbooks for the whole nation and different regions, except that capital stock per capita (total capital stock divided by the average total population), is calculated by perpetual inventory method with reference to the study of Shan (2008)[1] while the capital stock data for 29 regions is calculated based on the study of Zong and Liao (2014). The data of both aggregate and disaggregated Renewable Energy consumption are collected from statistical review of World Energy 2015 published by British Petroleum (2015). Due to the availability of data, disaggregated renewable energy includes solar, wind and hydropower. The series for other types of renewable energy such as geothermal and biomass are not available.

1.7 Structure of the study

Chapter 1 provides an introduction to the study by outlining the urgent global energy and environmental issues and the unique characteristics of China's economy and energy consumption. Then it follows with a problem statement, which helps form the study

[1] The data is updated up to 2013 by using the same method with Haojie (2008).

questions and research objectives that the study aims at as well as the significance and scope of the study.

Chapter 2 provides a thorough review of the most relevant empirical literature on the causal relationship between economic growth and energy consumption based on the econometric and empirical issues that the existing work aim to tackle. These reviews provide the basis for identifying the research gaps.

Chapter 3 describes the wavelet transform, autoregressive distributed lag model, bootstrapped Toda-Yamamoto causality test, nonlinear causality test and asymmetric causality test. The chapter ends with an analytical framework for the whole study.

Chapter 4 presents the examining of the energy-growth nexus in China at the national level. All the techniques described in Chapter 3 are employed.

Chapter 5 investigates the energy-growth nexus in China at the regional level. The bootstrapped Toda-Yamamoto causality test is adopted.

Chapter 6 examines the relationship between renewable energy consumption and economic growth using both aggregate and disaggregated data.

Chapter 7 summarizes all the results and highlights the key implications from both the methodological and policy-wise perspectives and explains the limitations and direction for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Theoretically, the mainstream economic theory does not consider energy as a primary factor of economic growth while recognizing labour and capital as crucial inputs for economic production (Stern, 2004). The conventional economists argue that due to the marginal cost share of energy as compared to that of capital and labour in economic growth, there is neutral relationship from energy to economic growth (Warr and Ayres, 2010). However, the recognition of the importance of energy to economics by Nicolas (1971) through elucidating the importance of the entropy law has caused the interest of researchers in confirming the important role of energy in the economic system as cited by Kroeger (1999). In addition, during the two energy crises in the 1970s, the impact of energy shortage and energy conservation policy provided evidence of the possibility that limiting the use of energy would have a negative effect on economic growth (Warr and Ayres, 2010). This has further triggered the studies on energy demand started in the 1980s.

There have been four major motivations of such studies including: policy implications derived from the information on the price and income elasticity of energy demand, energy demand forecasting, importance of understanding the substitutability between energy and other production factors and how demand for energy can be managed in order to tackle the issues of greenhouse gas emissions and climate change (Ryan and Plourde, 2009). With these motivations, studies at different directions have been conducted.

One group of these studies focuses on the causal relationship between energy consumption and economic growth. In the past decades, the literature on this topic has become rather considerable since understanding the causal relationship between energy consumption and economic growth is vital for designing proper energy policies.

The energy-growth nexus has been synthesized into four hypotheses within the literature (Ozturk, 2010; Payne, 2010b). Each of these hypotheses has its own policy implications. The hypotheses are as follows:

(a) Conservation hypothesis: there is a unidirectional causality running from economic growth to energy consumption, which implies that policies aiming at saving energy by direct reduction of energy consumption may be implemented without little or no negative impact on economic growth, e.g. Bastola and Sapkota (2015) and Ahmed et al. (2015).

(b) Growth hypothesis: there is a unidirectional causality running from energy consumption to economic growth, which indicates that increase in energy consumption may increase economic growth while reduction on energy consumption may negatively affect economic growth. The growth hypothesis implies that energy is an important input for economic growth other than labour and capital, e.g.: Alshehry and Belloumi (2015); Aslan (2016).

(c) Neutrality hypothesis: there is no causality running between energy consumption and economic growth, which implies that energy consumption and economic growth are independent of each other. Therefore, policies that affect either of them will not have any effect on the other, e.g. Yalta and Cakar (2012); Ozturk and Bilgili (2015).

(d) Feedback hypothesis: there is bidirectional causality between energy consumption and economic growth, which indicates that the energy consumption and economic growth are interdependent. Same as the growth hypothesis, feedback hypothesis implies that energy conservation policies will hamper the economic growth eventually, e.g. Esseghir and Khouni (2014) and Adams et al. (2016).

The empirical studies so far have not shown any consensus on any of these four hypotheses. To obtain some conclusive results on energy-growth nexus in the literature, Bruns et al. (2014) conducted a meta-analysis on the literature of the time series studies on the energy-growth nexus by analysing 72 studies. However, they also failed to identify "a genuine causal effect in the literature as a whole" (p. 1). Isa et al. (2015) also reviewed the existing studies. Similarly, they could not identify any consensus on energy-growth nexus as the empirical results of the literature are unevenly distributed according to the four hypotheses. Possible causes of such different empirical findings include: different data or econometric methods adopted, different characteristics of each countries relating to energy and economic development (Ozturk, 2010), different study periods and the problem of omitted variables (Payne, 2010b). In order to mitigate or solve some of these problems or issues, the empirical studies have constantly been seeking for new methods, new perspectives and directions. Therefore, in this chapter, we undertake the literature review by categorizing the empirical papers according to the research issues they are trying to tackle using a chronological criterion since in our opinion time determines the development stage of the solutions for each issue.

The objective of this chapter is to conduct a thorough literature review on energy-growth studies in order to identify possible research gaps. With this aim, the remaining part of the study is divided into 6 sections. Section 2 reviews the literature on omitted variable issues. Section 3 reviews the literature on nonstationarity issues. Section 4 reviews the literature on finite sample issues. Section 5 reviews the other issues and Section 6 discusses some recent trends. Section 7 provides concluding remarks.

2.2 Omitted variable issues

The early studies on energy-growth nexus initiated with the bivariate model. Kraft and Kraft (1978) identified unidirectional causal relationship running from GNP to energy consumption by adopting a bivariate model. Many studies have followed them by using bivariate model such as Masih and Masih (1996), Soytas and Sari (2003), Yoo (2005, 2006a; 2006b; 2006c), Yoo and Jung (2005), Lise and Montfort (2007), Chen et al. (2007) and Zachariadis (2007). However, literature has criticized the use of the bivariate model (Granger, 1969; Serletis, 1988; Sims, 1980). Lütkepohl (1982) then pointed out its drawback due to the omission of relevant variables, which has been recognized by later studies (Darrat and Suliman, 1994; Narayan and Smyth, 2005; Payne, 2010a; Stern, 2000). This may partially explain the cause of mixed results in many of the existing literature.

Therefore, many studies used additional yet relevant variables in the multivariate model to overcome the drawback of the bivariate model in examining the causal relationship between energy and output. Yu and Hwang (1984) and Stern (1993) were among the few early studies that recognized the problem of bivariate analysis and included extra variables in their models. The former incorporated employment into the model of energy consumption and GNP and their findings supported the neutrality hypothesis of energy-growth nexus though employment was found to lead energy consumption. The latter included one more additional variable: capital into the former's model and found unidirectional causality running from energy consumption to real GDP. Following the findings of Glasure and Lee (1998) and the suggestion of Ahsan et al. (1992) and Cheng and Lai (1997), Glasure (2002) included the oil price, money supply, government spending and oil price shocks in the error correction model to test the causal relationship between energy consumption and real income. The author reported bidirectional causality between real income and energy consumption therefore attributed the causality or a lack of causality in a bivariate model in the earlier studies to the failure of controlling the effects of omitted variables on the energy-growth nexus.

The development of multivariate cointegration technique by Johansen and Juselius (1990, 1992) enabled the testing of long-run cointegration relationship using multivariate model, which had not been possible with Engle-Granger cointegration test. Other tests that allow multivariate analysis were also introduced such as Autoregressive Distributed Lag models and Toda-Yamamoto causality tests. Subsequently, many more studies conducted multivariate causality studies. These studies can be divided into two categories.

The first category conducts multivariate analysis based on economic theoretical models therefore can be categorized further into two sub-groups (Rafiq, 2008; Wang et al., 2011b). The first sub-group uses a demand function that that incorporates prices, such as real energy prices or consumer price index (CPI) as a proxy, into the energy-output nexus model. Such studies include Masih and Masih (1997, 1998), Asafu-Adjaye (2000), Chang et al. (2001), Chandran et al. (2010), Tang and Tan (2012), Alshehry and Belloumi (2015) and Iyke (2015). The second sub-group uses a production function that incorporates labour, capital in the model including: Examples are Stern, Ghali and El-Sakka (2004), Oh and Lee (2004a, 2004b), Paul and Bhattacharya (2004), Soytas and Sari (2007), Wang et al. (2011b), Shahbaz et al. (2013), Esseghir and Khouni (2014), Lean and Smyth (2014), Pao et al. (2014), Shahbaz et al. (2014), Shahbaz et al. (2015) and Rafindadi and Ozturk (2016).

The second group uses disaggregated or sectoral data or other variables to mitigate the problem of bivariate analysis. Tang and Shahbaz (2013) examined the causal relationship between electricity consumption and aggregate and sectoral economic growth in Pakistan from 1972 to 2010. A unidirectional causal relationship from electricity consumption to real GDP was found at the aggregate level while at the sectoral level, an unidirectional causal relationship is only found from electricity consumption to real output in manufacturing and services sectors but not in the agricultural sector. Zhang and Yang (2013) investigated the energy-growth nexus in China at both aggregated and disaggregated level from 1978 to 2009. A negative bidirectional Granger causal relationship is found between total energy consumption and real income. The results for disaggregated energy consumption were complicated. A negative feedback relationship was found between real income and coal consumption while a positive feedback relationship was identified between the real income and the consumption of the other two types of energy: oil and gas. Chang (2010) included carbon dioxide (CO2) emission in their study using disaggregated energy consumption in China for the period of 1981 to 2006 and they reported that GDP and all types of energy consumption Granger causes CO2 while GDP Granger causes crude oil and coal consumption but Granger caused by electricity and natural gas consumption. Bastola and Sapkota (2015) also included pollution emission in their study on Nepal. They found that in the long run, the conservation hypothesis is valid from 1980 to 2010. Similarly, Long et al. (2015) examined the causal relationship between energy consumption, economic growth and carbon emissions in China from 1952 to 2012. Bidirectional causal relationships between GDP and energy consumption (coal, gas and electricity respectively) were identified. Kareem et al. (2012) also included carbon emission other than the two additional variables industrialization and capital. An unidirectional causality relationship running from economic growth to energy consumption was found.

In addition, Ozturk and Acaravci (2010b) included both carbon emission and employment ratio in their research model for Turkey from 1968 to 2005. No Granger causality relationship was found from Carbon emission or energy consumption to real GDP except that the employment ratio is found to Granger cause real GDP in the short term. Solarin and Shahbaz (2013) examined the causal relationship between economic growth and electricity consumption in Angola from 1971 to 2009 by incorporating urbanization in the trivariate model. A bidirectional causal relationship is found among all the three variables. Other than these, recent studies also include other control variables into the model such as energy exports and imports (Eggoh et al., 2011; Jebli and Youssef, 2015); foreign direct investment and financial development (Keho, 2016; Komal and Abbas, 2015; Kumar et al., 2015; Omri and Kahouli, 2014; Saidi and Hammami, 2015a, 2015b), internet usage (Salahuddin and Alam, 2015), trade (Kumar et al., 2015; Kyophilavong et al., 2015; Sebri and Ben-Salha, 2014), political regime (Adams et al., 2016), financial development and trade (Rafindadi and Ozturk, 2016) and so on and so forth.

Isa et al. (2015) reviewed the existing literature on energy-growth nexus by categorizing them into two groups: bivariate and multivariate analysis. They suggested that new research approaches using multivariate analysis should be conducted more as compared to bivariate analysis applying conventional techniques. They further elaborated that this could be done by adopting unprecedented additional variables.

2.3 Nonstationarity issues

The early studies on energy-growth nexus applied standard Granger causality test or Sims' causality test, which assumes the series under study to be stationary. However, if the series are actually non-stationary, then the test statistic may not have a standard x^2 distribution (Toda and Phillips, 1993). This discovery cast doubt on the statistical significance of the previous findings using Granger-causality. Furthermore, Engle and Granger (1987) recognized the possibility that two nonstationary time series may share a long-run common trend, in which case the two series are considered to be cointegrated. If this were true, then the standard or Sims' Granger causality test would no longer be appropriate. A so-called error-correction model should be adopted to test the causality in the short-run and the long-run. If no cointegration is identified between the series, then the standard or Sims' Granger causality can be applied on the first differences of the series.

Many studies have adopted Engle-Granger cointegration and error-correction model to examine energy-growth nexus including Nachane et al. (1988), Yu and Jin (1992), Cheng and Lai (1997), Glasure and Lee (1998), Yang (2000), Aqeel and Butt (2001), Morimoto and Hope (2004), Yoo and Kim (2006), Lise and Montfort (2007), Zamani (2007), Jinke et al. (2008). Nachane et al. (1988) applied Engle-Granger approach to 25 countries and found cointegration relationship in 16 countries. Further causality test provided evidence of a bidirectional causal relationship between commercial energy consumption and real GDP capita in all the 16 countries except Colombia and Venezuela. However, Yu and Jin (1992) and Cheng (1995) both used Engle-Granger cointegration technique to U.S. market but found no causal relationship between energy consumption and economic growth. Cheng and Lai (1997) adopted Engle-Granger approach but reported no cointegration relationship between GNP and energy consumption. Therefore, Hsiao's version of the Granger causality test was applied on the differenced series and unidirectional causality from GNP to energy consumption was found. Similarly, Yang (2000) and Aqeel and Butt (2001) failed to identify cointegration relationship between energy consumption and economic growth yet standard Granger causality tests managed to detect causal relationships although the relationships are different when total energy consumption and disaggregated energy consumptions are used. Asafu-Adjaye (2000), in contrary, reported unidirectional causal relationship from energy consumption to economic growth both in the short and long run by using an Engle-Granger model. From then on testing for cointegration becomes a prerequisite for causality testing.

However, Engle-Granger cointegration approach has a limitation that it was designed for the bivariate model. Therefore, cointegration technique proposed by Johansen and Juselius (1990, 1992) (J-J test henceforth) that is able to capture the multivariate cointegration relationship became popular then. Many studies applied J-J test including Masih and Masih (1996), Cheng (1999), Stern (2000), Paul and Bhattacharya (2004), Soytas and Sari (2006), Yoo (2006a; 2006b; 2006c), Zou and Chau (2006), Ho and Siu (2007), Jobert and Karanfil (2007), Yuan et al. (2007), Bastola and Sapkota (2015), Alshehry and Belloumi (2015) and Wang et al. (2016a).

Masih and Masih (1996) applied J-J test in 6 countries and found that energy consumption and real GNP (Gross National Product) are cointegrated in 3 countries and used this evidence to imply that there must exist causality in at least one direction. The further results confirmed this implication that either growth or feedback or conservation hypothesis on energy-growth was supported in each of the three countries. The justification of the non-cointegration causal relationship found in the other three countries was provided as there had been a great change in the implementation of economic policy relating to privatization in these countries that may have caused changes in the long-run relationship between energy consumption and economic growth over time. Cheng (1999) also identified cointegration between energy consumption and GNP by using J-J test. Using error-correction model, unidirectional causality running from GNP to energy consumption was found in both short and long run. Moreover, the study of Paul and Bhattacharya (2004) serves as a good example of the superiority of J-J tests over the previous techniques. The authors found only unidirectional causal relationship from energy consumption to economic growth using standard Granger causality and found only long run causality from economic growth to energy consumption using Engle-Granger approach. The combined results support feedback hypothesis on the energy-growth nexus. On the other hand, the multivariate J-J test managed to reveal the exact same bidirectional causal relationship, i.e. from energy consumption to economic growth in the short run and in the opposite direction in the long run.

The example studies that managed to find the existence of cointegration between economic growth and energy consumption using J-J test include Stern (2000), Hondroyiannis et al. (2002), Ghali and El-Sakka (2004), Oh and Lee (2004b), Shiu and Lam (2004), Ho and Siu (2007), Bastola and Sapkota (2015), Alshehry and Belloumi (2015), Azam et al. (2015), Naser (2015) and Wang et al. (2016a). On the other hand, some studies failed to detect any cointegration relationship using the same methods such as Ghosh (2002) and Jobert and Karanfil (2007).

Despite the popularity of Engle-Granger and J-J cointegration technique, both tests have the problem of pretesting by unit-root tests such as ADF, PP, and KPSS tests, on the integration properties of the variables, which are not so straightforward in practice. If the results of the unit root tests are wrong, then the subsequent cointegration and causality tests will not be able to provide reliable findings. The issue has been recognized much early as Phillips and Perron (1988) has shown that unit root tests must take possible structural breaks into consideration. More specifically, traditional unit root tests may fail to reject the null hypothesis of unit root when the variable is actually stationary around structural breaks. However, few studies on energy-growth nexus adopted the tests proposed by Perron (1989, 1997) and Zivot and Andrews (1992) that test the presence of unit root by considering the possible structural break.

Hondroyiannis et al. (2002) examined the causal relationship between energy consumption and economic growth in Greece by using a multivariate model that incorporated energy price. Initially, it was not able to run the multivariate J-J cointegration test since the traditional unit root tests showed that the variables have mixed order of integration. However, by considering structural break due to the 1973 oil crisis by conducting the Perron unit root test, it was confirmed that all the variables are actually I (1), which enabled the conduct of J-J cointegration analysis. Cointegration relationship was finally identified and a bidirectional causal relationship between energy consumption and economic growth was found. Altinay and Karagol (2004) emphasized the necessity of considering structural breaks in the variables when conducting unit-root tests. Both Perron and Zivot-Andrews unit root tests were adopted and the series were found to be trend-stationary with a structural break while the traditional unit root tests showed that the series are with one unit root. Therefore, the author concluded that conducting causality test on first difference of the data is not appropriate. The Hsiao's causality test was applied on the detrended data, however, no evidence of causal relationship between GDP and energy consumption was identified. The results further proved that conducting causality test based solely on the traditional unit root test results on the order of integration may provide spurious result since unidirectional causal relationship from energy consumption to GDP could be found if mistakenly the causality test was applied on the first differenced series.

Although unit root tests with structural breaks proved to be useful, the majority of the studies did not pay attention to this integration issue only until recently. Smyth (2013) complemented the surveys of Ozturk (2010) and Payne (2010a, 2010b) by reviewing the literature that test the integration properties of energy consumption and production. He found that a group of literature dedicating to test the integration properties of energy and production variables has emerged in recent years (especially from 2008 to 2012).

Furthermore, he concluded after an extensive review of the literature that it is vital to consider the possibility of one or more structural breaks when testing the energy variables' order of integration.

Other than adopting more robust unit-root tests that can reveal the true integration properties of the variables, some causality tests were proposed to tackle these issues without the need of pretesting stationarity.

One of them is called Autoregressive Distributed Lag Model (ARDL henceforth) that is developed by Pesaran et al. (2001). ARDL is useful in the way that it allows the use of a mixture of variables that are I(1) and I(0). In other words, when applying ARDL, the information of the exact integration properties of the variables is not necessary and the variables need not be integrated with the same order. In addition, it is rather easy to conduct the test since it uses the typical ordinary least square technique. Another benefit is that it is free from the potential drawback of the residual-based cointegration tests (e.g. Engle-Granger), which has been criticized in literature for pushing the short-term dynamic into the residuals (Banerjee et al., 1998; Banerjee et al., 1993; Pattichis, 1999). More importantly, as Squalli (2007) pointed out, J-J test can provide information on the existence of cointegration relationship between energy consumption and economic growth but it cannot provide the direction of such relationship while ARDL is able to detect cointegration and identify the direction of causality at the same time.

Due to these advantages, ARDL were adopted in many studies including Fatai et al. (2004), Narayan and Smyth (2005), Wolde-Rufael (2004), Squalli (2007), Zachariadis (2007), Akinlo (2008), Ghosh (2009), Ozturk and Acaravci (2010a, 2011), Hamdi et al. (2014), Shahbaz et al. (2014), Bastola and Sapkota (2015), Jebli and Youssef (2015), Bloch et al. (2015), Shahbaz et al. (2015), Aslan (2016), Rafindadi (2016) and Rafindadi and Ozturk (2016). Fatai et al. (2004) and Wolde-Rufael (2006) both found a bidirectional causal relationship between energy consumption and economic growth in the long run by using ARDL technique.

Another alternative test was proposed by Toda and Yamamoto (1995) (T-Y test henceforth). T-Y test likewise provides the similar advantages with ARDL that exact information on the integration properties of variables is not needed as it allows them to be integrated at different orders. Moreover, as compared to the limitation of ARDL that no variables in the model should be integrated more than unity, T-Y test is able to capture the causality between the variables integrated at a higher order. The only information needed before the T-Y test is conducted is the maximum order of integration of the variables. Given these benefits provided, T-Y test also became a popular tool in the empirical studies including Fatai et al. (2004), Wolde-Rufael (2004, 2005, 2006), Lee (2006), Soytas and Sari (2006), Mehrara (2007a), Soytas et al. (2007), Squalli (2007), Zachariadis (2007), Payne (2009), Bowden and Payne (2010), Payne and Taylor (2010), Zhang and Yang (2013), Kumar et al. (2015) and Rahman et al. (2015). Squalli (2007) examined the causal relationship between electricity consumption and economic growth in OPEC countries. Both ARDL and T-Y tests mostly provided consistent results that support either growth hypothesis or feedback hypothesis on the energy-growth nexus, which implied that most of OPEC countries are energy-dependent. Zhang and Yang (2013) identified a negative bidirectional causal relationship between economic growth and energy consumption using a multivariate T-Y test, which was greatly different from the previous empirical findings in China and provided new insights on energy policy implications. The authors addressed the difference to the adoption of the T-Y test in the study.

Other than the techniques discussed above, another useful tool proposed in the literature is Meboot, which is a type of bootstrap methods that uses maximum entropy developed by Vinod (2004). Yalta and Cakar (2012) explained the practical advantages of the Meboot technique relating to the nonstationarity issue in the literature. The technique can be applied even when the integration properties of the variables are difficult to identify, e.g. in the presence of multiple structural breaks. More specifically, Meboot is able to avoid the spurious regression problem even when the nonstationary data at level is used, which is proved by Vinod (2010) by conducting Monte Carlo analysis. Therefore, there is no need for pretesting which may incur specification errors. Less sophisticated models can be adopted subsequently. By adopting Meboot technique, Yalta and Cakar (2012) found evidence that support the neutrality hypothesis in most of the model estimations (53 out of 60) in China. However, the author suggested that the results should not be accepted simplistically. More studies using sectoral and provincial data should be conducted to understand the energy-growth nexus in China. If the sectoral and provincial studies also support neutrality hypothesis then it will be safer to confirm that energy consumption and economic growth are independent of each other. Inspired by the same advantages of the technique, Ahmed et al. (2015) also applied maximum entropy to examine the energy-growth nexus in Pakistan from 1971 to 2011. Using both bivariate and multivariate analysis, they confirm that the conservation hypothesis is valid in Pakistan.

2.4 Finite sample issues

One of the main issues of empirical studies on the energy-growth nexus is the finite sample. Given the availability of the data, empirical studies usually use annual data. Therefore, the sample size is usually small. The majority of the studies have observations ranging from 10 to 60.

Few studies managed to obtain relatively large sample size. Vaona (2012) used the data from 1861 to 2000, 140 observations to overcome the small sample size problem. By considering possible structural breaks using Perron and Zivot-Andrews unit root tests, Toda-Yamamoto causality test, J-J test and Lütkepohl et al. (2004) approach were applied in the study. J-J test failed to identify cointegration between nonrenewable energy and GDP while Lütkepohl et al. (2004) found cointegration by taking a structural break into consideration. A bidirectional causal relationship between non-renewable energy consumption and economic output was found while no any causal relationship was found between renewable energy consumption and economic output. If traditional energy sources were included in the renewable energy measure then a negative unidirectional causal relationship from energy consumption to economic output could be found. Stern and Kander (2012) used data on Sweden for 150 years and found that cointegration in one of the two research models using the nonlinear cointegration test proposed by Choi and Saikkonen (2010), which indicated the existence of causality between the variables. However, the study could not provide the direction of the causality. Stern and Enflo (2013) aimed at identifying the direction of causality. By using the same data, Toda-Yamamoto causality test and the cointegration test with structural breaks proposed by Johansen et al. (2000), it was found that the Granger causality tests results relied on the variables used, the selection of additional variable and the time periods of study.

In most of the cases, due to the data availability problem, it is no way to find the data sets with large size on energy consumption or GDP. Some studies tried to overcome such problem by interpolating. Tang (2008) used the interpolation method of Gandolfo (1981) to increase the data frequency of electricity consumption per capita and GNP per capita from annual to quarterly in Malaysia. However, consistent with the simulation of Smith (1998), increasing data frequency by interpolation did not alter the cointegration results as no cointegration was identified between the GNP per capita and electricity consumption per capita.

Nevertheless, the small sample size is still a big obstacle as it affects many aspects of the empirical research as many of the statistical tests are based on asymptotic theory. The power and size distortion problem relating to finite sample has been recognized in the literature. For example, Cointegration tests proposed by Engle and Granger (1987) and Johansen and Juselius (1990) are also considered inappropriate in small samples (Cheung and Lai, 1993; Narayan and Smyth, 2005).

One solution is to follow the approach of Reinsel and Ahn (1992) by using a scale factor multiplied by the Johansen statistics in order to correct the small sample bias. Studies adopting this approach include Lee and Chang (2005) and Ang (2007). Following the suggestion of Cheung and Lai (1993), Lee and Chang (2005) adjusted the trace test statistics and the maximum likelihood test statistics by Reinsel and Ahn scaling factor to overcome the finite sample issue. Cointegration relationship was found between the energy consumption and GDP in Taiwan from 1954 to 2003. However, such relationship was not stable and may have been affected by some economic events, i.e. structural breaks. Overall, it was found that Taiwan was energy-dependent and energy conservation policy may hamper its economic output. Similarly, Tang et al. (2016) applied the Barlett-corrected trace test proposed by Johansen (2002) to correct the small-sample bias in conducting Johansen cointegration test.

Another way to enhance the power of the cointegration test is to apply the combined cointegration test proposed by Bayer and Hanck (2013). This is done by combining various cointegration test results so that more conclusive findings may be achieved. Studies that adopted such approach includes Govindaraju and Tang (2013), Kyophilavong et al. (2015), Kumar et al. (2015) and Rafindadi (2016).

Besides these remedies applied on the traditional test approach, other tests that are able to tackle the finite sample issue are proposed. A good example is ARDL cointegration approach. In addition to the advantages discussed in the previous section, ARDL has also proven to be able to provide consistent estimators in small sample sizes (Pesaran and Shin, 1998). Ang (2007) applied both the modified version of the J-J test by using Reinsel and Ahn scaling factor and also ARDL bounds test as a sensitivity check to examine the causal relationship between economic growth and energy consumption in France. Both tests provided consistent results that supported the existence of cointegration between the variables from 1960 to 2000. Further causality tests confirmed unidirectional causal relationship from energy consumption to economic output in the short run and causality from economic output to energy consumption in the long run.

Besides ARDL, panel cointegration test developed by Pedroni (1999, 2004) is also a useful tool in tackling issues relating to small sample size. The panel tests are able to bring additional power by pooling the cross-section and time series data. Many studies have adopted Panel cointegration and error-correction models to examine the energy-growth nexus including Lee (2005), Al-Iriani (2006), Mahadevan and Asafu-Adjaye (2007), Mehrara (2007a), Apergis and Payne (2009), Lee and Chang (2008), Al-mulali et al. (2014), Ahmed et al. (2015), Saidi and Mbarek (2016), Wang et al. (2016b) and so on. Some other studies also adopted the cointegration test proposed by Westerlund (2006) that allows for structural breaks, e.g. Narayan and Smyth (2009).

Nevertheless, traditional panel cointegration tests assume that the samples under study are homogenous, i.e. a single entity. However, this assumption may be violated in reality, for example, Huang et al. (2008) pointed out that the energy-growth nexus should be different in countries with different levels of economic development.

A possible solution is to select the sample countries with homogenous characteristics since the heterogeneous elements may cause the typical panel models provide wrong causality results (Wilson and Butler, 2007). Possible selection criteria include: the status of being members of a same international organization (Al-Iriani, 2006; Alper and Oguz, 2016; Belke et al., 2011; Costantini and Martini, 2010; Esseghir and Khouni, 2014; Inglesi-Lotz, 2016; Lee and Chang, 2008; Menegaki and Ozturk, 2013; Narayan and Prasad, 2008; Narayan and Smyth, 2009; Soytas and Sari, 2006; Streimikiene and Kasperowicz, 2016), the stage or characteristics of economic development (Ajmi et al., 2015; Bildirici and Bakirtas, 2014; Huang et al., 2008; Lee, 2005; Lee and Chang, 2007a; Saidi and Mbarek, 2016; Śmiech and Papież, 2014; Wolde-Rufael, 2014), status of being energy exporting or importing countries (Damette and Seghir, 2013; Jalil, 2014; Mahadevan and Asafu-Adjaye, 2007; Mehrara, 2007a) and geographic location (Adams et al., 2016; Al-mulali et al., 2014; Chen et al., 2007; Eggoh et al., 2011; Lee and Chang, 2008; Narayan and Smyth, 2009; Saidi and Hammami, 2015a) . Liddle and Lung (2015) divided the sample countries according to different criteria: Geographic location, income levels and relative energy intensity. However, according to Śmiech and Papież (2014), these criteria may not guarantee in selecting the homogeneous countries and they proposed to choose the countries with "similar dynamics of energy consumption…and the modernization of economy" (p. 119). For example, Apergis et al. (2016) include in their panel analysis the 10 nations that ranked as the largest hydroelectricity consumers in the world.

Another solution is to apply the test proposed by Emirmahmutoglu and Kose (2011) that is able to examine heterogeneous panel by directly considering the difference in the causal relationship in each individual sample. The test is developed based on the meta technique of Fisher (1932). Individual Wald tests are conducted on each sample to obtain the individual p values, which are used then to calculate the Fisher test statistic that is used to determine the existence of causality for the whole panel. Studies adopted such test include: Chang et al. (2014) and Chang et al. (2015).

There is another problem associated with the panel cointegration tests. Again due to the treatment of the whole samples as one entity, it neglects the fact of cross-sectional dependence, i.e. there may be cross-section correlations. As a result, such test estimators are biased as suggested by Andrews (2005). To tackle such problem, Westerlund and Edgerton (2008) proposed a test that is able to provide robust results in dependent panels. Recent studies that applied such test include: Chang et al. (2014), Liddle and Lung (2015) and Jalil (2014).

Although the panel cointegration tests discussed so far provide information on the energy-growth nexus of groups of countries or regions, they are not able to provide any information on the individual country or region. In fact, if the research is to capture the effects of individual country or region, Chandran et al. (2010) suggested that studies on a single sample are still needed. Smyth and Narayan (2015) also concluded that it is not appropriate to apply panel technique if the research aims at providing policy recommendations to individual nations. Similarly, Sebri (2015) is of the view that "sing-country-based studies…are more reliable for policy makers" as well as the multi-country-based studies that group the countries rigorously (p. 663). However, as discussed earlier, the unavailability of time series with ideal length is an inevitable reality exists in the research field of energy-growth nexus. To examine the energy-growth nexus for a single sample with more reliable and robust results, so far the most viable way is bootstrapping, which has proven to be a useful tool in overcoming the finite sample issues.

The Meboot technique discussed in the previous section is one example. Other than the benefits discussed, Meboot is especially useful in providing accurate results when dealing with small sample size. Few recent studies applied such approach, e.g. Yalta (2011) and Yalta and Cakar (2012) as discussed in the previous section. In addition, inspired by the suggestion of Smyth and Narayan (2015), Ahmed et al. (2015) re-examined the energy-growth nexus in Pakistan from 1971 to 2011 by adopting the Maximum Entropy Bootstrap method, which is able to provide robust results in finite samples. Both the bivariate and multivariate analysis confirmed that the conservation hypothesis is valid during the study period in Pakistan.

Moreover, Hacker and Hatemi-J (2006) also proposed to adopt bootstrap technique in causality test based on Toda-Yamamoto approach. Since Toda-Yamamoto test performs poorly in small samples as criticized by Mantalos (2000) and Hacker and Hatemi-J (2006), the latter therefore proposed to calculate robust critical values by bootstrapping. According to Toda and Yamamoto (1995), the test statistics are based on the asymptotic distribution theory. However, Hacker and Hatemi-J (2006) managed to show that the test statistics tend to over-reject the null hypothesis of non-causality by Monte Carlo simulation especially when the residuals suffer from autoregressive conditional heteroscedasticity and non-normality problems. The authors also proved that as compared to the case based on asymptotic distribution, the bootstrapped size for the test statistic is much closer to the correct size. Some recent studies adopted such approach including Yildirim and Aslan (2012), Lin and Wesseh-Jr (2014) and Tang et al. (2016). By adopting Hacker and Hatemi-J (2006) causality test, Yildirim and Aslan (2012) managed to examine the energy-growth nexus on each of the 17 sample countries. The bootstrapping methods help overcome the potential finite sample issue and confirm the results using the Toda and Yamamoto procedure. It is safe to accept the causality results since the results according to Toda and Yamamoto procedure and the bootstrap-corrected causality tests are almost consistent, except some acceptable difference in the significance level of the test statistics.

Bootstrap Granger panel approach developed by Konya (2006) is another good example. This approach is able to provide statistical inference for the individual sample in the panel group by bootstrapping. Śmiech and Papież (2014) applied this approach to examine the causal relationship between economic growth and energy consumption in the EU member countries from 1993 to 2011. The sample countries that achieved the three energy policy targets were divided into four groups. Using the bootstrap Granger panel causality approach, the author managed to conduct analysis on individual countries since country-specific bootstrap critical values were used. The results show that causal relationships between energy consumption and economic growth were found in the countries that met the energy policy targets to the greatest extent while no causal relationships were found in other countries. Wolde-Rufael (2014) reassessed the electricity-growth nexus in 15 transition economies from 1975 to 2010 using this test. Growth hypothesis was only valid in Belarus and Bulgaria; Feedback hypothesis was valid only in Ukraine; for the rest of the sample countries, either neutrality or conservation analysis was valid. Based on the causality results for the individual countries, the author managed to provide policy implications for these transition countries. Mutascu (2016) also applied such test in the G7 countries. Bidirectional causality was found between energy consumption and GDP in Japan, Canada and the United States; Conservation hypothesis was found to be valid in France and Germany while neutrality hypothesis was confirmed in Italy and the United Kingdom. The author also proved that the results are very sensitive to the cross-sectional correlations between sample countries.

2.5 Other issues

Other than the three major issues discussed in the previous sections, there are some other issues on the literature of energy-growth nexus.

One issue, as pointed out by both Payne (2010b) and Kalimeris et al. (2013), is about the data used in the empirical studies.

For energy consumption, it can be divided into two main groups. First group uses aggregate energy consumption such as Oh and Lee (2004a, 2004b), Paul and Bhattacharya (2004), Wolde-Rufael (2005), Lee (2006), Soytas and Sari (2006), Al-Iriani (2006), Mahadevan and Asafu-Adjaye (2007), Mehrara (2007a, 2007b), Chiou-Wei et al. (2008) , Lee and Chang (2008) and Apergis and Payne (2009). The second group uses disaggregated energy consumption such as electricity, coal, natural gas, oil, nuclear energy, renewable energy and etc., and also by sectors, such as Yang (2000), Aqeel and Butt (2001), Ghosh (2002), Hondroyiannis et al. (2002), Fatai et al. (2004), Jumbe (2004), Morimoto and Hope (2004), Shiu and Lam (2004), Wolde-Rufael (2004), Altinay and Karagol (2004), Lee and Chang (2005), Narayan and Smyth (2005), Wolde-Rufael (2006), Yoo (2006a; 2006b; 2006c), Yoo and Kim (2006), Zou and Chau (2006), Narayan and Singh (2007), Reynolds and Kolodziej (2008), Sari et al. (2008), Narayan and Prasad (2008), Narayan and Wong (2009), Bowden and Payne (2010), Apergis and Payne (2009), Payne and Taylor (2010) and Wolde-Rufael (2010).

As Payne (2010b) suggested that using aggregate energy consumption may prevent us from revealing the hidden information on the impact of energy consumption of different types and sectors on the economy, therefore, the second group seems more useful. It provides the information on the energy-growth nexus at both aggregate and disaggregated or sectoral levels so that we can find out which specific type energy is dominating or contributing the most to the economic growth. Besides these two groups, some studies also use energy approach (Warr and Ayres, 2010) and the divisia energy index (Oh and Lee, 2004a; Stern, 1993, 2000).

For economic growth, the early studies used Gross National Product (GNP) rather than Gross Domestic Product (GDP) (Abosedra and Baghestani, 1991; Akarca and Long, 1980; Erol and Yu, 1987; Hwang and Gum, 1992; Kraft and Kraft, 1978; Yu and Hwang, 1984). Kalimeris et al. (2013) did not make a distinction between these two measurements. However, the use of aggregate GDP has been criticized by Bergh (2010), Bithas and Kalimeris (2013) and Daly (2013) for the similar drawback of only using aggregate energy consumption. To overcome such shortcomings, some studies use alternative variables. Oh and Lee (2004a) used non-agricultural GDP while Jumbe (2004) used agricultural GDP in addition to aggregate GDP. Similarly, Tang and Shahbaz (2013) used the economic output of three sectors: manufacturing, agricultural and services. In addition, Jobert and Karanfil (2007) used industrial value added while Soytas et al. (2007) used manufacturing value added. A similar approach was taken by Grossmann and Morlet (1984), Zachariadis (2007), Zamani (2007), Sari et al. (2008) and Feng et al. (2009).. The use of disaggregated or sectoral economic growth definitely provides much richer information on the energy-growth nexus.

Another issue as pointed out by Payne (2010b) on the data is that some studies used total energy or GDP(Zhang and Yang, 2013) while others used per capita measurement(Tang and Shahbaz, 2013). Others used a mixture of per capita and total measurement of energy consumption and GDP (Lee, 2006; Lee and Chang, 2005; Soytas and Sari, 2006). The per capita data should be considered more appropriate compared to the aggregate data as it removes the effect of population growth on the growth of energy consumption and GDP.

Lastly, as Payne (2010b) concluded that most of the existing studies ignore the analysis of the signs and magnitude of the coefficients of causality tests. However, as explained by Squalli (2007), a negative causal relationship will provide different policy implications comparing to a positive causality. Therefore, it is necessary to examine the signs of causality tests. The recent studies that analyze the energy-growth nexus by examining both the magnitude and the direction of the causality include Balcilar et al. (2010), Zhang and Yang (2013) and Rahman et al. (2015).

2.6 Some recent trends

Other than the studies that aim to tackle the three major issues discussed in Section 2, 3 and 4, there are some new research trends in recent years that worth discussing include nonlinear causality, asymmetric causality, and causality at different time and frequencies.

2.6.1 Nonlinear causality

The majority of the studies ignored the possible nonlinear causality between energy consumption and economic growth. However, literature has shown that energy consumption and macroeconomic variables may have some nonlinear causal relationships (Balke et al., 2002; Hamilton, 1996, 2003; Mork et al., 1994; Seifritz and Hodgkin, 1991).

In recent years, some studies have made the effort in filling this research gap. For example, Lee and Chang (2005) suggested that nonlinear nature should be considered when studying energy consumption data based on the previous literature that provided evidence that structural changes in energy consumption may be caused by economic events, environmental changes, energy price fluctuations and energy policy changes (Hamilton, 2003; Hooker, 2002; Moral-Carcedo and Vicens-Otero, 2005). In line with this study, Lee and Chang (2007b) further proved that the relationship between energy consumption and real GDP growth was nonlinear and reversely U-shaped in the case of

Taiwan. In addition, they addressed the cause of the mixed findings of the previous literature on energy and growth to this kind of nonlinearity.

Chiou-Wei et al. (2008) applied both linear and nonlinear causality tests in the sample countries including eight from Asian developing countries and the United States. Nonlinear causality relationships between energy consumption and economic growth were found in five developing countries while no causality relationship is identified for United States, Thailand and South Korea. The authors explained the possible cause of the nonlinear relationship as the structural shocks result from major economic incidents, e.g. financial or energy crisis. Although the findings seemed promising, they admitted the possibility of overly rejecting the null due to the potential drawback of the adopted nonlinear test as pointed out by Diks and Panchenko (2005, 2006).

Hu and Lin (2008) investigated the causal relationship between GDP and disaggregated energy consumption using a nonlinear cointegration technique: a threshold cointegration test proposed by Hansen and Seo (2002). Except for oil consumption, the nonlinear cointegration between disaggregated energy consumption and GDP was found. An asymmetric adjusting process was found for the long-run equilibrium relationship.

These studies have drawn attention from researchers to investigate the energy-growth nexus in the scope of nonlinear tests. For example, following the suggestion of Lee and Chang (2005) and Chiou-Wei et al. (2008), Cheng-Lang et al. (2010) applied nonlinear causality tests in addition to linear causality tests in order to identify the relationship between total electricity consumption (TEC) and real GDP. TEC was divided into industrial sector consumption (ISC) and residential sector consumption (RSC). A nonlinear causality from real GDP to RSC and a bidirectional nonlinear causality between TEC and real GDP were found while a bidirectional linear causality between

ISC and real GDP was also identified, except that no linear causality was found between RSC and real GDP.

Dergiades et al. (2013) applied both linear and nonlinear causality tests on the annual data of Greece from 1960 to 2008 in order to identify the true relationship between energy consumption and economic growth. Both linear and nonlinear causality tests indicate a unidirectional relationship from energy consumption to economic growth. However, based on the suggestion of Zachariadis (2007), they expressed doubt on the validity of the bivariate causality test results due to the potential omitted variables bias. This implied that more reliable and powerful nonlinear test should be adopted.

Iyke (2015) re-examined the causal relationship between electricity consumption and economic growth in Nigeria from 1971 to 2011 using both linear and nonlinear tests. The linear analysis indicated that growth hypothesis is valid. On the other hand, although nonlinear unit roots are found in the data-generating process of the time series, no nonlinear cointegrating relationship was captured among the series.

Besides the studies that apply the nonlinear causality test that consider nonlinearity caused by general factors, some studies consider the nonlinearity caused specifically by regime shift. Balcilar et al. (2010) applied bootstrap rolling window tests to capture the changes in causality for the subsamples. Their results further imply that it is inappropriate to use linear analysis as the energy-growth nexus is not stable through time. Hence, rather a nonlinear technique that can explicitly capture such instability (regime shift) should be adopted. Fallahi (2011) examined the energy-GDP nexus in U.S. from 1960 to 2005 by using Markov-switching vector autoregressive technique that incorporated the possibility of regime shifts. The results showed that there was a bidirectional causal relationship between energy consumption and the GDP in the first regime, which corresponded to events such as energy crises and recessions. However, no nexus was found in the second regime. These results prove that causality between energy use and GDP are indeed nonlinear (regime dependent).

2.6.2 Asymmetric causality

Other than the nonlinear causality studies reviewed above, Hatemi-J and Uddin (2012) argued that the previous studies had ignored the possibility of asymmetric causality between energy consumption and economic growth. More specifically, the author pointed out that a positive shock in energy consumption may have a different impact on economic growth than a negative shock. Therefore, it is worth studying the causality between positive and negative shocks of energy consumption and economic growth.

Hatemi-J (2012a) proposed an asymmetric causality test that is based on the bootstrapped Toda-Yamamoto causality test developed by Hacker and Hatemi-J (2006) using the cumulative positive and negative shocks. Studies applied this test include Hatemi-J and Uddin (2012), Tiwari (2014) and Destek (2016). Hatemi-J and Uddin (2012) investigated the asymmetric causality between energy utilization and economic growth in the US. Strong asymmetric causality was found that negative shock in economic growth was caused by negative shock in energy consumption while no such causality was found between positive shocks. The authors then concluded that there existed an optimal quantity of energy for the US to sustain the economy, below which the economic growth would be hampered while above which the economic growth may not be strengthened. Inspired by Hatemi-J and Uddin (2012), Tiwari (2014) studied the asymmetric causal relationship between disaggregated energy consumption GDP in the U.S. The results indicated that asymmetric causality existed between GDP and coal consumption, GDP and natural gas, GDP and primary energy, GDP and total renewable energy consumption. Similarly, Destek (2016) examined the asymmetric causal relationship between economic growth and renewable energy consumption in newly industrialized nations from 1971 to 2011. The results showed that for South Africa and Mexico, there was a unidirectional causality from negative shocks in renewable energy consumption to positive shocks in real GDP; for India, there was a unidirectional causality from negative shocks in renewable energy consumption to negative shocks in real GDP; for Brazil and Malaysia, no asymmetric causality was found.

Besides these studies, Araç and Hasanov (2014) examined the asymmetries in the energy-growth nexus from 1960 to 2010 in Turkey by adopting the smooth transition vector autoregressive model. The results showed that negative energy shocks affected the growth more than positive energy shocks; big negative energy shocks had greater effect on the output than small negative energy shocks; positive output shocks affected energy consumption more while negative output shocks did not affect energy consumption at all; small output shocks affected energy consumption more than large output shocks.

2.6.3 Causality at different time and frequencies

Granger (1969, 1980) suggested that it was more meaningful to conduct the causality tests across different time periods by adopting a spectral-density approach.

Yuan et al. (2007) took the initiative to capture the energy-growth nexus by using the cyclical components of electricity consumption and GDP. Hodrick-Prescott technique was used to decompose the time series. A long-run cointegration relationship was found between the trend components as well as the cyclical components. However, the HP filtering method was criticized by Harvey and Jaeger (1993), Cogley and Nason (1995), Baxter and King (1999), McCallum (2000) and others. The main drawback is that if the original series is stationary at first difference, the HP filtering causes distortion to its dynamics by inducing spurious information in the cyclical components. In contrary to this, wavelet decomposition which is used in this study is a better alternative. It formalizes the concept of decomposition (Ramsey, 1999) and it is proven to preserve the information in the series before and after the filtering.

Ozun and Cifer (2007) conducted the first study to examine energy-growth nexus using wavelet multiscale analysis for Turkey. They managed to identify causality relationships at different time scales which were not revealed by Soytas and Sari (2007) who used the same dataset.

Likewise, Aslan et al. (2013) conducted similar studies using wavelet decomposition method to the US energy market and found that energy consumption was influenced by GDP in the short term, but a bidirectional relationship had prevailed over the medium and long term. Therefore, the differences in the results in the time-frequency domain would not be discovered if the original series were used without decomposition.

In addition to wavelet analysis, Bozoklu and Yilanci (2013) used a Granger causality tests at different frequencies proposed by Breitung and Candelon (2006) since the traditional Granger causality test tend to neglect the possibility that the causality may vary in strength, direction or existence across different frequency domains (Lemmens et al., 2008). In their study, temporary and permanent causal dynamics were analysed separately. The temporary and permanent causal relationships were found to be different in the 20 OECD (Organization for Economic Co-operation and Development) countries. Therefore, they suggested that the information on whether the causal relationship is temporal or permanent is as important as the information on the direction of the causal relationship for the policy makers to design prudent policies.

2.7 Concluding remarks

Given the energy security and pollution issues all over the world, it is vital for the policy makers to understand the true causal relationship between energy consumption and economic growth in order to design and implement proper energy and environmental policies. This chapter has aimed to review the existing literature in the past three decades in order to synthesize the empirical results and provide directions for future research.

It is concluded that the existing literature provides evidence that supports the entire four well-known hypotheses on the energy-growth nexus. Therefore, no consensus can be achieved as to draw reliable policy implications for individual countries. Through the review of literature according to the issues that the empirical research has been seeking to tackle, it is observed that the economic models and techniques adopted in the studies have become more and more robust and sophisticated. This is reasonable. As new issues are identified, new methods will be proposed to tackle such issues. Therefore, it should be safe to conclude that although a consensus is hard to achieve given the differences of sample countries in energy consumption dynamics, economic development stage, climate or environmental conditions, etc., as time goes by, the empirical studies should be able to provide more reliable results.

Based on the review of the development of methods and responses to the issues raised, the following research gaps are identified:

(a) In order to eliminate the omitted variable problem, empirical researchers should make efforts to obtain more types of data in order to conduct the multivariate analysis. In addition, it is preferred that such multivariate analysis selects relevant variables based on some theoretical ground, e.g. neoclassical growth(production) or demand models rather than selecting them arbitrarily. If such selection is inevitable, then reasonable justification should be provided.

(b) If the data is not available, in which case only bivariate study is possible, then more robust technique should be adopted rather than applying the traditional technique. For example, the potential of bootstrapping methods should be explored more and further. The bootstrapping-based technique that the latest studies applied include the modified version of Toda-Yamamoto causality test proposed by Hacker and Hatemi-J (2006), the Meboot technique proposed by Vinod (2004). These tools are useful in the way that they are designed to solve more than one issues such as omitted variable bias, integration properties issue and finite sample issues. Therefore, the future methods proposed should seek to tackle as many issues as possible simultaneously. Such technique should prove to be robust and able to contribute in providing more reliable results in the future.

(c) More analysis should be conducted by using disaggregated, sectoral or regional (provincial) data to provide a rich picture on the energy-growth nexus.

(d) Future studies should use more consistent data measurement such as per capita data on energy consumption and economic growth. This will not only provide more meaning results but also more comparable results.

(e) When conducting panel causality test, the future studies should be more cautious in creating the homogeneous group of sample countries or regions as the heterogeneous elements in the group may cause wrong results if the traditional technique is adopted.

(f) Future research should put more effort on examining nonlinear and asymmetric causality relationship that has been neglected by the majority of the empirical studies so far. These studies should be able to complement the knowledge on energy-growth nexus obtained by linear causality studies. More reliable policy implications are expected to be provided by such studies based on richer and more complete information derived. Possible techniques available include Nishiyama et al. (2011) nonlinear causality test and Hatemi-J (2012a) asymmetric causality test.

(g) Another potential area that has also been ignored is the investigation on the causal relationship at different frequencies and time scales. These studies are able to provide useful information on energy-growth nexus across time periods or at different frequencies.

(h) Future studies should examine the signs and magnitudes of the coefficients for the causality tests. This will ensure that accurate policy implications will be drawn based on the correct signs and magnitudes of the causal relationship.

Based on the above research gaps identified, the current study aims at contributing to the existing literature by using the following research methods and approach:

(1) Multiscale granger causality

(2) Linear and nonlinear Granger causality

(3) Asymmetric Granger causality

(4) The combination of (1) to (3). This is inspired by the study of Balcilar et al. (2010), who suggest that research features including nonlinearity, asymmetry and time-varying should be considered to avoid misspecification of time series analysis based on their findings of time-varying energy-growth nexus in G-7 countries.

(5) Regional analysis on energy-growth nexus by using a robust technique that is able to tackle the finite sample issue.

CHAPTER 3: METHODOLOGY AND DATA

3.1 Introduction

This chapter will provide a comprehensive elaboration of the research techniques employed in this study. An analytical framework will be presented at the end of the chapter.

3.2 Empirical model and data

The main aim of this study is to examine the relationship between economic growth and energy consumption. We use the neoclassical production function following the previous works by Wang et al. (2011b) and Tang and Shahbaz (2013), in which energy is treated as a separate production input other than labour and capital:

$$GPC_t = f(K_t, L_t, EC_t) \quad (1)$$

where GPC_t, K_t, L_t, and EC_t are real GDP per capita, real capital stock per capita, average labour population, and energy consumption per capita respectively. The subscript t denotes the time period. All variables are expressed in natural logarithm.

In Chapter 4, the data used for study at the national level are annual time series from 1953 to 2013. The data of real GDP per capita is obtained by adjusting the nominal GDP per capita with the GDP deflator (GDP index) (base 1952=100). The data of energy consumption per capita is obtained by dividing total energy consumption by the average total population. The average labour population is the average of the total labour. All these data are collected from the National Bureau of Statistics of China. The capital stock per capita (total capital stock divided by the average total population), is calculated by perpetual inventory method with reference to the study of Haojie (2008)[2].

In Chapter 5, the data for regional studies are annual time series with different length for different regions:

(a) From 1986 to 2011: Chongqing
(b) From 1985 to 2011: Anhui, Gansu, Guangdong, Jiangxi, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang and Nei Menggu;
(c) From 1980 to 2011: Beijing, Hubei, Hebei, Hunan and Qinghai;
(d) From 1979 to 2011: Sichuan;
(e) From 1978 to 2011: Fujian, Guangxi, Guizhou, Hei Longjiang, Henan, Jilin, Liaoning, Ningxia, Shaanxi, Shanxi, Xinjiang and Yunnan.

The regional data of real GDP per capita is obtained by adjusting each region's nominal GDP per capita with its GDP deflator (GDP index) (base 1952=100). The regional data of energy consumption per capita is obtained by dividing each region's total energy consumption by its average total population. The regional data of labour is the average total labour population for each region. The regional capital stock data is calculated based on the study of Zong and Liao (2014).

In Chapter 6, the data for real GDP per capita, capital stock per capita and average labour population are obtained the same way with Chapter 4. The aggregate renewable energy consumption (1965 to 2013) is obtained by summing the consumption of hydro, solar, wind energy, which are collected from statistical review of World Energy 2015 published by British Petroleum (2015). The consumptions of the disaggregated energy, namely hydro, solar, wind energy, are collected from the same source.

[2] The data is updated up to 2013 by using the same method with Haojie (2008).

3.3. Time-frequency Wavelet Decomposition

In order to overcome the limitations of the traditional Fourier transform, which assumes the time series to be stationary[3], or in another sense with constant frequencies over time, wavelet transform was introduced so that time-varying characteristics of the time series could be studied. This improvement is possible due to the deliberately chosen or designed wavelets. A wavelet is a mathematical function, $x(t)$, that fulfills the following two conditions(Gençay et al., 2001):

$$\int_{-\infty}^{\infty} x(t)dt = 0 \tag{2}$$

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = 1 \tag{3}$$

These conditions ensure that the wavelet function must go up and down in waveform along the x-axis and the energy of the wavelet is unity. There are different types of wavelets available that suit the needs of studying a variety of time series. In this study, we choose the Daubechies Least Asymmetric wavelet with the length of 8(LA8) since Benhmad (2011) pointed out that it "is orthogonal, near symmetric and have a compact support and good smoothness properties" (p. 5).

Having selected the wavelet filter, we need to choose the suitable type of wavelet transform. There are two types of wavelet transforms. One is continuous wavelet transform (CWT), which is to project the original time series onto the wavelets, $\psi_{u,s}(t)$, in order to obtain the wavelet coefficients. $\psi_{u,s}(t)$ are generated by scaling (s) and translation (u) of a basis or mother wavelet, $\psi(t)$ (Aguiar-Conraria et al., 2008):

$$\psi_{u,s}(t) = \frac{1}{\sqrt{|s|}} \psi(\frac{t-u}{s}), \text{ s, u} \in R,\ S \neq 0 \tag{4}$$

[3] Therefore it has minimum applicability in economic time series study as it has been found that most of macroeconomic time series are nonstationary at level, (Nelson and Plosser, 1982).

where “s” and “u” are the scaling and translation parameter; “s” determines the wavelet length while “u” indicates the wavelet location and $\frac{1}{\sqrt{|s|}}$ is used to ensure the norm of the daughter wavelets to be unity.

CWT is presented as (Benhmad, 2012):

$$\mathrm{W(u,s)} = \int_{-\infty}^{\infty} f(t)\, \psi_{u,s}(t) dt \tag{5}$$

However, CWT has its drawback as it utilizes all possible integers for “s” and “u” in equations (4) and (5). Therefore, it has the problem of generating the redundant amount of information from the original time series (Gençay et al., 2001). Discrete wavelet transform (DWT) is developed to overcome this drawback by keeping the minimum but a sufficient number of coefficients that are able to preserve the complete information from the original time series by removing some unnecessary coefficients in CWT. The DWT is conducted by a critical sampling of the CWT coefficients by setting conditions for the parameter “s” and “u” in equation (4) as follows (Gençay et al., 2001):

$$s = 2^{-j} \tag{6}$$

$$u = k2^{-j} \tag{7}$$

where $j, k \in Z$.

It is clear from equation (6) and (7) that this sampling is dyadic. With these conditions, minimum basis functions for DWT is produced via (Gençay et al., 2001):

$$\psi_{j,k}(t) = 2^{\frac{j}{2}} \psi(2^j t - k)\ j, k \in Z \tag{8}$$

Equation (8) creates an orthogonal basis for DWT based on which, a time series with length N can be analysed by DWT at dyadic scales and the largest number of scales or decomposition level, "j", in equation (6), (7) and (8) is given by the formula (Gençay et al., 2001):

$$j = \log_2(N) \tag{9}$$

where N is the sample size.

To implement DWT, two filters are needed. A wavelet filter: $\psi_l = (\psi_1 \dots + \psi_{L-1})$ and a scaling filter: $\varphi_l = (\varphi_1 \dots + \varphi_{L-1})$. The wavelet filter is obtained by equation (8) and has the following properties:

$$\sum_{l=0}^{L-1} \psi_l = 0 \tag{10}$$

$$\sum_{l=0}^{L-1} \psi_l^2 = 1 \tag{11}$$

$$\sum_{l=0}^{l-1} \psi_l \, \psi_{l+2n} = 0 \tag{12}$$

where L stands for the even integer width of the filters.

These properties ensure that: (1) the wavelet filter must integrate to zero; (2) it must have unit energy; (3) it is orthogonal to its even shifts. The scaling filter is related to wavelet filter by a quadrature mirror filter relationship:

$$\varphi_l = (-1)^{l+1}\psi_{L-1-l} \text{ for } l = 0, \dots, L-1. \tag{13}$$

By using these filters, the original time series, $x(t)$, is decomposed into subseries that contain different information at different time scales. Practically, the DWT is implemented by using a pyramid algorithm introduced by Mallat (1989a). At the first decomposition level, $x(t)$ is filtered by wavelet filter $\psi_{1,l}$ (high-pass) and scaling filter $\varphi_{1,l}$ (low-pass) to obtain the wavelet and scaling coefficients $d_{1,t}$ (high frequency) and $s_{1,t}$ (low frequency). These coefficients are downsampled to be at half length of $x(t)$ by removing every 2^j coefficients. $d_{1,t}$ provide the details information or the short-term components that indicate the fluctuations or noise of the original series while $s_{1,t}$ contain the approximation information or the long-term component that represents the trend of the original series. In the next level, the scaling coefficients $s_{1,t}$ is further filtered or decomposed into high and low frequency components $d_{2,t}$ and $s_{2,t}$. This process is then repeated until the highest decomposition level j, which is determined by equation (9). A DWT with j decomposition level decompose the original time series into high frequency wavelet coefficients, $d_{1,t}, d_{2,t}, \ldots d_{j,t}$ and low frequency scaling coefficients $s_{j,t}$.

The DWT representation of the original time series is presented below (Tiwari et al., 2013):

$$x(t) = \sum_k s_{j,k}\varphi_{j,k}(t) + \sum_k d_{j,k}\ \psi_{j,k}(t) + \sum_k d_{j-1,k}\ \psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\ \psi_{1,k}(t) \tag{14}$$

where $s_{j,k}$ is the smooth/approximation coefficients that capture the trend of the original time series $x(t)$ while $d_{j,k}$ to $d_{1,k}$ represent the detail coefficients that contain the information on the short-term deviation from the trend.

Equation (14) also shows that the original time series can be reconstructed by adding up the short-term and trend components. This reconstruction process is regarded as the multiresolution analysis (MRA) (Mallat, 1989b).

In practice, Maximal Overlap DWT (MODWT), an alternative version of DWT, is usually preferred for the following reasons: (1) MODWT is able to handle data with any sample size, i.e. not only power of 2; (2) the transform is invariant to shift, i.e. a shift in the time series will not cause alterations in the transform coefficients (Tiwari et al., 2013). Moreover, it is not very crucial in choosing specific wavelet filter when MODWT is implemented (Percival and Walden, 2000). As compared to DWT, there is no downsampling of coefficients in MODWT. The MODWT Scaling coefficients $v_{j,t}$ and wavelet coefficients $w_{j,t}$ are obtained as:

$$w_{j,t} = \sum_{l=0}^{L-1} \omega_{j,l} X_{t-l \, mod \, N} \tag{15}$$

$$v_{j,t} = \sum_{l=0}^{L-1} \delta_{j,l} X_{t-l \, mod \, N} \tag{16}$$

where the wavelet filters ω_l and scaling filters δ_l for MODWT are obtained by rescaling their counterparts of DWT as:

$$\omega_{j,l} = \frac{\psi_{j,l}}{2^{j/2}} \tag{17}$$

$$\delta_{j,l} = \frac{\varphi_{j,l}}{2^{j/2}} \tag{18}$$

Equation (17) and (18) indicate that, in contrary to DWT filters, the filters of MODWT have half energy.

When applying MODWT, a practical issue facing the researcher is called boundary condition. Nason (2008) explains the problem in details that when calculating the wavelet coefficients, especially using long filters such as Daubechies', some sample values at the length boundary will be missing due to the calculation method. Gençay et al. (2001) state the similar cause that when one end of the data series is encountered during filtering, an established method is needed to calculate the remaining coefficients. In this study we use a common method, which is to assume that the original time series x(t) is with symmetric end reflection, i.e. x(-t)=x(t) and x(1+t)=x(1-t), e.g. x(-1)=x(1).

3.4 Unit Root Tests

The unit root tests commonly used to check data stationarity are Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979, 1981), PP test (Phillips and Perron, 1988) and KPSS test (Kwiatkowski et al., 1992). All these tests may be biased against rejecting the null of unit root when the variable is stationary with a structural break (Perron, 1989). Therefore, the applications of these tests may produce conflicting results. The order of integration of each of the series used in this study was further investigated using the Zivot-Andrew unit root test (ZA) as discussed in Zivot and Andrews (1992). The ZA test is an extension of the ADF test. To test the null hypothesis of a unit root against the alternative hypothesis of the stationary process with one structural break, we consider two models. Model A stated below allows for a change in the intercept and model B allows for a change in both the intercept and slope.

Model A: $\Delta x_t = \theta + \beta x_{t-1} + \mu DU_t(TB) + \gamma t + \sum_{j=1}^{n} \delta_i \Delta x_{t-j} + e_t$ (19)

Model B: $\Delta x_t = \theta + \beta x_{t-1} + \mu DU_t(TB) + \gamma t + \sigma DT_t(TB) + \sum_{j=1}^{n} \delta_i \Delta x_{t-j} + e_t$ (20)

where TB is the time of the structural break and DU_t and DT_t are the dummy variables for a break in the intercept and a shift in the trend respectively, $DU_t(TB) = 1$ if $t > TB$ and zero otherwise; $DT_t(TB) = t - TB$ if $t > TB$ and zero otherwise, Δ is the operator for first differencing. The null hypothesis tested for the two models is $\beta = 0$, i.e. the time series x_t contains a unit root. The alternative hypothesis is $\beta < 0$ indicating that the time series is trend stationary with a potential structural time break appearing at an unknown time point. The unit root tests were conducted to examine stationarity of the original as well as decomposed GPC_t and EC_t series.

3.5 Bounds Testing Procedure for Cointegration

This study adopted the ARDL bounds testing procedure, which was initially proposed by Pesaran and Shin (1998) and then extended by Pesaran et al. (2001), to examine the long-run cointegration relationship between energy consumption and economic growth. The cointegration test is conducted to avoid spurious regression problem using the data series with long-run equilibrium relationship. The ARDL approach is selected based on its advantages over other methods. First, the series under study need not be integrated of the same order. They can be a mixture of I(0) and I(1). Second, it can be applied to the data with small sample size. Third, it provides relatively reliable results even if some of the series is endogenous (Harris and Sollis, 2003) and it does not have the problem of pushing the short-term dynamic into the residuals since it is not residual-based test (Banerjee et al., 1998; Banerjee et al., 1993; Pattichis, 1999). The ARDL model is presented below:

$$\Delta EC_t = a_0 + \sum_{i=1}^{n} a_{1i}\Delta EC_{t-i} + \sum_{i=1}^{n} a_{2i}\Delta GPC_{t-i} + \sum_{i=1}^{n} a_{3i}\Delta K_{t-i} + \sum_{i=1}^{n} a_{4i}\Delta L_{t-i} + a_5 EC_{t-1} + a_6 GPC_{t-1} + a_7 K_{t-1} + a_8 L_{t-1} + \mu_t \quad (21)$$

$$\Delta GPC_t = b_0 + \sum_{i=1}^{n} b_{1i}\Delta GPC_{t-i} + \sum_{i=0}^{n} b_{2i}\Delta EC_{t-i} + \sum_{i=1}^{n} b_{3i}\Delta K_{t-i} + \sum_{i=1}^{n} a_{bi}\Delta L_{t-i} + b_5 EC_{t-1} + b_6 GPC_{t-1} + b_7 K_{t-1} + b_8 L_{t-1} + \mu_t \quad (22)$$

where Δ is the first difference operator and μ_t is the white noise error term, and n is the maximum lag length.

The bounds testing procedure examines the long-run relationship by restricting the lagged level variables: EC_{t-1}, GPC_{t-1}, K_{t-1} and L_{t-1}. A joint significance F-statistic is used to test the null hypothesis of no cointegration as H_0: $a_5=a_6=a_7=a_8=0$ and H_0: $b_5=b_6=b_7=b_8=0$ against the alternative hypothesis of cointegration as H_a: $a_5 \neq a_6 \neq a_7 \neq a_8 \neq 0$ and H_a: $b_5 \neq b_6 \neq b_7 \neq b_8 \neq 0$ in equation (21) and (22) respectively. Two sets of critical values for the large sample size (500 to 1000 observations) are reported by Pesaran et al. (2001). Narayan (2005) calculated critical values for sample size (30 to 80 observations), which is more suitable and therefore used in this study. The set of upper bound assumes that all the variables are I (1) while the set of lower bound assumes them to be I (1). If the F-statistic is greater than the upper bound critical value, the null hypothesis of no cointegration is rejected. If it is smaller than the lower bound critical value, the null hypothesis cannot be rejected. But if it falls in between the two bounds, the cointegration test becomes inconclusive.

3.6 Bootstrapped Toda-Yamamoto Causality Test

Other than ARDL technique, this study will employ the Toda and Yamamoto (1995) procedure with the bootstrapped critical values based on the suggestion of Hacker and Hatemi-J (2006) in order to overcome the problem with finite samples, such as normality issue. The procedure is implemented by five steps.

(a) Firstly, the maximum integration order of the variables is determined by unit root tests, which will be used as the number of the additional lags (d) in the Toda-Yamamoto procedure[4]. The unit root tests used in this study are: Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979, 1981), PP test by Phillips and Perron (1988) and KPSS test by Kwiatkowski et al. (1992). And since these tests may be biased against rejecting the null of unit root when the variable is stationary around some structural break (Perron, 1989), the unit root test with one endogenously identified structural break by Zivot and Andrews (1992) is adopted.

(b) Secondly, an optimal lag length (p) will be selected for the vector autoregressive (VAR) model. Common practice is to choose such lag based on certain

[4] The additional unrestricted lags that equal to the maximal order of integration of the variables are included in the VAR model to ensure that the usual Wald test statistic still has the standard asymptotic distribution so that the test results is valid as proposed by Toda and Yamamoto (1995) Hence it is called the modified Wald test (MWALD).

information criteria. By simulation, it is proved that Schwarz (1978) Bayesian information criteria (SIC) and Hannan and Quinn (1979) information criterion (HQC) perform the best in selecting the optimal lag length (Hatemi-J, 2008; Lütkepohl, 1985). However, if the decisions of these two criteria differ, which is usual in practical studies, it is hard to confirm which one is more reliable. To solve this problem, Hatemi-J (2003) proposes to combine the two criteria into a new criterion, Hatemi-J information criteria (HJC), which is shown, by simulation, to be capable of selecting the true lag in both stable and unstable VAR models. Therefore, in this study, HJC is employed in selecting the true lag order for the Toda-Yamamoto test.

(c) Thirdly, Toda-Yamamoto Granger causality test is conducted. Granger and Newbold (1974) proved by Monte Carlo simulation that the standard test based on the asymptotic distribution theory may be spurious if the variables in the regression are non-stationary. To overcome such problem, Toda and Yamamoto (1995) proposed a modified Wald test statistic that is based on lag augmented VAR model which can be presented as follows:

$$Y_t = \alpha + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \cdots + B_{p+d} Y_{t-p-d} + u_t \quad (23)$$

where Y_t is the 4×1 vector of the variables (i.e. energy consumption per capita, GDP per capita, capital stock per capita, labour), α is the 4×1 vector of intercepts, d is the additional lag determined in step 1 and u_t is a 4×1 vector of error terms. The matrix B_r is a 4×4 matrix of parameters for lag order r (r=1,…,p), which is selected based on aforementioned information criterion HJC.

To define a modified Wald (MWALD) test in a compact form, it is better to present equation (23) in a compact way following Hacker and Hatemi-J (2006):

$$M = PX + \delta \quad (24)$$

where:

$\mathrm{M} = (y_1, \ldots, y_t)$, which is a $(n \times T)$ matrix,

$\mathrm{P} = (\alpha, B_1, \ldots, B_p, \ldots B_{p+d})$, which is a $(n \times (1 + n(p + d)))$ matrix,

$X_t = \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ . \\ y_{t-p-d-1} \end{bmatrix}$, which is a $((1 + n(p + d)) \times 1)$ matrix, for $\mathrm{t} = 1, \ldots, \mathrm{T}$,

$\mathrm{X} = (X_0, \ldots, X_{T-1})$, which is a $((1 + n(p + d)) \times T$ matrix,

$\delta = (u_1, \ldots, u_T)$, which is a $(n \times T)$ matrix.

The MWALD test statistic is defined as:

$$\mathrm{MWALD} = (\mathrm{F}\theta)'[\mathrm{F}((\mathrm{X}'\mathrm{X})^{-1} \otimes V_U)\mathrm{F}']^{-1}(\mathrm{F}\theta) \sim \chi_p^2 \qquad (25)$$

where:

$\theta = \mathrm{vec}(\mathrm{P})$, vec denotes the column-stacking operator,

$\otimes$ indicates the Kronecker product,

F is of order $\mathrm{p} \times (1 + \mathrm{n}(\mathrm{p} + \mathrm{d}))$, an indicator matrix (1 for restricted parameter while 0 for other parameters),

$V_U = \frac{\hat{\delta}'_U \hat{\delta}_U}{T}$ is the estimated variance-covariance matrix of residuals in equation (24),

the null hypothesis of non-Granger causality is then given by H_0: $\mathrm{F}\theta = 0$.

(d) The fourth step is to obtain the bootstrapped distribution and critical values[5].The MWALD test statistic defined in step (c) will have an asymptotic χ^2distribution if the error terms satisfy the normality assumption and the number of degrees of freedom equal to p, i.e. the number of restrictions to be tested. However, as illustrated by Hacker and Hatemi-J (2006), Toda-Yamamoto test performs poorly in the series with small sample size and there is an issue of over rejection of the null hypothesis by MWALD test statistic when the error term suffers from

[5] This approach is conducted based on the study of Hacker and Hatemi-J (2006) and the code developed by Hacker and Hatemi-J (2010).

normality problem and autoregressive conditional heteroskedasticity (ARCH) effect. In order to reduce the size distortions for MWALD test, they propose to use the leveraged bootstrapping technique for MWALD test. Hacker and Hatemi-J (2012) further proves by simulation that the proposed bootstrap method works well even with smaller sample size (20 and 40 observations).

To calculate the bootstrap-corrected causality test, firstly the equation (24) is estimated with the null hypothesis of no Granger causality. Then the bootstrapped data M^* is obtained by:

$$M^* = \hat{P}X + \delta^* \tag{26}$$

where $\hat{P}$ is the estimated coefficients from equation (24) while the bootstrapped residuals δ^*, each carries each the equal probability of 1/T, is obtained by T random draws with replacement from the regression's modified residuals. The regression's original residuals are adjusted to generate the modified residuals by using leverages[6] in order to have constant variance. To ensure, in each bootstrap sample, the mean of the bootstrapped residuals is zero, the bootstrapped residuals are mean-adjusted by deducting the mean of these bootstrapped residuals from each modified residuals. Finally, the bootstrapped distribution is produced by estimating MWALD tests based on each of the 100,000 bootstrap simulations. The αth upper quantile of the bootstrapped distribution is taken to obtain the ∝-level bootstrapped critical values, i.e. at three significance levels: 1%, 5% and 10%.

(e) The last step is to compare the MWALD test statistic from step (c) with the bootstrapped critical values from step (d). If the MWALD test statistic is greater than the bootstrapped critical values, the null hypothesis of non-Granger causality can be rejected.

[6] The more detailed descriptions on leverage adjustment approach is referred to Hacker and Hatemi-J (2006)

3.7 Nonlinear Causality Method

Payne (2010b) suggested that the information captured by linear causality test may not be adequate to reveal the energy-growth nexus, therefore, research adopting nonlinear causality is worthwhile. Few studies have been done in order to detect the nonlinear causality in the international market, e.g. Lee and Chang (2007b), Chiou-Wei et al. (2008) and Dergiades et al. (2013). However, the techniques adopted in these studies seem not be able to draw reliable conclusions. For example, Chiou-Wei et al. (2008) admitted the drawback of the technique used that may have caused over-rejection problem despite the promising results found in their study. In this study, we adopt the newly proposed consistent technique by Nishiyama et al. (2011) to capture the nonlinear causality relationship between energy consumption and economic growth in China. By Using Monte Carlo simulation, the test is proved to have nontrivial power against $\sqrt{T}$ local alternatives, where T is the sample size. The simulation also shows that the test has good size and power properties. We describe the test in this section following Nishiyama et al. (2011).

To test for causality between two stationary time series, i.e. series A and B, the standard Granger causality is defined based on the concept of the optimum linear predictor.[7] Hence the causality from A to B is found when the linear prediction of B can be improved by the current and the past information of A as shown in equation (27).

$$E[B_t - P(B_t|B_{t-1}, \dots, B_1)]^2 > E[B_t - P(B_t|B_{t-1}, \dots, B_1, A_{t-1}, \dots, A_1)]^2 \tag{27}$$

where P is the optimum linear predictor.

[7] The nonlinear causality test proposed assumes that the time series under study are stationary.

Nishiyama et al. (2011) replaced the linear predictor by the conditional expectation to capture the nonlinear relationship. Therefore, the possible nonlinear causality in mean (first moment) is defined as:

$$E[B_t - E(B_t|B_{t-1}, \dots, B_1)]^2 > E[B_t - E(B_t|B_{t-1}, \dots, B_1, A_{t-1}, \dots, A_1)]^2 \qquad (28)$$

where E is the conditional expectation.

By rearrangement, the null hypothesis becomes:

$$E[(E(B_t|B_{t-1}, \dots, B_1, A_{t-1}, \dots, A_1)] - E(B_t|B_{t-1}, \dots, B_1)^2 = 0 \qquad (29)$$

while the alternative hypothesis is:

$$E[(E(B_t|B_{t-1}, \dots, B_1, A_{t-1}, \dots, A_1)] - E(B_t|B_{t-1}, \dots, B_1)^2 > 0 \qquad (30)$$

They also constructed the test statistic, S, based on the moment conditions.[8] This test is considered as an omitted variable test, extensively discussed by Bierens (1982, 1984), Robinson (1989), Bierens and Ploberger (1997), and Chen and Fan (1999), among others. Simulation is used to calculate the critical values for the S test statistic, which are independent of the data (Gonzalo and Taamouti, 2011). We applied this procedure in testing for nonlinear causality between energy consumption and output in the different time-frequency domain.[9]

3.8 Asymmetric Granger causality test

Inspired by Granger and Yoon (2002), Hatemi-J (2012b) proposed an asymmetric causality test to investigate the causality between positive and negative shocks. The idea is to split the original time series into positive and negative shocks in cumulative terms. In our study, we are interested in studying the causal relationship between GDP per

[8] The detailed construction of the test statistics can be found in Nishiyama et al. (2011).
[9] We thank Professor Nishiyama for sharing the code for the computation of the test and critical values.

capita (GPC) and energy consumption per capita (EC). The two variables can be presented by following random walk process:

$$EC_t = EC_{t-1} + e_{1t} = EC_0 + \sum_{i=1}^{t} e_{1i} \quad (31)$$

$$GPC_t = GPC_{t-1} + e_{2t} = GPC_0 + \sum_{i=1}^{t} e_{2i} \quad (32)$$

Where t=1, 2,…, T. EC_0 and GPC_0 are the initial values as constants. e_{1i} and e_{2i} represent white noise error terms. With this definition, positive and negative shocks are obtained in the following way: e_{1i}^{+}=max (e_{1i}, 0), e_{2i}^{+}=max (e_{2i}, 0), e_{1i}^{-}=min (e_{1i}, 0), and e_{2i}^{-}=min (e_{2i}, 0). In other words, e_{1i}=e_{1i}^{+}+e_{1i}^{-} and e_{2i}= e_{2i}^{+}+e_{2i}^{-}. Based on this, $lnec_t$ and $lngpc_t$ can be represented as:

$$EC_t = EC_{t-1} + e_{1t} = EC_0 + \sum_{i=1}^{t} e_{1i}^{+} + \sum_{i=1}^{t} e_{1i}^{-} \quad (33)$$

$$GPC_t = GPC_{t-1} + e_{2t} = GPC_0 + \sum_{i=1}^{t} e_{2i}^{+} + \sum_{i=1}^{t} e_{2i}^{-} \quad (34)$$

Finally, in a cumulative form, Hatemi-J (2012b) defined the positive shocks of the two variables as $EC_t^{+} = \sum_{i=1}^{t} e_{1i}^{+}$ and $GPC_t^{+} = \sum_{i=1}^{t} e_{2i}^{+}$ and the negative shocks as $EC_t^{-} = \sum_{i=1}^{t} e_{1i}^{-}$ and $GPC_t^{-} = \sum_{i=1}^{t} e_{2i}^{-}$. It is worth noting that, by this definition, these positive and negative shocks have permanent impact on the respective underlying variable[10].

After obtaining the positive and negative shocks, we then conduct the asymmetric causality test by applying the Bootstrapped Toda-Yamamoto causality test as described in Section 3.6 on each combination of these shocks, e.g. we can test the causality between the positive shocks of the two variables (EC_t^{+}, GPC_t^{+}).

[10] If the time series are stationary at level, then the original positive and negative shocks rather than their cumulative forms are used in the asymmetric test.

3.9 Analytical framework

There are three research objectives of this study. To achieve these objectives, different techniques are adopted:

1. The first objective of the study is to investigate the relationship by using linear, nonlinear and asymmetric causality techniques. ARDL modeling and bootstrapped T-Y causality test proposed by Hacker and Hatemi-J (2006; 2012) are applied to examine the linear causality. Nonlinear causality test proposed by Nishiyama et al. (2011) is used to capture the nonlinearity in causality. Lastly, the asymmetric causality test introduced by Hatemi-J (2012a) is adopted to investigate the asymmetric causality.
2. The second objective is to uncover the causal relationship between energy consumption and economic growth at multiscale levels in both the time and frequency domains. To achieve this, wavelet decomposition technique is applied on the original time series to obtain the subseries that correspond to short, medium and long run.
3. The third objective is to examine the causal relationship between energy consumption and economic growth at the regional level. Bootstrapped T-Y causality test proposed by Hacker and Hatemi-J (2006; 2012) is applied on each individual sample/region to examine the causality.

Overall, the analytical framework adopted for this study is given in Figure 5.

The original time series are subjected to the unit root test. The results determine whether the level or first differences of the variables are used in the subsequent steps. ARDL models are estimated to test for the presence of the long-run relationship in the original series. The causality tests, namely, the nonlinear, asymmetric and bootstrapped T-Y causality test are then applied if no long-run relationship is found. This procedure is followed by Chapter 4 and Chapter 6.

The original series are also decomposed to obtain the multiscale level data using the wavelet decomposition. The decomposed series are then passed through the linear (bootstrapped T-Y causality test), nonlinear and asymmetric causality tests. This procedure is used in Chapter 4.

As the regional time series are shorter, not all the same methods can be applied. Therefore only the T-Y test is used in Chapter 5.

The empirical results obtained from all the procedures described above are then used for deriving policy implications for the policy makers.

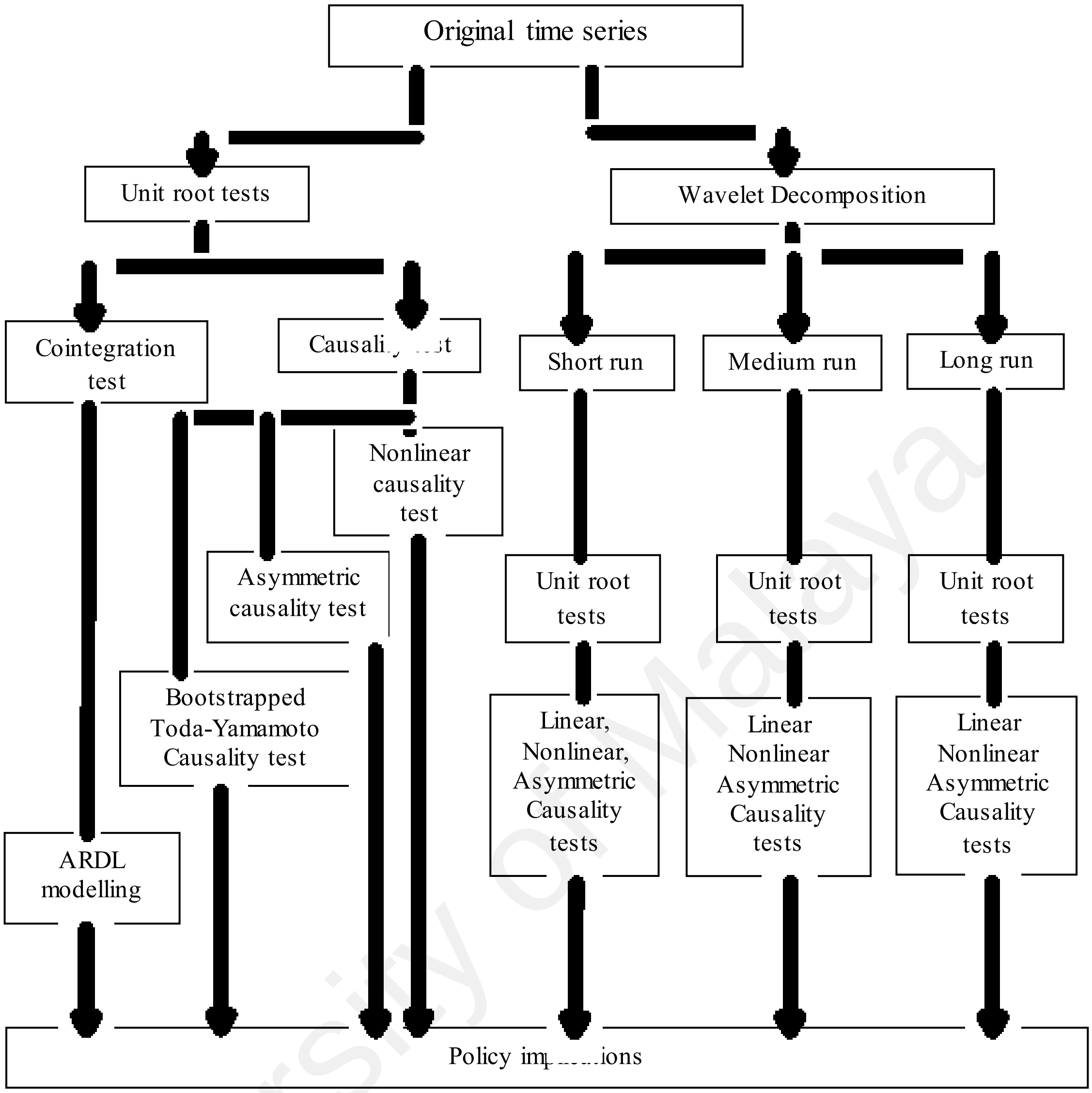

Figure 5: Analytical framework

CHAPTER 4: CAUSALITY RELATIONSHIP BETWEEN ECONOMIC GROWTH AND ENERGY CONSUMPTION AT NATIONAL LEVEL

4.1 Introduction

In this chapter, the relationship between economic growth and energy consumption is examined at the national level. It aims at achieving research objective 1 and objective 2. ARDL bounds test (refer to Section 3.4) is used to detect the presence of a long-run relationship between the original time series. The causality tests will be applied to both the original time series, i.e., not decomposed by wavelet transform technique, and wavelet decomposed time series, i.e., time series that are decomposed by wavelet transform. These tests include the bootstrapped Toda-Yamamoto causality test (refer to Section 3.6) and the two newly proposed methods which are nonlinear causality test (refer to Section 3.7) and asymmetric causality test (refer to Section 3.8).

4.2 Causality analysis on the original time series

We first examine the relationship between economic growth and energy consumption at original level, i.e. before they are decomposed by wavelet technique.

4.2.1 Unit root tests

Firstly, ARDL modeling approach is adopted to check for the presence of a long-run relationship. Although ARDL test does not require the information on the exact order of integration for the data series, none of the series should be integrated of the order greater than 1. Therefore, we carry out unit root tests on the original time series of energy consumption per capita (EC), GDP per capita (GPC), capital stock per capita (K) and labour population (L). Table A.1 in Appendix A shows that all the four series are stationary at first differencing except for GPC, there are conflicting results between

ADF, PP and KPSS test, although the first two tests strongly reject the null hypothesis of a unit root. The results of ZA test in Table A.5 in Appendix A confirm that GPC is stationary at first differencing, I (1). Therefore, we may safely proceed to test the long-run relationship between energy consumption and economic growth using ARDL test.

4.2.2 ARDL test

The initial step in applying ARDL test is to determine the optimal lag order for each variable in the testing equation. We choose the maximum lag order as 3 years for our annual data as suggested by Enders (2004) to be relatively long in order to capture the dynamic relationship between the series. Based on Akaike's Information Criterion (AIC), the optimal combination lag order is selected as ARDL (2, 3, 3, 2), when EC is the dependent variable and ARDL (2, 3, 2, 1) when GPC is the dependent variable.

Table 4.1: Results of ARDL test

Bounds testing Dependent Variable	F-stats	Diagnostic tests χ^2Serial	χ^2ARCH	χ^2RESET	χ^2Normal
EC	2.486	1.610	0.330	3.872	1.895
GPC	1.999	3.207	0.087	12.105***	5.308
Significance level			Critical values		
		Lower bounds I(0)			Upper Bounds I(1)
5%		3.415			4.615
1%		4.748			6.188

Note: The asterisk *** denote the significance at the 1% level. The optimal lag is determined by AIC. Critical values for small sample are collected from Case III as in Narayan (2005): Unrestricted intercept and no trend (k=3).

Both models pass serial correlation test, ARCH test and normality test. However, the functional form test shows that second model (GPC as the dependent variable) has some problem of misspecification but the first model (EC as the dependent variable) is free from such problem. This kind of problem is quite common. In fact, Pesaran et al. (2001) also identified some functional form problem and they addressed the cause to "some nonlinear effects or asymmetries in the adjustment" (p. 314). Overall, these two equations should provide a sound basis for cointegration test. The calculated F-statistics for cointegration and the results of the diagnostic tests on the ARDL model are reported in Table 4.1. In both models, the null of no cointegration relationship between energy consumption and economic growth cannot be rejected at 5% level. We cannot find any evidence of a long run relationship in the original series of the variables.

4.2.3 Bootstrapped Toda-Yamamoto Test

Since ARDL test failed to detect any long-run relationship between energy consumption and economic growth, we apply the Bootstrapped Toda-Yamamoto test (refer to Section 3.6) to assess the causality relationship. The results of Section 4.2.1 indicate that all the time series under study are I (1). Therefore, one additional unrestricted lag is added to the VAR model in equation (23). After confirming the maximal order of integration, we proceed to test the causal relationship using Toda-Yamamoto approach on the original series EC and GPC. Following the same logic of Enders (2004), maximum lags order is chosen to be 3 years. Table 4.2 presents the results of Toda-Yamamoto test and the bootstrap-corrected critical value. It is found that there is no causal relationship between energy consumption and economic growth based on both the p values of MWALD test statistics and the comparison of MWALD test statistics with the bootstrapped critical values.

Table 4.2: The bootstrapped Toda-Yamaoto causality test results for the original time series

Null Hypothesis	MWALD Stats	p value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
EC⇏GPC	2.356	0.502	13.716	9.103	7.088
GPC⇏EC	2.130	0.546	13.897	9.056	7.107

Note: The optimal numbers of lags were selected based on HJC criteria. ⇏ stands for “does not Granger cause”.

4.2.4 Nonlinear causality test

The bootstrapped Toda-Yamamoto test indicates that neutrality hypothesis on the energy-growth nexus is valid in China from 1953 to 2013. We then apply the test proposed by Nishiyama et al. (2011) to detect the possible nonlinear causal relationship.

The results are presented in Table 4.3. It is shown that there is no nonlinear causal relationship between energy consumption and economic growth.

Table 4.3: Nonlinear causality test results for the original time series

Null hypothesis	Test statistic	Null hypothesis	Test statistic
$\Delta EC \nRightarrow \Delta GPC$	8.467	$\Delta GPC \nRightarrow \Delta EC$	7.405

Note: "$\nRightarrow$" stands for "does not Granger cause". Δ is the operator for first differencing.

4.2.5 Asymmetric causality test

Although the results of the two causality tests in previous sections all support the neutrality hypothesis, there is a possibility that the causal relationship is asymmetric, which is mostly ignored in the literature. Therefore, the asymmetric causality test proposed by Hatemi-J (2012b) is adopted. By following the procedure described in Section 3.8, we obtain the positive and negative shocks for energy consumption (EC^+ and $EC^{-)}$ and for GDP per capita (GPC^+ and GPC^-). The unit root test for these time series presented in Table A.2 in Appendix A show that all of them are I (1) except GPC^-. The results of ZA test in Table A.5 in Appendix A confirm that GPC^- is I (0). Therefore, one additional unrestricted lag is added to the VAR model. Then the asymmetric test is conducted (refer to Section 3.8). The results are presented in Table 4.4. The results show that there is a bidirectional causal relationship between positive energy shock (EC^+) and negative GDP shock (GPC^-) and between negative energy shock (EC^-) and positive GDP shock (GPC^+).

Table 4.4: The asymmetric causality test results for the original time series

Null Hypothesis	MWALD	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
$EC^+ \nRightarrow GPC^+$	2.116	2	0.347	11.001	6.865	5.205
$EC^- \nRightarrow GPC^-$	0.710	2	0.701	17.402	8.438	5.660
$EC^+ \nRightarrow GPC^-$	22.105***	3	0.000	14.004	9.086	7.083
$EC^- \nRightarrow GPC^+$	18.198***	2	0.000	10.535	6.537	4.990
$GPC^+ \nRightarrow EC^+$	2.526	2	0.283	10.954	6.794	5.143
$GPC^- \nRightarrow EC^-$	0.693	2	0.707	17.983	8.542	5.555

Table 4.4: The asymmetric causality test results for the original time series (Cont.)

Null Hypothesis	MWALD	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
$GPC^{+} \nRightarrow EC^{-}$	12.364***	2	0.002	11.197	6.791	5.1
$GPC^{-} \nRightarrow EC^{+}$	12.883**	3	0.005	13.649	8.864	6.775

Note: The asterisk **, *** denote the significance at the 5% and 1% level respectively according to the bootstrap critical values. The optimal numbers of lags were selected based on HJC criteria. $\nRightarrow$ stands for "does not Granger cause".

4.3 Causality analysis on the wavelet decomposed time series

The two tests other than asymmetric causality test conducted using the original time series failed to detect any causal relationship between energy consumption and economic growth. The usual practice is to difference the time series and apply standard Granger causality test on the differences, which are stationary. However, this approach may ignore long-run information on the causal relationship. Therefore, this study aims to utilize an alternative approach, wavelet multiscale analysis, which allows us to examine the causal relationship at multiscale levels, i.e. in the short, medium and long run.

4.3.1 Wavelet decomposition

The series GPC and EC were decomposed by wavelet transform into six series, denoted as d1, d2, d3, d4, d5 and s5. The original series is now converted into different frequencies in the time domain, where d1 represents the lowest time scale (highest frequency) that occurs at a time horizon of 2 to 4 years, while d5 represents the highest time scale (lowest frequency) of 32 to 64 years, and S5 represents the trend of the original series that occur at a time horizon longer than 64 years. We combined d1 and d2 to be the series that corresponds to the short-run (less than 8 years), d4 and d5 to be the long-run series (more than 16 years), while d3 represents the medium-run series (8 to 16 years).

4.3.2 Unit root tests

The unit root test results of the short-, medium- and long-run decomposed time series are presented in Table A.3 in Appendix A. The results of the three unit root tests strongly suggest that the short- and medium-run time series are stationary at level. The results of the unit root tests on the long-run time series are inconsistent. Therefore, their stationarity is reexamined by ZA test. As presented in Table A.5 in Appendix A, the results confirm that the long-run series of energy consumption per capita and GDP per capita are both I (0).

4.3.3 Bootstrapped Toda-Yamamoto Test

After obtaining the stationarity information on the decomposed time series, the bootstrapped Toda-Yamamoto causality test (refer to Section 3.6) was subsequently applied. Table 4.5 shows that in the short run, there is a unidirectional causal relationship from energy consumption to economic growth while there is a unidirectional causal relationship from economic growth to energy consumption in the medium run. In the long-run, the causal relationship between economic growth and energy consumption is bidirectional. These results are supported by both the *p*-values and comparison of the test statistics to the critical values. The findings suggest that the tests without taking into account the time-frequency information of the series may produce misleading results. With multiscale information on the time series variables, the causal relationship between EC and GPC is now uncovered.

Table 4.5: Bootstrapped Toda-Yamamoto causality test results for the decomposed time series

Null Hypothesis	MWALD	Lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
EC ⇏ GPC						
Short run	11.680**	3	0.009 (-0.679)	13.089	8.486	6.745
Medium run	7.838	3	0.05	17.083	11.257	8.569
Long run	25.246***	3	0.000 (0.212)	23.956	15.554	12.372

Table 4.5: Bootstrapped Toda-Yamamoto causality test results for the decomposed time series (Cont.)

Null Hypothesis	MWALD	Lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
GPC ⇏ EC						
Short run	7.318	3	0.062	13.07	8.643	6.88
Medium run	5.211***	3	0.000 (-0.046)	17.907	11.872	9.265
Long run	13.501**	3	0.003 (0.212)	17.568	11.574	9.503

Note: **, *** denote significance at the 5% and 1% level respectively according to the bootstrap critical values. The optimal number of lags was selected based on HJC criteria. "⇏" stands for "does not Granger cause". The numbers in parentheses are the sum of the lagged coefficients.

4.3.4 Nonlinear causality test

Although the nonlinear causality test on the original time series failed to detect any causal relationship between economic growth and energy consumption, there is a possibility that nonlinear causality does exist but over different time horizons. Therefore, with the help of wavelet decomposition, nonlinear causality test is conducted on the decomposed time series. Table 4.6 shows that there is no nonlinear causal relationship in the short and medium run, however, a bidirectional nonlinear causal relationship between energy consumption and economic growth only is found in the long run.

Table 4.6: Nonlinear causality test results for the decomposed time series

Null Hypothesis		Null Hypothesis	
EC ⇏ GPC	Test statistic	GPC ⇏ EC	Test statistic
Short run	7.06	Short	5.129
Medium run	6.99	Medium	9.733
Long run	22.410*	Long	25.484*

Note: * denote significance level 1%. "⇏" stands for "does not Granger cause".

4.3.5 Asymmetric causality test

As confirmed in the previous section, the nonlinear causality may vary across time periods. Therefore it is possible that the asymmetric causality can also change over different time horizons. Therefore, the asymmetric causality test is conducted on the decomposed time series. The results of unit root test for the positive and negative shocks of the wavelet decomposed time series are presented in Table A.4 in Appendix A. It shows that all of them are I (1). Therefore, one additional unrestricted lag is added to the VAR model. Then the asymmetric test is conducted (refer to Section 3.8). The results are presented in Table 4.7. In the short run, it is found that there is a bidirectional causal relationship between positive energy shocks (EC+) and negative growth shocks (GPC-) and between negative energy shocks (EC^-) and positive growth shocks(GPC^+) at 1% level according to both the p values of MWALD statistics and the bootstrap critical values; in the medium run, there is a bidirectional causality between negative energy shocks(EC^-) and positive growth shocks (GPC^+) and a unidirectional causal relationship from negative growth shocks (GPC^-) to negative energy shocks (EC^-) at 1% level in general[11].No asymmetric causality was identified for the long run.

Table 4.7: The asymmetric causality test results for the decomposed time series

Null Hypothesis	MWALD	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
Short						
$EC^+ \nRightarrow GPC^+$	2.031	3	0.566	13.777	8.839	6.870
$EC^- \nRightarrow GPC^-$	3.457	2	0.178	12.407	6.851	4.924
$EC^+ \nRightarrow GPC^-$	49.515***	3	0.000	13.238	8.589	6.775
$EC^- \nRightarrow GPC^+$	19.891***	3	0.000	12.745	8.467	6.544
$GPC^+ \nRightarrow EC^+$	3.873	3	0.276	13.439	8.418	6.819
$GPC^- \nRightarrow EC^-$	0.916	2	0.632	12.503	7.381	5.296
$GPC^+ \nRightarrow EC^-$	15.426***	3	0.002	13.361	8.899	6.878
$GPC^- \nRightarrow EC^+$	14.680***	3	0.002	12.815	8.440	6.618
Medium						
$EC^+ \nRightarrow GPC^+$	1.328	2	0.515	11.337	6.948	5.255
$EC^- \nRightarrow GPC^-$	5.232	2	0.073	11.323	6.991	5.245
$EC^+ \nRightarrow GPC^-$	4.188	2	0.123	11.525	6.824	5.130
$EC^- \nRightarrow GPC^+$	40.690***	3	0.000	14.387	9.448	7.253
$GPC^+ \nRightarrow EC^+$	5.786	2	0.055	10.978	6.783	5.114
$GPC^- \nRightarrow EC^-$	25.681***	2	0.000	12.380	7.108	5.095
$GPC^+ \nRightarrow EC^-$	15.234**	3	0.002	15.299	10.020	7.621
$GPC^- \nRightarrow EC^+$	4.697	2	0.096	10.552	6.660	5.113

[11] In the medium run, the causal relationship from positive growth shocks (GPC+) to negative energy shocks (EC-) is at 5% and 1% level according to the bootstrap critical values and the p value of MWALD statistics respectively.

Table 4.7: The asymmetric causality test results for the decomposed time series (Cont.)

Null Hypothesis	MWALD	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
Long						
$EC^+ \nRightarrow GPC^+$	0.007	2	0.997	13.404	7.593	5.522
$EC^- \nRightarrow GPC^-$	4.228	2	0.121	11.566	6.963	5.304
$EC^+ \nRightarrow GPC^-$	0.408	2	0.816	12.970	7.839	5.791
$EC^- \nRightarrow GPC^+$	2.731	2	0.255	12.483	7.393	5.447
$GPC^+ \nRightarrow EC^+$	2.847	2	0.241	12.550	7.397	5.527
$GPC^- \nRightarrow EC^-$	5.504	2	0.064	13.958	8.383	6.165
$GPC^+ \nRightarrow EC^-$	3.566	2	0.168	15.675	8.998	6.684
$GPC^- \nRightarrow EC^+$	2.524	2	0.283	12.120	7.437	5.585

Note: The asterisk **, *** denote the significance at the 5% and 1% level respectively according to the bootstrap critical values. The optimal numbers of lags were selected based on HJC criteria. "$\nRightarrow$" stands for "does not Granger cause".

4.4 Discussion on findings

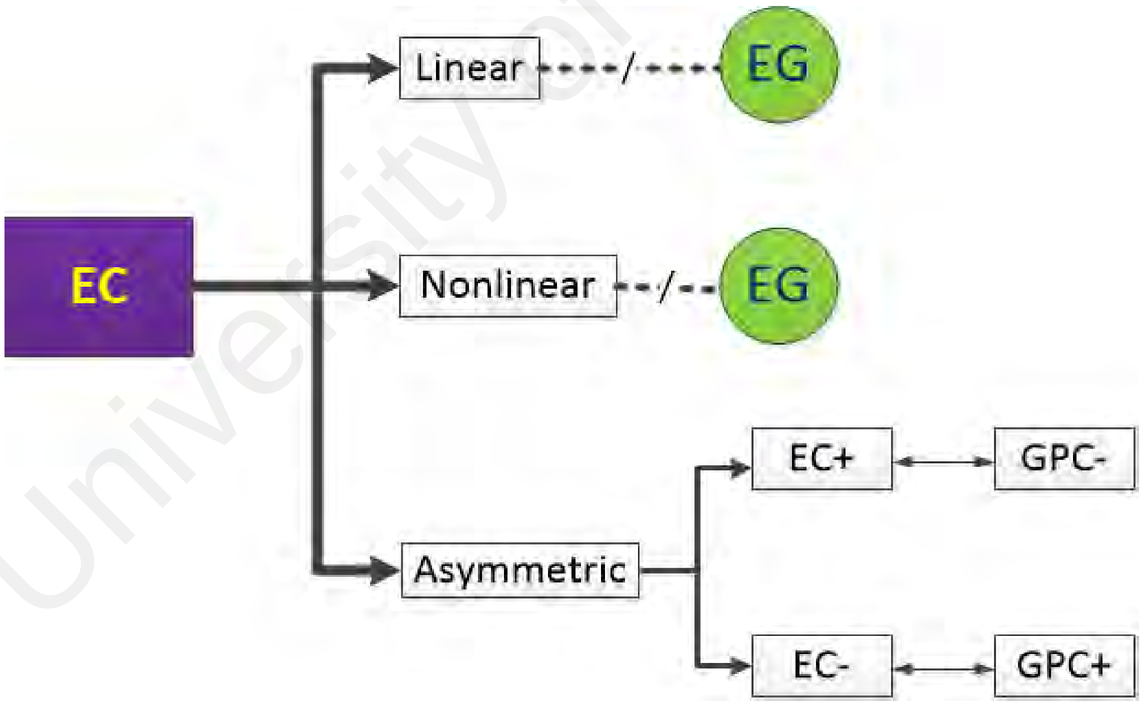

Figure 6: Summary of the energy-growth nexus at the national level using the original time series

Note: EC stands for "energy consumption", EG stands for economic growth, "--/--" stands for "no Granger causality", "→" stands for "unidirectional Granger causality" from the left to the right hand-side variable, "↔" stands for "bidirectional Granger causality".

The causality results of section 4.2 and 4.3 are summarized in Figure 6 and Figure 7 respectively. As shown in Figure 6, the results of both linear and nonlinear causality tests on the original time series support the neutrality hypothesis, i.e., there is no any causal relationship between energy consumption and economic growth in China from 1953 to 2013. These findings are consistent with the studies of Soytas and Sari (2006), Chen et al. (2007) and Yalta and Cakar (2012) but contradictory with other studies such as Wang et al. (2011b), Zhang and Yang (2013), Wang et al. (2016a) and Wang et al. (2016b). Cautions, however, must be taken before drawing any policy implications from these results. Ma and Oxley (2012) suggested that short-run energy-growth nexus may be different from the long-run relationships.

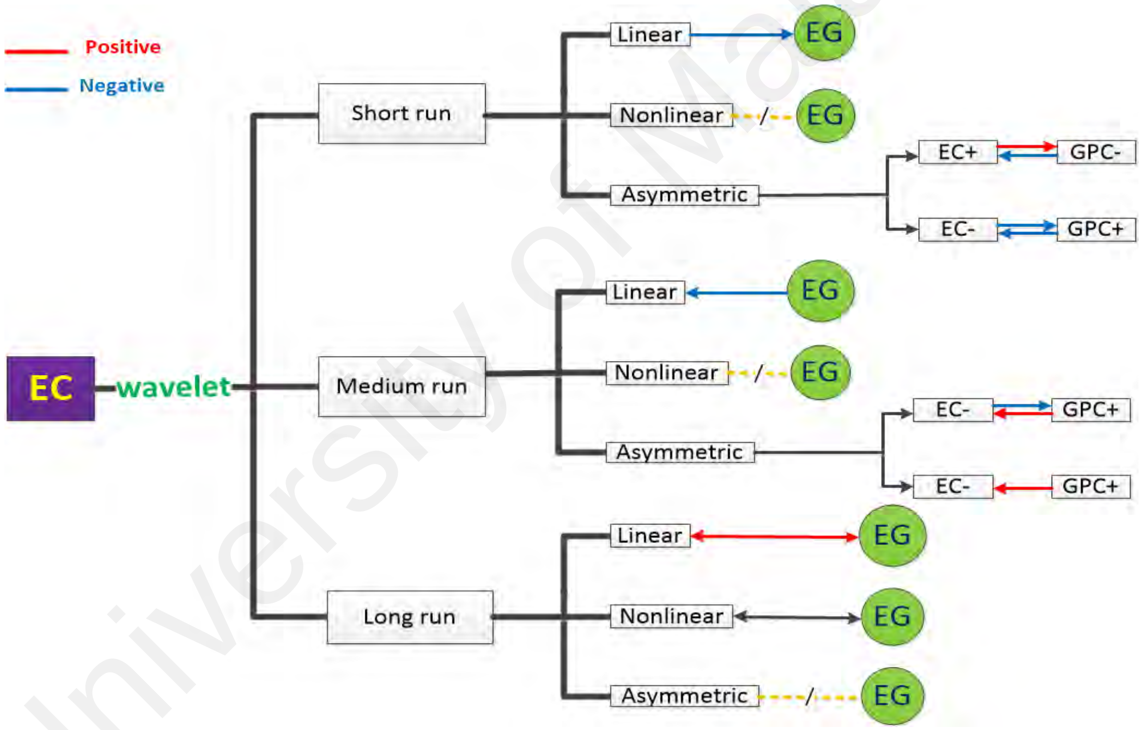

Figure 7: Summary of the energy-growth nexus at the national level using the wavelet decomposed time series

Note: EC stands for "energy consumption", EG stands for economic growth, "--/--" stands for "no Granger causality" "→" stands for "unidirectional Granger causality" from the left to the right hand-side variable, "↔" stands for "bidirectional Granger causality", "wavelet" stands for "wavelet decomposition".

As shown in Figure 7, the results of the tests conducted on the decomposed time series confirm the conjecture of Ma and Oxley (2012). In the short run, energy consumption is found to Granger cause economic growth. The causality direction is from economic growth energy consumption in the medium run. In the long run, energy consumption and economic growth mutually Granger cause each other. These results show that the energy-growth nexus in China is much more complex than the neutrality hypothesis can explain. It is evident that the wavelet multiscale analysis in this study reveals the information on energy-growth nexus across different time horizons that may otherwise be hidden if only the whole long-term time series is used.

Zhang and Yang (2013) reported a negative bidirectional causal relationship between real GDP and energy consumption in China. Consistent with their findings, the wavelet multiscale analysis identifies a negative nexus between energy consumption and real economic output in this study. However, the negative causality is not bidirectional but consists of two unidirectional negative causal relationships running from opposite directions at different time horizons (as shown in Figure 2). In the short-run, the estimated causal parameter is -0.679, which means a 1% increase in energy consumption per capita will cause a 0.679% decrease in real GDP per capita. In the medium run, the estimated causal parameter is -0.046, which means a 1% increase in real GDP per capita will cause a decrease in energy consumption per capita. In line with Squalli (2007), there are some explanations on these two negative causal relationships.

In the short run, the negative causality running from energy consumption per capita to real GDP per capita may result from the shift of production to less energy intensive service sectors. The excessive energy consumption in unproductive sectors combining with capacity constraints may also contribute to such negative causality. In the medium run, many factors can lead to negative causality running from real GDP per capita to energy consumption per capita. One is that the constraints due to hindrances related to infrastructure may force energy consumption to reduce as the economy expands. In addition, the demand of energy for any other goods and services can decrease due to the combined effect of factors such as politics, mismanagement or inequitable distribution of national income.

In the long-run, it is interesting that the estimated causal parameters for causality running from both directions have about the same magnitude, 0.212. This suggests that 1% increase in energy consumption per capita will cause real GDP per capita to increase by 0.212% and vice versa. This positive bidirectional causal relationship between energy consumption per capita and real GDP per capita supports the feedback hypothesis, i.e. energy and economic output are interdependent. The results of linear causality test are further strengthened by the nonlinear bidirectional energy-growth nexus in the long run found by applying the nonlinear causality test on the decomposed time series. The nonlinear causal relationship also reveals that energy consumption per capita and real GDP per capita in China have been affected by structural changes due to economic events or changes in energy policy.

Although both the linear and nonlinear causality tests help provide useful information on energy-growth nexus in China, these tests neglect the fact that the causality relation could be asymmetric, i.e. a positive change or shock may have a different impact as compared to a negative change or shock. In fact, to draw more prudent and comprehensive policy implications, it is necessary to understand the possible different impacts of positive and negative energy shocks on either positive or negative growth shocks or vice versa.

As shown in Figure 6, the results of asymmetric causality test on the original time series reveal that asymmetric energy-growth nexus does exist in China. There are two bidirectional causal relationships. One is between positive energy shocks and negative growth shocks while another is between negative energy shocks and positive growth shocks. The experiences on the previous analysis using linear and nonlinear causality tests suggest that to see a complete picture regarding energy-growth nexus, it is helpful to conduct multiscale analysis using wavelet transform, i.e. using the analogy based on the suggestions of Ma and Oxley (2012), it is possible that the asymmetric causal relationship between economic growth and energy consumption could vary across different horizons(short, medium and long run). Therefore, the asymmetric causality tests were applied on the decomposed time series.

As presented in Figure 7, the results show exactly same asymmetric causal relationships in the short run as the original time series; in the medium run, there is less and weaker asymmetric causal relationship; in the long run, there is no any causal relationship. Following the interpretation of Aslan et al. (2013), it can be argued that, overall, the long-run asymmetric energy-growth nexus was dominated by the short-run dynamics in China.

In the short run, for the causality running from positive energy shocks to negative growth shocks, the estimated causal parameter is -0.699, which indicates that a 1% permanent positive energy shocks will cause a 0.699% reduction in negative growth shocks; for the causality running from negative energy shocks to positive growth shocks, the estimated causal parameter is -0.551, which means a 1% permanent negative energy shocks will cause a 0.551% reduction in positive growth shocks. These findings imply that in the short run, the increase in energy consumption can help slow down the decrease in economic growth while decreasing energy consumption can reduce the increase in economic growth. In return, for the causality running from positive growth shocks to negative energy shocks, the estimated causal parameter is -0.427, which means that a 1% permanent positive shock in economic growth will cause 0.427% reduction in negative energy shocks; for the causality running from negative growth shocks to positive energy shocks, the estimated causal parameter is -0.894, which means a 1% permanent negative shock in economic growth will cause a 0.894% reduction in positive energy shocks.

The first result can be interpreted that if the economic growth increases it will force more consumption of energy(Hatemi-J and Uddin, 2012). There are two explanations for the second result following Squalli (2007) and Zhang and Yang (2013). One is that when the economic growth decreases, in order to stimulate the economy back on the track less energy consumption is needed since more economic production may shift to less energy-intensive sectors. Second is that the government may slow down the increase in energy consumption in order to mitigate the possible negative impact of excessive energy use in some unproductive segments and capacity constraints on economic growth and avoid possible further waste of energy due to excessive use.

Following Hatemi-J and Uddin (2012), in the short run in China, there is lacking of an optimal quantity of energy consumption, i.e. the view that the level of energy consumption in the short run in China is the optimum cannot be supported. In the medium run, the negative causality running negative energy shocks to positive growth shocks remains, with an estimated causal parameter of -0.193. Unexpectedly, the negative causality from positive energy shocks to negative growth shocks disappear. These findings show that the reduction in energy consumption will cause a decrease in economic growth while the increase in energy consumption will no longer strengthen economic growth in the medium run. In line with the reasoning of Hatemi-J and Uddin (2012), this implies that, in the medium run, the government must consume an optimal amount of energy consumption in China in the medium run to sustain its level of economic growth. However, energy consumption exceeds such optimal amount will not contribute to economic growth.

In addition to these findings, for the causality from positive growth shocks to negative energy shocks, the estimated causal parameter is 0.208, which means a 1% permanent positive growth shocks will cause a 0.208% reduction in energy consumption. This is in line with the findings of negative causality from economic growth to energy consumption in the medium run based on the linear (bootstrapped Toda-Yamamoto causality test) test on the decomposed series in Section 4.3.3. Moreover, for the causality from negative growth shocks to negative energy shocks, the estimated causal parameter is 0.261, which means a 1% negative growth shocks will cause a 0.261% reduction in energy consumption. This indicates that reduction of economic growth will cause energy consumption to decrease.

CHAPTER 5: CAUSALITY RELATIONSHIP BETWEEN ECONOMIC GROWTH AND ENERGY CONSUMPTION AT REGIONAL LEVEL

5.1 Introduction

In this chapter, the causal relationship between economic growth and energy consumption is examined at the regional level to achieve research objective 3. The bootstrapped Toda-Yamamoto multivariate causality test (refer to Section 3.6) is adopted in order to overcome the problems resulted from nonstationarity, omitted variable and finite sample issues. The original series are analysed because the time series of all the variables at the regional level are not sufficiently long for wavelet analysis. The asymmetric causality test cannot be applied for the same reason.

5.2 Unit root tests

Although it is not required for Toda-Yamamoto causality test to pretest the stationarity of the variables under study, unit root tests are conducted to identify the maximal integrity in order to determine the additional lag for the VAR model. Therefore, we carry out unit root tests on the four variables energy consumption per capita (EC), GDP per capita (GPC), capital stock per capita (K) and labour population (L). Table B.1 in Appendix B shows that overall, according to all the three tests (ADF, PP and KPSS), these four variables are non-stationary at level. At the first differences, it appears that the four variables seem to be a mixture of integration order 1 and higher. Moreover, there are also some conflicting results between the three tests. Therefore ZA test is conducted. The results are presented in Table B.2 in Appendix B. Considering the results of both Table B.1 and B.2, it is found that the four variables for most of the regions are a mixture of I (1) and I (0). As most of the macroeconomic variables are I (1) (Ayres and Warr, 2010), We attribute the conflicting results and the cases where the results suggest that the variables to be integrated at the order higher than one to the low power of the unit root test and the finite sample that are adopted due to availability. Therefore, we choose the maximal integration order as 1 for all the regions.

5.3 Causality analysis

After determining the maximal order of integration, we proceed to conduct the Multivariate Granger causality test using the bootstrapped Toda-Yamamoto Causality test. The results are presented in Table 5.1.

According to the results, the P value of MWALD tests and the bootstrap critical values reach the same results that there is no energy-growth nexus in the regions including: Anhui, Heilongjiang, Henan, Hubei, Hunan, Jilin, Ningxia, Qinghai, Shaanxi, Shanxi, and Sichuan i.e. neutrality hypothesis is supported. In addition, Beijing, Chongqing, Fujian, Guizhou, Jiangsu and Shandong, the P values of MWALD test indicate unidirectional causality running from economic growth to energy consumption for Beijing, Chongqing, Fujian at 10% significance level and for Neimenggu at 5% significance level; unidirectional causality running from energy consumption to economic growth for Guizhou, Jiangsu and Shandong at 10% significance level and for Gansu and Zhejiang at 5% significance level. However, according to bootstrap critical values, these identified causality relationships are not significant even at 10% level. Therefore, these results again supported neutrality hypothesis for more regions.

On the other hand, for some regions, the P values of MWALD test and the bootstrap critical values indicate the same direction of causality, except that the significance levels are different. The details of such changes are provided in Table 5.2. It is found that some of the significance levels have changed to 10% when the bootstrap critical values are used. Following the study of Yildirim and Aslan (2012), if 10% significance level is enough to ensure the validity of the MWALD test, then we can conclude that the causality results identified by the Toda-Yamamoto causality test are valid.

Table 5.1: Toda-Yamamoto causality test results for different regions

Null Hypothesis	MWALD Stats	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
Anhui						
EC⇏GPC	4.996	3	0.172	33.383	16.404	11.060
GPC⇏EC	1.620	3	0.655	31.021	15.575	10.699
Beijing						
EC⇏GPC	1.989	3	0.575	21.194	11.863	8.747
GPC⇏EC	6.396	3	0.094	25.177	14.024	10.125
Chongqing						
EC⇏GPC	0.710	3	0.871	39.841	16.851	10.921
GPC⇏EC	7.563	3	0.056	44.907	19.936	13.350
Fujian						
EC⇏GPC	0.696	3	0.874	18.534	11.141	8.409
GPC⇏EC	6.340	3	0.096	19.784	11.580	8.527
Gansu						
EC⇏GPC	6.880	2	0.032	18.312	9.889	6.931
GPC⇏EC	2.162	2	0.339	15.199	8.262	5.992
Guangdong						
EC⇏GPC	11.588*	3	0.009	34.135	16.154	11.135
GPC⇏EC	16.224**	3	0.001	33.525	16.034	11.211
Guangxi						
EC⇏GPC	11.432**	3	0.009	20.014	11.358	8.538
GPC⇏EC	0.920	3	0.821	22.079	13.090	9.602
Guizhou						
EC⇏GPC	5.354	2	0.069	12.868	7.310	5.487
GPC⇏EC	1.224	2	0.542	13.078	8.012	5.953
Hebei						
EC⇏GPC	9.927*	3	0.019	19.411	11.710	8.551
GPC⇏EC	15.822**	3	0.001	21.791	12.294	9.154
Heilongjiang						
EC⇏GPC	0.427	1	0.513	8.089	4.366	2.957
GPC⇏EC	0.302	1	0.583	8.143	4.444	3.076
Henan						
EC⇏GPC	0.154	1	0.695	8.588	4.802	3.349
GPC⇏EC	0.411	1	0.522	9.361	4.723	3.277
Hubei						
EC⇏GPC	0.719	2	0.698	16.772	8.829	6.485
GPC⇏EC	2.545	2	0.280	14.228	8.229	6.048
Hunan						
EC⇏GPC	0.921	1	0.337	8.647	4.640	3.212
GPC⇏EC	0.681	1	0.409	9.102	4.783	3.306
Jiangsu						
EC⇏GPC	6.269	3	0.099	32.214	15.013	10.419
GPC⇏EC	14.977*	3	0.002	31.926	15.322	10.739
Jiangxi						
EC⇏GPC	1.072	3	0.784	32.281	16.017	11.104
GPC⇏EC	28.640**	3	0.000	41.255	19.550	13.533
Jilin						
EC⇏GPC	2.537	3	0.469	20.586	12.139	9.025
GPC⇏EC	0.675	3	0.879	18.641	11.322	8.551

Table 5.1: Toda-Yamamoto causality test results for different regions (Cont.)

Null Hypothesis	MWALD Stats	lag	*p* value	1% bootstrap critical value	5%bootstrap critical value	10% bootstrap critical value
Liaoning						
EC⇏GPC	1.973	2	0.373	13.730	7.979	5.880
GPC⇏EC	8.439*	2	0.015	14.967	8.714	6.295
Neimenggu						
EC⇏GPC	3.188	3	0.364	31.837	16.389	11.008
GPC⇏EC	7.920	3	0.048	32.274	15.027	10.090
Ningxia						
EC⇏GPC	0.020	1	0.888	9.324	4.904	3.315
GPC⇏EC	0.046	1	0.830	8.588	4.534	3.115
Qinghai						
EC⇏GPC	1.463	2	0.481	13.283	7.845	5.574
GPC⇏EC	1.047	2	0.593	13.783	7.943	5.833
Shaanxi						
EC⇏GPC	4.014	2	0.134	14.161	8.377	6.169
GPC⇏EC	0.121	2	0.942	12.957	7.771	5.654
Shandong						
EC⇏GPC	5.626	2	0.060	17.564	9.585	6.836
GPC⇏EC	0.392	2	0.822	17.699	9.855	6.959
Shanghai						
EC⇏GPC	4.535	3	0.209	39.813	19.217	12.921
GPC⇏EC	14.050*	3	0.003	34.470	17.108	11.901
Shanxi						
EC⇏GPC	0.381	1	0.537	8.098	4.533	3.142
GPC⇏EC	0.150	1	0.699	8.075	4.477	3.116
Sichuan						
EC⇏GPC	1.074	3	0.783	19.750	11.502	8.515
GPC⇏EC	2.901	3	0.407	20.981	11.819	8.798
Tianjin						
EC⇏GPC	1.469	3	0.689	32.982	16.548	11.228
GPC⇏EC	48.684***	3	0.000	39.689	18.670	12.929
Xinjiang						
EC⇏GPC	4.268*	1	0.039	7.871	4.401	3.030
GPC⇏EC	0.243	1	0.622	8.249	4.692	3.083
Yunnan						
EC⇏GPC	6.564**	1	0.010	8.387	4.418	3.011
GPC⇏EC	5.032**	1	0.025	8.734	4.502	3.106
Zhejiang						
EC⇏GPC	9.195	3	0.027	48.664	22.320	15.339
GPC⇏EC	1.834	3	0.608	35.627	16.884	11.775

Note: The asterisk *,**, *** denote the significance at the 10%, 5% and 1% level respectively according to the bootstrap critical values. The optimal numbers of lags were selected based on HJC criteria. "⇏"stands for "does not Granger cause".

Table 5.2: The changes of significance level for some regions

Null Hypothesis	Significance levels at which the null of non-causality is rejected	
	Based on P values	Based on Bootstrap critical values
Guangdong		
EC⇏GPC	1%	10%
GPC⇏EC	1%	5%
Guangxi		
EC⇏GPC	1%	5%
Hebei		
EC⇏GPC	5%	10%
GPC⇏EC	1%	5%

Table 5.2: The changes of significance level for some regions (Cont.)

Null Hypothesis	Significance levels at which the null of non-causality is rejected	
	Based on P values	Based on Bootstrap critical values
Jiangsu		
GPC⇏EC	1%	10%
Jiangxi		
GPC⇏EC	1%	5%
Liaoning		
GPC⇏EC	5%	10%
Shanghai		
GPC⇏EC	1%	10%
Xinjiang		
EC⇏GPC	5%	10%

Note: "⇏" stands for "does not Granger cause".

Lastly, for two regions: Tianjin and Yunnan. The P values of MWALD test and the bootstrap critical values identify the same direction of causality at the same significance level. For Tianjin, a unidirectional causal relationship from economic growth to energy consumption is found at 1% significance level while for Yunnan bidirectional causal relationship between economic growth and energy consumption is found at 5% significance level.

5.4 Discussion on findings

Table 5.1 shows that there are four types of causality relationship among the 29 regions in China:

(a) Unidirectional causality from energy consumption to economic growth: Guangxi and Xinjiang.

(b) Unidirectional causality from economic growth to energy consumption: Jiangsu, Jiangxi, Liaoning, Shanghai and Tianjin.

(c) Bidirectional causality between energy consumption and economic growth: Guangdong, Hebei and Yunnan.

(d) No causality between energy consumption and economic growth: Anhui, Beijing, Chongqing, Fujian, Gansu, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jilin, Neimenggu, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan and Zhejiang.

Table 5.3 compares the results of this study with the earlier study of Akkemik et al. (2012), who employ bivariate analysis using the panel Granger causality test proposed by Venet and Hurlin (2001). The results of this study differ greatly from their study. As Yildirim and Aslan (2012) suggest that different sample period and variables included could explain the differences in findings. In this study, we adopt multivariate analysis, i.e. including two control variables: capital stock per capita and labour.

In addition, due to the limitation of the panel test adopted by Akkemik et al. (2012), the authors have to use the sample period from 1986 to 2008 for all the regions. In contrast, this study uses different sample periods for different regions based on availability. All the sample periods used in this study are longer. For example, 10 regions have sample period from 1985 to 2011 while 12 regions have sample period from 1978 to 2011[12]. In addition, bootstrap critical values that are specially designed for small sample size (20 and 40 observations) are used to correct the results of Toda-Yamamoto causality tests.

It is found that adopting multivariate analysis by including labour and capital stock in the model, the causal relationships either changed direction or disappeared for all regions except Guangxi, Heilongjiang, Jiangsu, Liaoning, Shanxi, Sichuan and Tianjin[13] as compared to the findings of Akkemik et al. (2012).

As discussed in Section 2.5, most of the previous studies did not examine the signs and magnitude of the estimated coefficients of the causality test. In the case of China, most of the studies also neglected this aspect of research except the recent study by Zhang

[12] Please refer to section 3.2 for details on the sample size of the data used in this study.
[13] These findings are similar to those of the study by Yildirim and Aslan (2012) who used the same methods with this study on 17 OECD countries and found that, after adding employment and gross fixed capital in the analysis, for four countries causality either changed directions or disappeared and for one country a unidirectional causal relationship from real GDP to energy consumption appeared as compared to the previous literatures.

and Yang (2013), who found a negative bidirectional causal relationship between energy consumption and economic growth, which is uniquely different from the findings of the previous studies. Therefore, this study also takes such approach to providing more accurate information on energy-growth nexus in different regions of China.

Table 5.3: Comparison of findings of this study with those of the previous study

Regions	Akkemik et al. (2012) (1986 to 2008) for all regions	Findings of this study
Anhui	EC←EG	EC≠EG (1985-2011)*
Beijing	EC←EG	EC≠EG (1980-2011)*
Chongqing	EC←EG	EC≠EG (1986-2011)*
Fujian	EC↔EG	EC≠EG (1978-2011)*
Gansu	EC←EG	EC≠EG (1985-2011)*
Guangdong	EC→EG	EC↔EG (1985-2011)*
Guangxi	EC→EG	EC→EG (1978-2011)
Guizhou	EC←EG	EC≠EG (1978-2011)*
Hebei	EC→EG	EC↔EG (1980-2011)*
Heilongjiang	EC≠EG	EC≠EG (1978-2011)
Henan	EC→EG	EC≠EG (1978-2011)*
Hubei	EC→EG	EC≠EG (1980-2011)*
Hunan	EC→EG	EC≠EG (1980-2011)*
Jiangsu	EC←EG	EC←EG (1985-2011)
Jiangxi	EC↔EG	EC←EG (1985-2011)*
Jilin	EC↔EG	EC≠EG (1978-2011)*
Liaoning	EC←EG	EC←EG (1978-2011)
Neimenggu	EC↔EG	EC≠EG (1985-2011)*
Ningxia	EC←EG	EC≠EG (1978-2011)*
Qinghai	EC←EG	EC≠EG (1980-2011)*
Shaanxi	EC←EG	EC≠EG (1978-2011)*
Shandong	EC→EG	EC≠EG (1985-2011)*
Shanghai	EC↔EG	EC←EG (1985-2011)*
Shanxi	EC≠EG	EC≠EG (1978-2011)
Sichuan	EC≠EG	EC≠EG (1979-2011)
Tianjin	EC←EG	EC←EG (1985-2011)
Xinjiang	EC←EG	EC→EG (1978-2011)*
Yunnan	EC←EG	EC↔EG (1978-2011)*
Zhejiang	EC↔EG	EC≠EG (1985-2011)*

Note: EC stands for energy consumption, EG stands for economic growth. EC→EG means that the causality runs from energy consumption to economic growth. EC←EG means that the causality runs from economic growth to energy consumption. EC↔EG means that there is bidirectional causality between energy consumption and economic growth. EC≠EG means that no causality between energy consumption and economic growth. * indicates that the causal relationship when labour and capital stock are used in this study is different from the causal relationship reported by Akkemik et al. (2012).

The results that present the regional causal relationships with the signs of the estimated coefficients are summarized in Figure 8. It is found that for the causal relationship running from economic growth to energy consumption, the estimated coefficients for four regions are negative, including Guangdong (-0.273), Hebei (-1.497), Liaoning (-

0.428) and Tianjin (-0.464), which means that if the respective regional economic growth increases 1%, it will cause a 0.273% decrease in energy consumption in Guangdong, a 1.497% decrease in Hebei, a 0.428% decrease in Liaoning and a 0.464% decrease in Tianjin. According to Squalli (2007), these findings indicate that in regions of Guangdong, Hebei, Liaoning and Tianjin, there are constraints due to hindrances related to infrastructure, politics and management that force energy consumption to reduce; in addition, the demand for energy in these regions as same as any other goods and services decrease due to the combined effect of factors such as politics, mismanagement or insufficient distribution of the regional income. Moreover, it is found that for the regions of Jiangsu, Jiangxi, Shanghai and Yunnan, the estimated coefficients of the causality from economic growth to energy consumption are positive, i.e. 1.775, 4.01, 0.514 and 1.118 respectively.

As for the causality from energy consumption to economic growth, the estimated coefficients are negative for three regions: Guangdong (-0.696), Hebei (-0.07) and Xinjiang (-0.242); positive for two regions: Guangxi (0.34) and Yunnan (0.273). The negative causality means that if the respective energy consumption increases 1%, it will cause economic growth a 0.696% decrease in Guangdong, 0.07% decrease in Hebei and 0.242% decrease in Xinjiang. According to Squalli (2007), in these three regions, there are two possible reasons for such negative causality. First is that the economic production is shifting to less energy intensive service sectors. The second is that there may be excessive use of energy in some unproductive sectors combining with capacity constraints.

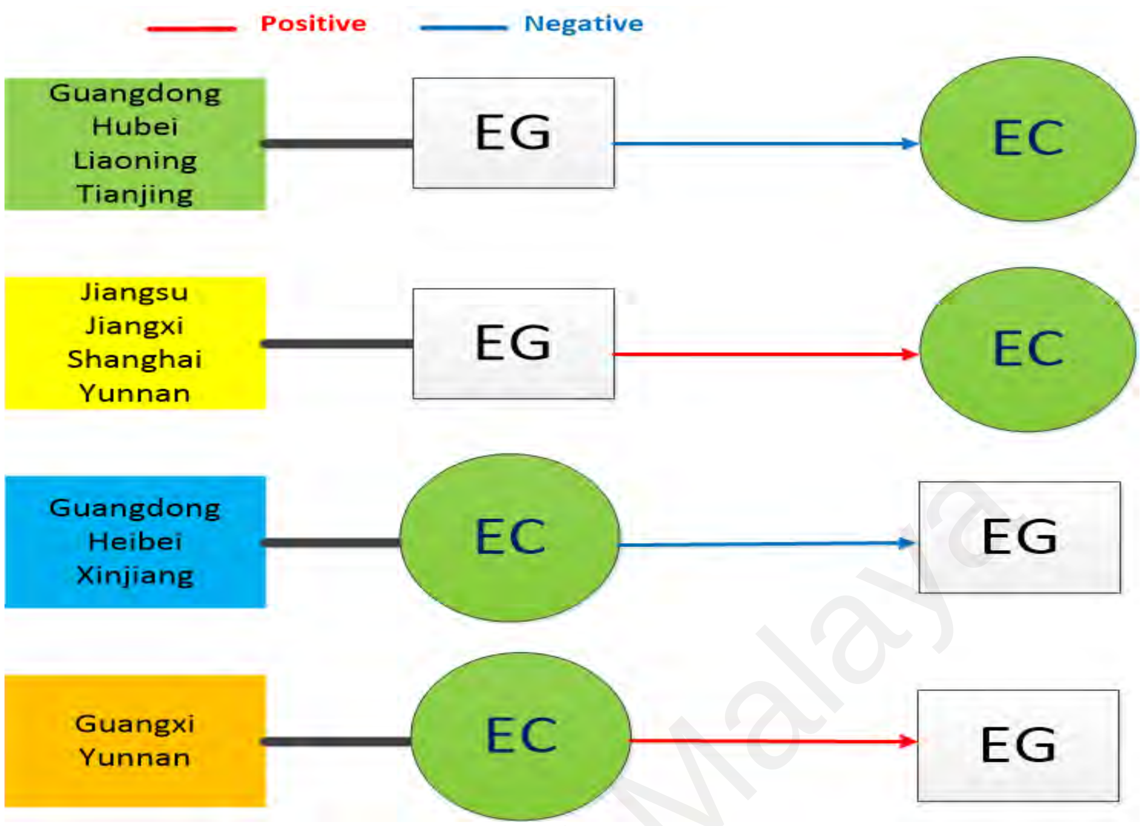

Figure 8: Summary of the energy-growth nexus at the regional level using the time series

Note: EC stands for "energy consumption", EG stands for economic growth, "→" stands for "unidirectional Granger causality" from the left to the right hand-side variable.

CHAPTER 6: CAUSALITY RELATIONSHIP BETWEEN ECONOMIC GROWTH AND RENEWABLE ENERGY CONSUMPTION

6.1 Introduction

In this chapter, the relationship between economic growth and renewable energy consumption is examined at the aggregate and disaggregated level. The purpose is to achieve research objective 1 with a focus on renewable energy. At the aggregate level, ARDL bounds test (refer to Section 3.4) is used to detect the presence of a long-run relationship between the time series. Then the nexus between renewable energy consumption and economic growth will be examined by using causality tests including the bootstrapped Toda-Yamamoto causality test (refer to Section 3.6) and the two newly proposed methods which are nonlinear causality test (refer to Section 3.7) and asymmetric causality test (refer to Section 3.8). On the other hand, at the disaggregated level the bootstrapped Toda-Yamamoto Causality will be applied.

6.2 Causality test at the aggregate level

First, we examine the relationship between economic growth and renewable energy consumption at the aggregate level.

6.2.1 Unit root tests

At the aggregate level, before the aforementioned tests are conducted, the unit root tests are conducted for aggregate renewable energy consumption per capita (EC), GDP per capita (GPC), capital stock per capita (K) and labour population (K). Table C.1 in Appendix C shows that over all the four series are stationary at first differencing although for GPC and K there are some conflicting results between ADF, PP and KPSS test. Therefore, we may proceed to test the long-run relationship between energy consumption and economic growth using ARDL test.

6.2.2 ARDL test

Similar to Section 4.2.2, we choose the maximum lag order as 3 years for our annual data. Based on Akaike's Information Criterion (AIC), the optimal combination lag order is selected as ARDL (1, 2, 1, 2), when renewable energy consumption per capita is the dependent variable and ARDL (1, 1, 3, 1) when GDP per capita is the dependent variable.

Table 6.1: Results of ARDL test

Bounds testing		Diagnostic tests			
Dependent	F-stats	χ^2Serial	χ^2ARCH	χ^2RESET	χ^2Normal
EC	3.348	1.141	0.356	2.499	0.400
GPC	3.043	3.433	0.128	0.027	12.116*
Significance level		Critical values			
		Lower bounds I(0)		Upper Bounds I(1)	
5%		3.500		4.700	
1%		4.865		6.360	

Note: The asterisk * denote the significance at the 1% level. The optimal lag is determined by AIC. Critical values for small sample are collected from Case III as in Narayan (2005): Unrestricted intercept and no trend (k=3).

Both models pass the diagnostic tests, i.e., serial correlation test, ARCH test, normality test and Functional form test, except that the second model has the problem of non-normal errors. However, this will not affect the coefficient estimates according to Paruolo (1997) as cited by MacDonald and Ricci (2004), Hanif et al. (2011) and Nordin et al. (2014). Overall, these two equations should provide a sound basis for cointegration test. The calculated F-statistics for cointegration and the results of the diagnostic tests on the ARDL model are reported in Table 6.1. In both models, the results indicate that the null of no cointegration between energy consumption and economic growth cannot be rejected at 5% level.

6.2.3 Bootstrapped Toda-Yamamoto Test

Since ARDL test failed to detect any long-run relationship between renewable energy consumption and economic growth, we apply the Bootstrapped Toda-Yamamoto test (refer to Section 3.6) to reassess the causality relationship. The series are confirmed to be stationary at first differencing in the previous subsection. Therefore one additional unrestricted lag is added to the VAR model in equation (23). After confirming the maximal order of integration, we proceed to test the causal relationship using Toda-Yamamoto approach on the original series EC and GPC. Following the same logic in Section 4.2.2, maximum lags order is chosen to be 3 years. Table 6.2 presents the results of Toda-Yamamoto test and the bootstrap-corrected critical value. It is found that there is no causal relationship between renewable energy consumption and economic growth based on both the p values of MWALD test statistics and the bootstrapped critical values, which further confirm the results of ARDL test.

Table 6.2: The bootstrapped Toda-Yamamoto causality test results at aggregate level

Null Hypothesis	MWALD Stats	P value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
EC⇏GPC	0.522	0.914	15.596	9.346	7.234
GPC⇏EC	0.732	0.866	15.170	9.762	7.5

Note: The optimal numbers of lags were selected based on HJC criteria. "⇏" stands for "does not Granger cause".

6.2.4 Nonlinear causality test

The bootstrapped Toda-Yamamoto test indicates that neutrality hypothesis on the nexus between renewable energy consumption and economic growth is valid in China from 1965 to 2013. We then apply the test proposed by Nishiyama et al. (2011) to detect the possible nonlinear causal relationship. The results are presented in Table 6.3. It is shown that there is no nonlinear causal relationship between renewable energy consumption and economic growth.

Table 6.3: Nonlinear causality test results at aggregate level

Null hypothesis	Test statistic	Null hypothesis	Test statistic
$\Delta EC \nRightarrow \Delta GPC$	5.724	$\Delta GPC \nRightarrow \Delta EC$	10.195

Note: $\nRightarrow$" stands for "does not Granger cause".

6.2.5 Asymmetric causality test

Although the results of the three tests in previous sections all support the neutrality hypothesis, there is a possibility that the causal relationship is asymmetric, which is mostly ignored in the literature. Therefore, the asymmetric causality test proposed by Hatemi-J (2012b) is adopted. By following the procedure described in Section 3.8, we obtain the positive and negative shocks for renewable energy consumption (EC^+ and EC^-) and for GDP per capita (GPC^+ and GPC^-). One additional unrestricted lag is added to the VAR model since the series are confirmed to be I(1). Then the asymmetric test is conducted (refer to Section 3.8). The results are presented in Table 6.4. The results show that there is unidirectional causal relationship running from negative energy shock (EC^-) to negative GDP shock (GPC^-).

Table 6.4: The asymmetric causality test results at aggregate level

Null Hypothesis	MWALD	lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
$EC^+ \nRightarrow GPC^+$	1.542	2	0.463	11.717	7.130	5.357
$EC^- \nRightarrow GPC^-$	5.018**	1	0.025	7.830	4.177	2.855
$EC^+ \nRightarrow GPC^-$	0.407	1	0.523	7.147	4.058	2.828
$EC^- \nRightarrow GPC^+$	0.939	2	0.625	11.981	7.340	5.433
$GPC^+ \nRightarrow EC^+$	0.467	2	0.792	12.254	7.284	5.525
$GPC^- \nRightarrow EC^-$	1.423	1	0.233	6.952	4.085	2.889
$GPC^+ \nRightarrow EC^-$	2.231	2	0.328	12.247	7.373	5.500
$GPC^- \nRightarrow EC^+$	0.068	1	0.795	7.461	4.230	2.900

Note: The asterisk **, *** denote the significance at the 5% and 1% level respectively according to the bootstrap critical values. The optimal numbers of lags were selected based on HJC criteria. "$\nRightarrow$" stands for "does not Granger cause".

6.3 Causality test at the disaggregated level

To examine the causality between disaggregated renewable energy consumption (hydro, solar, and wind) and economic growth, the bootstrapped Toda-Yamamoto Causality test is adopted.

6.3.1 Unit root test

The results of unit root test presented in Table C.2 in Appendix C show that all disaggregated renewable energy consumption are stationary at first differencing, i.e. I (1) except solar energy consumption. The results of ZA test in Table C.3 in Appendix C indicate that solar energy consumption is stationary at level. Therefore, the maximal order of integration is one.

6.3.2 Bootstrapped Toda-Yamamoto causality test

Table 6.5: The bootstrapped Toda-Yamamoto causality test results at disaggregated level

Null Hypothesis	MWALD	Lag	*p* value	1% bootstrap critical value	5% bootstrap critical value	10% bootstrap critical value
Hydro						
EC⇏GPC	0.919	3	0.821	14.838	9.478	7.220
GPC⇏EC	1.189	3	0.756	15.129	9.592	7.492
Solar						
EC⇏GPC	37.064*	3	0.000	133.208	43.965	25.979
GPC⇏EC	67.050**	3	0.000	108.28	37.033	21.941
Wind						
EC⇏GPC	0.645	3	0.724	20.390	10.494	7.303
GPC⇏EC	1.778	3	0.411	21.147	10.708	7.326

Note: The optimal numbers of lags were selected based on HJC criteria. "⇏" stands for "does not Granger cause".

Following the same logic in Section 4.2.2, maximum lags order is chosen to be 3 years. Table 6.5 presents the results of Toda-Yamamoto test and the bootstrap-corrected critical value. For hydro and wind energy, it is found that there is no causal relationship between renewable energy consumption and economic growth based on both the *p* values of MWALD test statistics and the comparison of MWALD test statistics with the bootstrapped critical values. However, for solar energy, it is found that there is a bidirectional causal relationship between solar energy consumption and economic growth.

6.4 Discussion on findings

The empirical results are summarized in Figure 9. At the aggregate level, the results of ARDL test indicate that there is no long-run relationship between renewable energy consumption and economic growth. And the results of the bootstrapped Toda-Yamamoto causality test and nonlinear causality test support neutrality hypothesis, i.e. there is no any causal relationship between renewable energy consumption and economic growth in China from 1953 to 2013.

These findings are consistent with Menegaki (2011) but contradictory with other studies such as Lin and Moubarak (2014) and Long et al. (2015) that found a bidirectional causal relationship between renewable energy consumption and economic growth in China. The difference with the previous findings may be attributed to the data adopted and the methodologies adopted.

Firstly, regarding the data adopted, per capita data is used in this study as compared to the aggregate data used in the previous studies: Lin and Moubarak (2014) and Long et al. (2015). By conducting a meta analysis of the existing studies that focus on identifying the nexus between renewable energy consumption and economic growth, Sebri (2015) concluded that the studies using per capita data have a relatively higher probability of getting neutrality and conservation hypothesis than the studies employing aggregate data.

Secondly, in terms of the method applied, Sebri (2015) also found that the studies that employed either Toda-Yamamoto or Hatemi-J Granger causality test tended to have a greater chance of supporting growth and neutrality hypothesis. Lin and Moubarak (2014) applied ARDL test while Long et al. (2015) employed Johansen cointegration test and Standard Granger causality test. In contrary, this study applied Hatemi-J Granger causality test that is able to tackle several research issues simultaneously. The neutrality hypothesis confirmed in this study indicates that renewable energy consumption is playing a minor role in promoting the economic growth in China currently. Given the fact that renewable energy consumption still accounts for a relatively small portion of the total energy consumption in China, this finding should not be surprising. In addition, this may be due to the trend that the economy is less energy dependent. As the economy grows, it tends to shift towards less energy-intensive productive activities, for example, service sectors(Ghali and El-Sakka, 2004).

On the other hand, the asymmetric causality test reveals that there is a positive unidirectional causal relationship running from negative renewable energy shock to negative growth shock. This finding is consistent with Destek (2016) in the case of India. The estimated causal parameter is 0.127, which indicates that a 1% increase in the reduction of renewable energy consumption will cause a 0.127% increase in the drop in economic growth. This finding shows that a reduction in renewable energy consumption will cause a decrease in economic growth while an increase in renewable energy consumption will not strengthen economic growth. In line with the reasoning of Hatemi-J and Uddin (2012), this implies that, although renewable energy consumption has not been contributing greatly to the economic growth (as confirmed by the results of the previous causality tests), the government must consume an optimal amount of renewable energy consumption in China to sustain its level of economic growth. However, renewable energy consumption exceeds such optimal amount will not contribute to economic growth. This is reasonable. Given the relatively small portion of the renewable energy consumption in the total energy mix in China, the significant contribution from it to the economic growth has not yet been observed. However, since the country is still energy-dependent in the long run (as shown in the results of Chapter 4), the reduction in fossil energy consumption must be compensated by the adoption in renewable energy consumption, whose role is minor at the current status quo, however, is vital to the economy in the long run. Therefore, although the effect of promoting economic growth by renewable energy consumption has not been captured, it is found that reducing renewable energy consumption is not allowed as it may hamper the economic growth in the long run.

Lastly, the results on disaggregated renewable energy are mixed. For hydropower consumption, there is no any causality identified with economic growth. This is inconsistent with the findings of Apergis et al. (2016) whose findings supported feedback hypothesis for the 10 largest hydroelectricity consuming countries. The difference in the findings is due to the three possible reasons: firstly, this study adopts Hatemi-J Granger causality test. This reason is explained previously; secondly, Sebri (2015) found that, as compared to time series studies, the studies applied panel technique had less probability to support neutrality hypothesis. Apergis et al. (2016) adopted panel test in their study; thirdly, this study uses a multivariate model that incorporated capital and labour as additional variables while Apergis et al. (2016) used bivariate analysis. Nevertheless, Apergis et al. (2016) also failed to provide any information for China alone but for a whole panel. The neutrality hypothesis confirmed by this study implies that hydroelectricity consumption is not contributing greatly to the economic growth in China. Therefore, any policies to reduce hydroelectricity consumption will not adversely affect the economic growth. Similarly, the results on wind energy consumption also support neutrality hypothesis. More interestingly, the results on solar energy consumption indicate that there is a bidirectional causal relationship between economic growth and solar energy consumption. More specifically, the estimated causal parameter is -20.827, which means a 1% increase in economic growth will cause a 20.827% decrease in solar energy consumption; the estimated causal parameter is -0.77, which means a 1% increase in solar energy consumption will cause a 0.77% decrease in economic growth. In line with Squalli (2007), there are some explanations on these two negative causal relationships. The negative causality running from solar energy consumption to economic growth may result from the shift of production to less energy intensive service sectors. The negative causality running from economic growth to solar energy consumption reflected the constraints due to hindrances related to infrastructure, politics and management may force energy consumption to reduce.

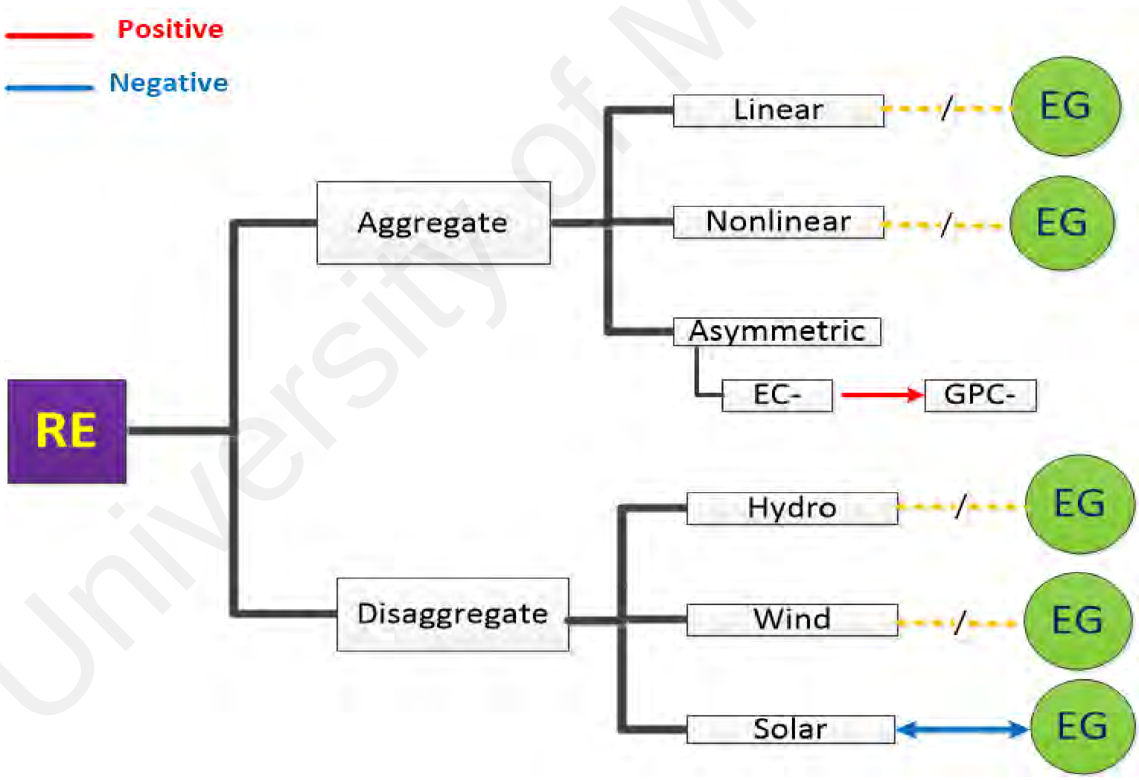

Figure 9: Summary of the causal relationships between renewable energy consumption and economic growth at both aggregate and disaggregate level using time series

Note: RE stands for "renewable energy consumption", EG stands for economic growth, "--/--" stands for "no Granger causality" "→" stands for "unidirectional Granger causality" from the left to the right hand-side variable, "↔" stands for "bidirectional Granger causality".

CHAPTER 7: CONCLUSION

7.1 Summary of the Study

This study reassessed the relationship between energy consumption and economic growth in China by applying time series techniques using national and regional approaches. Chapter 1 of this study provided an overview of the world environmental problem resulting from energy consumption and the unique characteristics of China's economic structure and energy consumption. Then it outlined the important but overlooked research aspects in the problem statement, which helped form the research questions and objectives. A comprehensive literature review focusing on the development of the research techniques adopted was conducted in order to identify potential research gaps in Chapter 2. Subsequently, in Chapter 3, the economic techniques employed to resolve the problem statement were explained in details. Chapter 4 then analysed the energy-growth nexus at the national level in China using time series data by applying all the economic techniques described in Chapter 3. Chapter 5 investigated the energy-growth nexus for 29 regions in China by applying the bootstrapped Toda-Yamamoto causality test. Finally, Chapter 6 examined the relationship between economic growth and renewable energy consumption using both aggregate and disaggregated data.

There were three objectives of this study. Chapter 4 aimed at the first two objectives. The first objective of the study was to investigate the existence of linear, nonlinear and asymmetric causality between energy consumption and economic growth. At the beginning of Chapter 4, the long-run relationship between energy consumption and economic growth was examined by employing multivariate ARDL model using capital stock per capita and labour as control variables. No long-run relationship was identified. Then the newly proposed bootstrapped Toda-Yamamoto causality test and nonlinear causality test were conducted. These tests failed to capture any linear or nonlinear causal relationship between economic growth and energy consumption in China at the national level. However, the recently proposed asymmetric causality test revealed that there were bidirectional relationships between positive energy shocks and negative growth shocks and between negative energy shocks and positive shocks.

The second objective was to uncover the causal relationship between energy consumption and economic growth at multiscale levels in both the time and frequency domains. Hence the original time series were decomposed into subseries that correspond to short, medium and long run. With the help of such analysis, it was revealed that the linear energy-growth nexus are different at short, medium and long run in China. It is interesting to note that the causality from energy consumption to economic growth in the short run and the causality from economic growth to energy consumption in the medium run are both negative while the causal relationship in the long run turned to positive and bidirectional. Moreover, a bidirectional nonlinear energy-growth nexus was found only in the long run. In addition, the asymmetric causal relationships found in the short run were exactly same with the ones found on the original time series, which indicated the dominance of the short-run asymmetric energy-growth nexus over all time horizons. In details, in the short run, there were negative bidirectional causal relationships between positive energy shocks and negative growth shocks and between negative energy shocks and positive growth shocks. In the medium run, a negative bidirectional causal relationship between negative energy shocks and positive growth shocks and a positive unidirectional causal relationship from negative growth shocks to negative energy shocks were found.

The third objective was to examine the causal relationship between energy consumption and economic growth at the regional level. In line with this, Chapter 5 investigated the energy-growth nexus for 29 regions of China by applying the newly developed bootstrapped Toda-Yamamoto causality test using capital stock and labour as control variables. The empirical results showed that for Guangdong, Hebei, Liaoning and Tianjin, there was negative causality running from economic growth to energy consumption while for Jiangsu, Jiangxi, Shanghai and Yunnan, there was positive causality from economic growth to energy consumption. Moreover, for Guangdong, Hebei and Xinjiang, there was negative causality from energy consumption to economic growth while for Guangxi and Yunnan the causality was positive.

Lastly, Chapter 6 aimed at identifying the relationship between renewable energy consumption and economic growth which was part of the first objective. At the aggregate level, the ARDL technique failed to capture any long-run relationship. Then the results of the bootstrapped Toda-Yamamoto causality test and nonlinear causality test supported neutrality hypothesis. However, the asymmetric causality test identified a positive unidirectional causal relationship from negative renewable energy shock to negative growth shock. On the other hand, at the disaggregated level, there was no causal relationship found between economic growth and both hydro and wind energy consumption. Yet, a negative bidirectional causal relationship was captured between solar energy consumption and economic growth.

7.2 Methodological implications

As noted in the problem statement, multiscale analysis, nonlinear and asymmetric causality and regional analysis are some of the important but usually neglected research aspects in the empirical study on the energy-growth nexus. Based on the econometric results, the possibility of different causality at different time scale has been proven. Therefore, it is reasonable to conclude that future studies should incorporate the multiscale analysis with the use of wavelet transform technique. Moreover, the empirical results also reveal that there is a necessity that study on energy-growth nexus should take nonlinear and asymmetric causality into consideration.

On the other hand, the results of the regional analysis in Chapter 5 prove that the causality does differ in different regions. This indicates two points. First, the regional studies are necessary in order to draw more comprehensive energy policy implications. Second, all the previous studies that assume homogeneous panel or categorize the regions based on certain criteria before causality test was conducted may have provided biased results. Therefore, if the regional analysis is needed, such as in the case of China, it is advised that the economic techniques that are able to provide information on causality for individual regions should be adopted. Lastly, the results of renewable energy consumption in Chapter 6 confirms the conclusion of Payne (2010b) that using aggregate energy consumption may prevent us from revealing the hidden information on the impact of energy consumption of different types on the economy. Although at the aggregate level the neutrality hypothesis was supported, at a disaggregated level, feedback hypothesis was confirmed between solar energy consumption and economic growth, which revealed vital information for renewable energy development policy-making.

Overall, the present study shows that it is the combination of wavelet multiscale analysis with linear, nonlinear and asymmetric causality tests help provide the more comprehensive and accurate information on energy-growth nexus in China. The outcome of the research is further enhanced by conducting the regional analysis.

7.3 Discussion and Policy Implications

In this section, policy recommendations based upon findings in Chapter 4, Chapter 5 and Chapter 6 are delineated.

In Chapter 4, for the original time series, both linear and nonlinear causality tests failed to detect any causal relationship between the two variables. However, the wavelet multiscale analysis revealed hidden information on energy-growth nexus in China. A negative unidirectional linear causality running from energy consumption to real output was found in the short run while the direction of this unidirectional causality reversed in the medium run. Both the linear and nonlinear causality tests supported the feedback hypothesis for the long run. In addition, the asymmetric causal relationships were identified in the short and medium run but not in the long run. The results of asymmetric causality tests actually are consistent with the results of linear causality tests. The asymmetric causal relationships were only identified in the short and medium run where the negative linear causality was identified but disappeared in the long run where only positive linear causality was identified. In other words, the negative linear causality implies potential asymmetric causality. Overall, the energy-growth nexus is rather complex for China. The results effectively complement existing research by revealing the interaction between energy consumption and economic growth for different time scales in China. These findings are useful for policy makers of China to plan prudently to meet the developmental goals in different time horizons.

In the short run, the negative linear causality from energy to growth and the negative causality from negative growth shocks to positive energy shocks imply a shift of production to less energy-intensive sectors. This is reflected in energy policies of China during recent years.

In its plan, the National Development and Reform Commission of China (2005) sets adjustment of the industrial structure as one important way to move towards energy conservation. It aims to speed up the growth of tertiary industry (service industry) and high technology industry (information technology industry) and designed policies to limit the dependence on energy-intensive sectors. For example, in terms of production capacity, the expansion of energy-intensive enterprises must be justified at the initial stage. Major energy consuming enterprises that consume more than 10,000 tons (coal equivalent) must report their state of energy consumption. Moreover, old and energy intensive products and equipment are to be discarded regularly and any business activities related to these discarded products and equipment will be severely punished. Besides these actions, China has reduced tax rebate and increased export tariffs on energy-intensive products step by step since 2004 to limit the exports of energy-intensive products (Qi et al., 2014).

There may also be other explanations, e.g. excessive energy consumption in unproductive sectors. The low productivity of the state-owned sectors in China has been studied by many researchers, e.g. Brandt et al. (2013) and Huang et al. (2010). The domestic state-owned industrial companies, both consumers and producers of energy, have all been profiting from massive energy subsidies (Economist, 2013). The discussion by Haley and Haley (2013) showed that the policy of energy subsidies caused distortion of price and led to the excessive usage of energy by Chinese companies (Wei and Li, 2016), highlighting the problem of excessive energy usage in unproductive sectors in China.

Based on the two justifications of negative linear and asymmetric causality in the short-run, there are several policy suggestions. First, the plan on industrial structure adjustment should be constantly monitored. The transformation in industrial structure from energy-intensive to less energy-intensive and knowledge-based in the process of industrialization poses a big challenge. Reasonably, it cannot be achieved in the near future. The restructuring process should be kept on the right track not only in the short run but the momentum should also be maintained in the long run. The reduction of energy consumption by these implemented mechanisms should not be the only focus but also their effectiveness in solving environmental problems. Qi et al. (2014) found that the production of machinery and equipment contributed the most to the export-embodied CO_2 of China compared to energy-intensive products. They showed by simulation that the shift "from industry-based to service-based" development in China would significantly influence its trade-embodied CO_2 emission only if trade surplus decreased as a result of this shift (p. 211). Therefore, if solving the environmental problem is one of the prioritized targets, the effectiveness of economic restructuring on emission reduction should be evaluated regularly.

Second, the development of the less energy-intensive sectors should also be monitored closely so that no excessive energy is consumed and an improvement in productivity is achieved. Yao (2013) was of the view that the development of service industry does not necessarily lead to energy saving and emission reduction. In fact, differences within the service industry among different sectors make a blanket definition of service industry as environmentally friendly arbitrary. Hence, a thorough investigation on the structure and characteristics of the service industry should be implemented, especially on the energy intensity and energy consumption patterns of its inner sectors. Effective policies should be designed to ensure that the service industry will be more energy-efficient and able to contribute effectively to China's green development. Third, the government should identify the excessive energy consumption in the unproductive sectors, especially in the state-owned industrial companies. The heavy energy subsidies should be eliminated gradually to avoid price distortion that causes excessive energy consumption. International Monetary Fund (2013) advised that reforms on energy subsidies should be implemented globally since they may greatly benefit the world both economically and environmentally. In line with this, China is planning to set the timetable for the removal of the subsidies of fossil energy step by step in its short-, medium- and long-term plans for fossil energy reform (Phoenix finance and Economics, 2016).

In the medium run, the negative causality running from economic growth to energy consumption and the positive causality from positive growth shocks to negative energy shocks may augur well for sustainable development, i.e., increasing economic growth with less energy input. However, it must be ensured that the negative causality from growth to energy is not caused by other factors such as hindrances related to infrastructure and management. These hindrances, if identified, must be removed to avoid unnecessary energy shortage in the economy.

For example, the shortage of coal supply during the reform period of China was partially due to the lack of railway capacity for supply delivery. China has made substantial investments in improving transportation and other economic infrastructures. For example, 55 main infrastructure projects were approved by the National Development and Reform Commission (KPMG China, 2013). Out of these projects, 45 are related to transportation infrastructure. As for the management issue, Zhao et al. (2012) concluded that power shortage and surplus were caused by the reliance on centralized electricity management system for price determination. Wei and Li (2016) found that energy supply was misallocated among manufacturing companies in Zhejiang Province, China. Therefore, the energy management must be improved by focusing on price reforms and mitigation of energy misallocation.

In addition, the results of asymmetric causality also suggest that an optimal amount of energy needs to be consumed in order to maintain the level of economic growth in the medium run. Hence, the government should pay more attention to mismanagement, inefficiency and infrastructure constraints to ensure that adequate energy is consumed efficiently.

For the long run, the bidirectional linear and nonlinear causality relationships between economic growth and energy consumption suggest that the energy conservation policy must be carefully crafted to avoid undesirable impact on economic development. The dependence of economic growth on energy consumption implies that any energy shocks such as those that resulted from energy conservation policies with poor structure and inappropriate approach may hamper economic growth. Given that the main source of energy is still coal, oil and gas, direct energy conservation policy alone will not reasonably benefit the country in the long run. Therefore, policies should aim more on the development of energy efficiency technologies and the green technology such as the wind and solar energy, rather than reducing the total energy consumption directly.

Realizing this, the Chinese government has set the target in the 12th five-year plan to make major investments in clean energy and clean energy cars besides energy conservation (KPMG China, 2011). The Strategic Action Plan for Energy Development (2014-2020) focuses on the implementation for energy efficiency improvement and aims to vigorously develop renewable energy so that by 2020 non-fossil energy is expected to account for 15% of the primary energy consumption (The State Council of China, 2014). However, two important points must be borne in mind.

First, clean energy is a must, not an alternative. This means that the government must ensure that the targets set for the coming years are to be achieved to sustain the economic growth. Yet, the empirical results of Chapter 6 revealed that renewable energy consumption (both aggregate and disaggregated) has not been playing a significant role in promoting economic growth. Moreover, Lin and Moubarak (2014) found that renewable energy was "not considerably exploited" therefore has not yet been contributing to mitigate carbon emission in China (p. 111). These findings deserve serious attention from the policy makers. It is understandable that the adopting of renewable energy by developing countries may be accompanied by short-term economic cost (Pearce et al., 2013), which may neutralize the positive impact of renewable energy consumption on the economic growth. However, inspired by Shahbaz et al. (2016), these findings should warn the government to focus more on the proper implementation and development of the technology on utilizing the renewable energy available efficiently and effectively.

In fact, the studies that have been conducted to evaluate the policy impact of China's renewable energy plan showed that while some achievements have been made, problems and challenges still exist (Hong et al., 2013; Zhang et al., 2013). Zhang et al. (2013) found that China's renewable energy plan has put the development of renewable energy manufacturing industry as the priority over the generation of the renewable energy. Such approach has caused overcapacity of the renewable energy industry and may compromise the effectiveness and contributions of renewable energy for the economy. In addition, Hong et al. (2013) analysed the possible outcome of the impact of the energy policy of the government in the 12th five-year plan under different scenarios by simulations. Challenges and constraints were identified that may reduce the renewable energy contribution in the coming years include: grid bottleneck, weak technical performance and low energy efficiency of the related technologies.

In line with this, the empirical result of negative causality from economic growth to solar energy consumption in Chapter 6 implies that there are constraints on infrastructure in China that prevent renewable energy consumption from benefiting the economy. In fact, there is very high curtailment rate[14] of solar energy in China. The three provinces in the north-western regions have the largest rate of curtailment, 52% for Xinjiang, 39% for Gansu and 20% for Ningxia (Shaw, 2016). And there is an

[14] Curtailment rate refer to the decrease in power generation since the solar power capacity could not be optimally utilized (Xinhua Finance, 2016).

increasing trend of such curtailment. The overall curtailment rate of the total power generation by solar photovoltaic (PV) cells is approximately 14% in quarter 1 of 2016, which is greater than the 10% curtailment rate for quarter 1 to quarter 3 of 2015 (Shaw, 2016).

One reason is the "lack of sufficient grid infrastructure, and because coal power plants are given priority dispatching" (Energy post, 2016). In addition, the conventional energy is preferred by the grid operators as compared to the renewable energy that is less stable (Kathy and Dominique, 2015). Another possible cause is the location of the renewable energy (solar). A Large portion of the renewable energy is located in North and West of China, which is distant from the areas that of high energy demand (Energy post, 2016).

The Chinese government has made efforts to tackle such problems. For example, it has installed more and more solar PV cells in the eastern, middle and southern China than the traditional areas such as north and west of China (Shaw, 2016). Moreover, the grid companies in over 10 regions, which are characterized as "of network congestion and idled plants", received the rulings from the National Development and Reform Commission to purchase at least "1,300 hours of solar energy" annually (Clover, 2016). Such annual quotas for minimum usage of renewable energy come with "guaranteed purchasing price" which may benefit the renewable power industry by ensuring investment returns and reducing curtailment rate (Xinhua Finance, 2016). Moreover, the authority also forces the power grid companies to sign agreements with renewable power generators (solar and wind) each year for the next year starting this June to prioritize their power generation and dispatch (Xinhua Finance, 2016). This may temporarily help solve the high curtailment rate issue. Yet, the government is advised to focus more on the development of better grid system.

Yasuda et al. (2015) compared the wind energy development between China and Texas in the United States. Both started installing wind power capacity in the inner area before the long-distance transmission system to the coastal areas was completed. Therefore, both faced relatively high curtailment rate. Fortunately, the curtailment rate in Texas reduced recently after the transmission system has been gradually completed. Hence, the Chinese government should speed up in ensuring the long-distance transmission. Recognizing the fact that the "transmission capabilities are lagging generating capacity" by about 3 to 5 years, it is building new ultra-high voltage (UHV) lines for long-distance transmission to aid in delivering power generated in the remoter areas to the east of China with high energy demand (Chen and Stanway, 2016). Currently, there are "17 UHV transmission lines in operation or under construction" (Chen and Stanway, 2016).

Above all, the government should ensure that the energy policy targets on renewable energy can be met by identifying and tackling all problems and challenges. A more comprehensive plan on the renewable energy production and technology should be designed.

Second, given that the relationship between energy consumption and economic growth is inextricably connected to each other in the long run (i.e. nonlinear bidirectional causality), the impact of structural changes, such as policy changes, on this relationship must be studied. The ambitious plan of developing renewable energy that is relatively new to China comes with drastic structural change. The process of increasing the share of renewable energy rapidly, which is expected to replace some traditional energy, will not be easy. To sustain its economic growth with no abrupt shock, the government must take the nonlinear causal relationship between energy and growth into consideration to design and implement appropriate energy policy with extra caution.

Besides the results of the study at the national level, the regional analysis on the energy-growth nexus also provides us useful information to draw policy recommendations. This is very important since the effectiveness and viability of the policy recommendations derived from the national study rely on the proper cooperation and coordination among the different regions.

The negative causality from economic growth to energy consumption in Guangdong, Hebei, Liaoning and Tianjin may imply sustainable development in these regions, i.e. promoting economic growth with less energy input. However, cautions should be made that it may also suggest that possible hindrances of infrastructure and inefficiency are present in these regional economies to force energy consumption to decrease.

For Hebei province, The efficiency of energy utilization is low and the improvement is slow (Zheng and Wang, 2011). Its energy intensity was 1.64 tons standard coal equivalent per 10000 yuan, which ranked 23rd among the 30 regions in China. In line with this, Hebei has become the pioneer region in China for increasing energy efficiency. For example, endorsed by the Chinese Ministry of Construction, Hebei Province was supported by the Deutsche Energie-Agentur GmbH (the German Energy Agency) to build "an Efficient House Research Centre" (Pillen, 2015). In addition, as the second biggest energy consumer among regions in China, it has received energy efficiency investment with the aid from the Asian Development Bank (ADB) through the "Heibei Energy Efficiency Improvement and Emission Reduction Project" (Asian Development Bank, 2015). The loan proceeds of ADB are directed into the targeted sectors and an ongoing fund is established for financing a series of energy efficiency investment. Similarly, "Guangdong Energy Efficiency and Environment Improvement Investment Program" was also implemented by ADB to help "retrofit existing equipment with proven energy-efficiency technologies" (Asian Development Bank,

2013) while "Liaoning Environment Improvement Project" was conducted to increase efficiency other than improving environment (Asian Development Bank, 2012). Other than increasing efficiency, infrastructure should also be improved for these regions. The State Grid has made the effort to mitigate the power shortages for regions including Tianjin and Hebei by building UHV system, for example, a 1,000-kilovolt transmission project is implemented in Tianjin, which will be enabled to utilize renewable energy up to 50 billion kilowatt-hours (Chang, 2016).

For Guangdong, Hebei and Xinjiang, the negative causality from energy consumption to economic growth implies a shift of production to less energy-intensive sectors in these regions. This is well reflected in the trends of the industrial restructuring of these provinces that have been shifting away from manufacturing sectors towards other sectors such as service jobs and high-tech firms.

Guangdong is the major contributor to the manufacturing growth in China. It created over USD$ 600 billion from export in 2015, which is greater than 25% of the country's total export revenue (Bland, 2016). In the meantime, manufacturing sector contributes to almost 90% of the industrial energy consumption which accounts for over 60% of the total provincial energy consumption (Liu et al., 2013). The contribution of the sectors such as mining and quarrying, manufacturing and etc. to the provincial GDP was 50.3% in 2005 but has decreased to 46.2% in 2014[15]. On the other hand, the contribution of other industries such as services sectors has increased from 43.3% in 2005 to 49.1% in 2014.

In the case of Xinjiang, manufacturing energy consumption is also very high and accounts for over 50% of the provincial total energy consumption (Gao, 2013). Yet, the contribution of the industrial sectors including manufacturing to the region's GDP has

[15] The data of GDP contributions of different sectors for the three regions discussed subsequently are obtained from Hewitt (2015) who generated the statistics based on the data of National Bureau of Statistics of China.

decreased from 50.3% in 2005 to 46.2% in 2014 while the contribution of the service and other sectors has increased from 43.3% in 2005 to 49.1% in 2014.

A similar trend is observed in Hebei, which is the second largest energy consumer among all the regions in China, with the amount of energy consumption accounting for almost 9% of the national energy consumption (Asian Development Bank, 2015). In 2013, the industrial energy consumption was 249.427million tons standard coal equivalent which accounted for over 80% of the provincial total energy consumption (Jiang and Shen, 2016). From 2005 to 2014, the contribution of the industrial sectors to the provincial GDP has decreased from 52.7% to 51.1% while the contribution of the service sectors has increased from 33.4% to 37.2%. The decrease of the contribution of the industrial sectors towards its economic growth is relatively low in Hebei. This is due to the industrial restructuring of the province. Hebei heavily relies on steel production, which consumes more than 60% of the provincial energy consumption yet contributed only 20% to the production value tax of the whole province (Lei, 2015). Realizing such fact, the provincial government has put more effort not only on developing modern service sectors but also on restructuring its industries. By this spirit, the government focused on the development of the equipment manufacturing sector, which is the largest steel consumer. This sector is contributing greatly to the provincial economic growth. For example, from 2010 to 2014, the value-added of the equipment manufacturing sector maintained an average annual growth rate of 20.1% and its percentage of the industrial value-added also increased at an average rate of 0.7% every year (Lei, 2015). And this momentum is maintained as the provincial government is targeting 1.13 trillion yuan and 1.52 trillion yuan of revenue in this subsector in 2016 and 2017 respectively (Government of Hebei Province, 2016). By focusing on the development of high-end manufacturing sector, the added value of the equipment manufacturing sector is expected to accounts for over 20% of the provincial total value added by the end of 2016 (Government of Hebei Province, 2016).

In addition, for Guangxi and Yunnan, the positive causality from energy consumption to economic growth indicates that the recent energy conversation policy of the central government will have a negative impact on their regional economic growth. Therefore, renewable energy exploration could be important strategies to mitigate such negative effect and ensure the sustainment of its economic development.

In fact, these two regions are among the pioneers in developing renewable energy in China (China National Renewable Energy Centre, 2013). In 2012, Yunnan ranked 3rd among the top ten provinces with highest renewable energy power capacity with a total capacity of 34,520 million watts (MW) while Guangxi ranked 6th with a total capacity of 15,520 MW. In addition, among the top ten regions, Yunnan is one of the four regions that have a balanced development of the renewable energy, i.e. installed power capacity for all types of renewable energy, e.g. for the case of Yunnan: hydropower with 33,060 MW; wind power with 1,310MW; solar power with 30 MW; biomass power with 122 MW. Similarly, Guangxi is among the three regions that develop three types of renewable energy generation capacity, i.e. hydropower with 15,360 MW; wind power with 100 MW; biomass power with 60 MW.

Moreover, Jiangsu, Jiangxi, Shanghai and Yunnan, the positive causality from economic growth to energy consumption imply that the energy-saving policy implemented by the central government will not hamper the economic growth of these regions. In fact, the rapid economic development in these regions may boost the energy consumption further.

Lastly, cautions must be made before implementing these policy recommendations. Although the results of regional analysis do help reveal more information on energy-growth nexus in China, which support well the suggestions by Yalta and Cakar (2012), who confirmed neutrality hypothesis in China using national data yet advised future studies to utilize regional analysis to gain deeper understanding, more studies with updated data should be conducted on an ongoing basis as causality direction can change over time. Moreover, the regional analysis should be enhanced by incorporating disaggregated and sectoral data to derive more comprehensive and accurate information on energy-growth nexus in China.

In conclusion, the Chinese government should design a comprehensive plan that incorporates all the considerations based on the policy recommendations derived from the results of both national and regional analysis on energy-growth nexus in China.

7.4 Limitations and direction for future research

Regional data are not sufficiently long for further analysis. Data disaggregated by industry and different economic sectors are limited. Many series are short and suffer from the problem of missing data. With the availability of data for different sectors, future studies could identify the sectors that contribute to economic growth without burdening the energy sector excessively and causing environmental degradation. If more data can be collected at the regional and sectoral level, further analysis could be performed using the bootstrapped panel causality test. Future research can perhaps devote more attention to the renewable energy sector and introduce variables that measure the environmental impact of energy consumption and economic development.

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PRESENTATIONS AND AWARDS

BEST PAPER AWARD

Ha Junsheng, Tan Pei Pei, Goh Kim Leng, "*Linear and nonlinear causal relationship between energy consumption and economic growth in china: new evidence based on wavelet analysis*", Postgraduate Conference on Economics, Public Administration and Business (PCEPAB 2015), September 5th, 2015, Kuala Lumpur, Malaysia

APPENDIX A: SUPPLEMENTARY RESULTS FOR CHAPTER 4

Table A.1 Unit root test results for the original time series

Variables	Specification	ADF test	PP test	KPSS
GPC	Intercept	1.908	3.365	0.957**
	Intercept & trend	-1.435	-1.140	0.241
ΔGPC	Intercept	-5.490***	-4.888***	0.578**
EC	Intercept	-1.394	-1.508	0.982**
	Intercept & trend	-3.210*	-3.359*	0.068
ΔEC	Intercept	-4.449***	-4.634***	0.104
K	Intercept	0.827	0.345	0.979***
	Intercept & trend	-1.609	-1.197	0.195**
ΔK	Intercept	-4.070***	-2.878*	0.186
L	Intercept	-1.759	-2.229	0.962***
	Intercept & trend	-0.788	0.302	0.175**
ΔL	Intercept	-3.678***	-3.502**	0.453*

Note: The optimal number of lags for ADF tests was selected based on Schwarz information criterion (SIC). The bandwidths for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Table A.2 Unit root test results for positive and negative shocks of the original time series

Variables	Specification	ADF test	PP test	KPSS
GPC+	Intercept	1.850	2.940	0.963***
	Intercept & trend	-1.332	-0.809	0.235***
ΔGPC+	Intercept	-5.277***	-5.199***	0.419*
EC+	Intercept	-2.033	-3.465**	0.950***
	Intercept & trend	-4.647***	-4.025**	0.194**
ΔEC+	Intercept	-3.522**	-4.713***	0.380*
GPC-	Intercept	-33.774***	-3.153**	0.592**
	Intercept & trend	-5.533***	-1.819	0.202**
ΔGPC-	Intercept	-2.241	-6.015***	0.516**
EC-	Intercept	-2.718*	-2.747*	0.613**
	Intercept & trend	-4.335***	-1.978	0.178**
ΔEC-	Intercept	-8.851***	-4.489***	0.368*

Note: The optimal number of lags for ADF tests was selected based on Schwarz information criterion (SIC). The bandwidths for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Table A.3 Unit root test results for wavelet decomposed series of the original time series

Variables	Specification	ADF test	PP test	KPSS
Short-run (d1+d2)				
GPC	Intercept	-11.299***	-6.104***	0.181
EC	Intercept	-6.799***	-6.983***	0.166
Medium-run (d3)				
GPC	Intercept	-3.192**	-3.906***	0.026
EC	Intercept	-5.807***	-3.639***	0.029
Long-run (d4+d5)				
GPC	Intercept	-9.465***	0.731	0.222
ΔGPC	Intercept	-0.385	-1.394	0.551**
EC	Intercept	-3.362**	-2.445	0.127
ΔEC	Intercept	-1.889	-2.052	0.187

Note: The optimal numbers of lags for ADF tests were selected based on SIC. The bandwidths for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and ***denote significance at 10%, 5% and 1% respectively.

Table A.4 Unit root test results for the positive and negative shocks of wavelet decomposed series

Variables	Specification	ADF test	PP test	KPSS
Short-run (d1+d2)				
GPC+	Intercept	-1.783	-5.283***	0.807***
	Intercept & trend	-2.221	-5.616***	0.170**
ΔGPC+	Intercept	-12.125***	-14.258***	0.172
GPC-	Intercept	-1.880	-6.846***	0.718**
	Intercept & trend	-3.905**	-13.892***	0.500***
ΔGPC-	Intercept	-6.236***	-30.644***	0.146
EC+	Intercept	-3.033**	-5.678***	1.048***
	Intercept & trend	-2.653	-6.316***	0.122*
ΔEC+	Intercept	-14.439***	-23.147***	0.149
EC-	Intercept	-1.243	-6.561***	0.742***
	Intercept & trend	-1.908	-9.145***	0.500***
ΔEC-	Intercept	-9.364***	-24.906***	0.135
Medium-run (d3)				
GPC+	Intercept	-6.193***	-2.042	0.369*
	Intercept & trend	-6.021***	-1.815	0.139*
ΔGPC+	Intercept	-8.444***	-4.615***	0.181
GPC-	Intercept	-3.706***	-2.737*	0.188
	Intercept & trend	-4.420***	-2.690	0.043
ΔGPC-	Intercept	-8.175***	-3.899***	0.080
EC+	Intercept	-5.790***	-2.690*	0.454*
	Intercept & trend	-6.322***	-2.869	0.132*
ΔEC+	Intercept	-6.776***	-3.957***	0.030
EC-	Intercept	-3.146**	-2.986**	0.219
	Intercept & trend	-3.604**	-3.104	0.056
ΔEC-	Intercept	-6.227***	-2.963**	0.043
Long-run (d4+d5)				
GPC+	Intercept	-3.279**	-1.535	0.516**
	Intercept & trend	-3.613**	-1.984	0.180**
ΔGPC+	Intercept	-3.264**	-0.834	0.083
GPC-	Intercept	-1.716	-1.738	0.302
	Intercept & trend	-2.497	-2.078	0.133*
ΔGPC-	Intercept	-3.925***	-2.716**	0.120
EC+	Intercept	-7.190***	-2.068	0.216
	Intercept & trend	-6.948***	-2.083	0.190*
ΔEC+	Intercept	-4.506***	-3.864***	0.057
EC-	Intercept	-4.180***	-2.366	0.153
	Intercept & trend	-4.177***	-2.362	0.149*
ΔEC-	Intercept	-4.669***	-3.377**	0.077

Note: The optimal numbers of lags for ADF tests were selected based on SIC. The bandwidths for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and ***denote significance at 10%, 5% and 1% respectively.

Table A.5 Zivot and Andrews Test

Variables	Specification	T statistics	Break Point
Original series			
GPC	Intercept	-1.856	1971
	Intercept & trend	-3.548	1976
ΔGPC	Intercept	-5.176**	1982
	Intercept & trend	-7.004***	1963
Negative shocks of the original series			
GPC-	Intercept	-6.156***	1973
	Intercept & trend	-6.590***	1970
Long run (d4+d5)			
GPC	Intercept	-5.366***	1997
EC	Intercept	-7.112***	1971

Note: *, ** and *** denote significance at 10%, 5% and 1% respectively. The optimal number of lags was selected based on Akaike information criterion.

APPENDIX B: SUPPLEMENTARY RESULTS FOR CHAPTER 5

Table B.1 Unit root test results

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Anhui						
EC	1.314	-1.916	1.577	-1.263	0.777***	0.164
GPC	1.467	-2.888	2.218	-1.434	0.775***	0.148**
K	1.24	-2.565	3.783	0.874	0.765***	0.187**
L	-1.576	-2.426	-3.312**	-2.514	0.77***	0.179**
ΔEC	-3.142***	-3.176	-3.226**	-3.158	0.193	0.846
ΔGPC	-2.438	-3.193	-2.489	-3.269*	0.47*	0.633
ΔK	-2.388	-2.926	-1.759	-3.363*	0.422*	0.139*
ΔL	-2.657***	-2.835	-2.616	-2.793	0.458*	0.173**
Beijing						
EC	0.445	-2.995	0.429	-3.432	0.741***	0.117
GPC	-0.356	-3.634**	-0.418	-2.534	0.749***	0.687
K	-4.355***	-0.695	-1.533	-0.664	0.744***	0.172**
L	-0.277	-2.424	0.159	-1.214	0.668**	0.128*
ΔEC	-5.539***	-4.858***	-4.99***	-4.834***	0.127	0.775
ΔGPC	-4.523***	-4.535***	-4.533***	-4.776***	0.293	0.22***
ΔK	-2.694	-5.272***	-2.29	-2.777	0.223	0.794
ΔL	-2.142	-2.212	-2.142	-2.363	0.159	0.175
Chongqing						
EC	1.677	-0.822	1.677	-0.822	0.694**	0.185**
GPC	1.267	-1.199	2.991	-1.563	0.755***	0.154**
K	1.384	-2.313	7.922	0.667	0.723**	0.287**
L	-3.228***	-2.763	-1.697	-1.936	0.221	0.159**
ΔEC	-3.473***	-4.114**	-3.465**	-4.183**	0.384*	0.726
ΔGPC	-2.37	-2.182	-2.389	-2.686	0.444*	0.844
ΔK	-0.675	-4.754**	-0.675	-4.387**	0.646**	0.115
ΔL	-1.267	-0.437	-1.436	-0.645	0.248	0.147**
Fujian						
EC	2.338	-1.325	2.161	-1.429	0.665**	0.182**
GPC	-0.264	-3.336*	0.544	-2.267	0.683**	0.647
K	1.946	-1.413	1.894	-0.87	0.685**	0.156**
L	1.666	-1.643	-0.219	-1.612	0.68**	0.134*
ΔEC	-4.586***	-4.712***	-4.974***	-4.714***	0.45*	0.559
ΔGPC	-4.385***	-4.272**	-4.385***	-4.273**	0.113	0.798
ΔK	-2.918***	-3.677**	-1.457	-1.947	0.314	0.589
ΔL	-1.345	-1.132	-1.345	-1.352	0.134	0.135*

Table B.1 Unit root test results (Cont.)

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Gansu						
EC	2.394	-0.236	2.153	-0.447	0.716**	0.185**
GPC	2.744	-0.357	2.839	-0.357	0.783***	0.195**
K	2.946	3.541	9.872	2.477	0.757***	0.275**
L	-2.593	-2.447	-2.875*	-1.595	0.556**	0.193**
ΔEC	-2.827***	-3.451*	-2.827*	-3.465*	0.451*	0.928
ΔGPC	-3.785***	-5.866***	-3.765***	-5.169***	0.52**	0.562
ΔK	0.269	-2.934	0.269	-3.292	0.674**	0.165**
ΔL	-2.264	-2.721	-2.223	-2.761	0.42*	0.147
Guangdong						
EC	-0.594	-2.58	-0.348	-1.893	0.773***	0.947
GPC	-0.834	-2.997	-1.343	-1.664	0.779***	0.13*
K	-1.676	-2.786	-0.64	-1.746	0.782***	0.116
L	0.723	-2.381	0.869	-1.115	0.776***	0.161**
ΔEC	-3.153***	-2.778	-3.153**	-3.782	0.713	0.737
ΔGPC	-3.633***	-3.646**	-2.453	-2.679	0.186	0.563
ΔK	-2.769***	-2.842	-2.228	-2.226	0.123	0.632
ΔL	-2.983***	-3.439	-2.253	-2.298	0.218	0.922
Guangxi						
EC	1.352	-2.353	1.986	-2.473	0.667**	0.175**
GPC	2.223	-1.13	3.112	-1.154	0.679**	0.176**
K	2.146	1.782	5.888	2.728	0.677**	0.197**
L	-1.967	-2.118	-7.632***	-1.775	0.667**	0.271**
ΔEC	-3.573***	-3.95**	-3.475**	-3.912**	0.437*	0.645
ΔGPC	-1.582	-3.113	-2.998**	-3.474*	0.498**	0.613
ΔK	-0.156	-1.512	0.289	-1.674	0.589**	0.147*
ΔL	-1.348	-1.426	-1.232	-2.515	0.658**	0.141*
Guizhou						
EC	-0.934	-2.359	-0.999	-2.34	0.67**	0.156**
GPC	1.912	1.292	2.129	0.565	0.686**	0.15**
K	2.939	0.753	5.433	1.272	0.668**	0.227**
L	-2.217	1.3	-2.35	0.415	0.587**	0.186**
ΔEC	-7.535***	-6.874***	-6.987***	-6.746***	0.921	0.515
ΔGPC	-1.665	-1.982	-2.698*	-3.297*	0.389*	0.16**
ΔK	0.474	-1.255	0.474	-1.498	0.644**	0.127*
ΔL	-2.948***	-3.299*	-2.963	-3.136	0.448*	0.922
Hainan						
EC	-0.568	-2.294	-0.568	-2.294	0.666**	0.887
GPC	3.313	-2.272	-0.865	-2.454	0.671**	0.987
K	1.727	-1.73	-0.588	-2.154	0.67**	0.995
L	2.195	-1.257	1.239	-0.315	0.622**	0.153**

Table B.1 Unit root test results (Cont.)

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Hainan						
ΔEC	-3.894***	-3.789**	-3.894***	-3.789**	0.113	0.114
ΔGPC	-1.866	-7.792***	-2.669*	-2.6	0.138	0.131*
ΔK	-2.196	-1.341	-1.592	-1.729	0.169	0.166**
ΔL	-1.686	-2.356	-1.625	-2.338	0.385	0.139*
Hebei						
EC	0.522	-1.656	0.414	-1.265	0.732**	0.159**
GPC	0.596	-6.743***	1.158	-2.914	0.75***	0.124*
K	1.894	-1.357	3.978	-1.692	0.742***	0.189**
L	-2.867	-1.534	-4.265***	-2.622	0.732**	0.187**
ΔEC	-4.597***	-4.223**	-4.597***	-4.232**	0.172	0.997
ΔGPC	-2.387	-2.293	-4.592***	-4.274**	0.235	0.888
ΔK	-2.765***	-3.674**	-2.726*	-3.696**	0.575**	0.795
ΔL	-2.298	-2.283	-1.562	-2.318	0.48**	0.174**
Heilongjiang						
EC	-0.171	-1.758	-0.222	-1.952	0.749***	0.155
GPC	7.485	1.732	1.326	1.568	0.678**	0.27**
K	2.75	-2.25	1.3	-0.267	0.687**	0.129*
L	-2.454	-1.869	-2.543	-2.587	0.676**	0.172**
ΔEC	-5.134***	-5.171***	-5.137***	-5.183***	0.186	0.946
ΔGPC	-1.469	-5.442***	-3.627**	-5.443***	0.713**	0.182
ΔK	-1.474	-1.674	-1.759	-1.887	0.276	0.157**
ΔL	-3.616***	-3.898**	-2.577	-2.273	0.363*	0.222***
Henan						
EC	0.697	-0.928	1.626	-1.339	0.626**	0.182**
GPC	3.599	0.628	1.582	-1.556	0.684**	0.169**
K	1.728	-2.341	3.269	0.978	0.682**	0.175**
L	-2.647***	-1.625	-2.729*	-0.188	0.672**	0.183**
ΔEC	-3.628***	-3.747**	-3.597**	-3.774**	0.37*	0.724
ΔGPC	-4.985***	-5.69***	-4.984***	-5.246***	0.327	0.524
ΔK	-1.755	-3.734**	-1.796	-2.24	0.441*	0.134*
ΔL	-2.386	-3.964**	-2.454	-2.574	0.426*	0.992
Hubei						
EC	0.648	-1.418	0.637	-1.219	0.736**	0.132*
GPC	4.197	-0.622	2.279	-0.428	0.753***	0.174**
K	3.844	-1.242	2.694	-0.785	0.752***	0.179**
L	-2.796	-1.393	-2.368	-0.562	0.684**	0.179**
ΔEC	-2.859***	-2.99	-2.865*	-3.889	0.192	0.118
ΔGPC	-3.66***	-5.144***	-3.717***	-4.616**	0.383*	0.715
ΔK	-2.599	-4.963***	-2.242	-2.589	0.436*	0.532
ΔL	-2.99***	-3.959**	-2.923*	-3.484	0.377*	0.749

Table B.1 Unit root test results (Cont.)

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Hunan						
EC	1.629	-1.643	1.629	-0.97	0.734**	0.143*
GPC	2.382	-0.482	3.845	-0.164	0.749***	0.193**
K	8.499	2.379	7.952	2.584	0.744***	0.195**
L	-2.733***	-1.525	-5.237***	-1.332	0.719**	0.194**
ΔEC	-3.34***	-3.365*	-3.339**	-3.275*	0.222	0.145*
ΔGPC	-2.262	-4.748**	-2.486	-3.167	0.547**	0.594
ΔK	-1.749	-2.833	-1.686	-2.779	0.631**	0.143*
ΔL	-1.875	-2.943	-1.133	-2.159	0.582**	0.165
Jiangsu						
EC	-0.644	-2.177	0.756	-1.135	0.732**	0.166**
GPC	-0.748	-4.894***	0.415	-2.213	0.781***	0.617
K	0.725	-3.265*	-0.824	-3.379*	0.788***	0.962
L	-6.712***	-7.679***	-3.212**	-1.846	0.638**	0.163**
ΔEC	-2.215	-2.292	-2.215	-2.462	0.229	0.769
ΔGPC	-4.415***	-4.272**	-3.345**	-3.263*	0.959	0.666
ΔK	-3.579***	-3.327*	-3.565**	-3.386*	0.152	0.119*
ΔL	-2.672***	-3.118	-2.572	-2.856	0.382*	0.988
Jiangxi						
EC	1.376	-0.626	1.689	-0.854	0.715**	0.183**
GPC	4.256	-0.194	11.187	-0.414	0.779***	0.198**
K	2.119	-1.376	5.263	-0.479	0.772***	0.194**
L	-1.813	-2.663	-1.395	-1.998	0.757***	0.126*
ΔEC	-3.472***	-3.958**	-3.447**	-3.958**	0.353	0.895
ΔGPC	-1.717	-6.189***	-2.725*	-5.364***	0.715**	0.283***
ΔK	-1.675	-3.371*	-1.544	-3.158	0.589**	0.577
ΔL	-3.19***	-3.149	-2.349	-2.338	0.185	0.158
Jilin						
EC	0.472	-1.553	0.453	-1.291	0.712**	0.137
GPC	1.894	-0.356	3.163	-0.665	0.683**	0.166**
K	0.775	-2.893	3.227	0.678	0.677**	0.166**
L	-2.976***	-2.672	-3.815***	-2.662	0.629**	0.186**
ΔEC	-4.531***	-4.526***	-4.775***	-4.732***	0.161	0.139*
ΔGPC	-3.763***	-4.764***	-3.681**	-4.576***	0.415*	0.953
ΔK	-2.252	-1.998	-1.94	-2.25	0.439*	0.127*
ΔL	-2.817	-2.551	-1.938	-2.583	0.458*	0.149**
Liaoning						
EC	1.124	-1.932	2.415	-1.969	0.654**	0.167**
GPC	2.382	1.718	3.123	-1.187	0.68**	0.184**
K	0.374	-3.457*	1.842	0.552	0.683**	0.125*
L	-0.673	-0.583	-5.242***	-4.912***	0.716**	0.174**

Table B.1 Unit root test results (Cont.)

Specification	ADF Intercept	ADF Trend	PP Intercept	PP Trend	KPSS Intercept	KPSS Trend
Liaoning						
ΔEC	-5.922***	-6.489***	-5.924***	-6.994***	0.336	0.118
ΔGPC	-3.317***	-4.172**	-2.786*	-3.352*	0.527**	0.718
ΔK	-2.131	-2.152	-1.452	-1.894	0.318	0.145*
ΔL	-2.742***	-0.962	-2.632*	-1.337	0.449*	0.222***
Neimenggu						
EC	-0.343	-2.17	1.375	-1.391	0.718**	0.187**
GPC	1.111	-2.657	1.588	-2.657	0.759***	0.184**
K	1.817	-1.23	2.952	-0.615	0.755***	0.19**
L	0.573	-2.113	-0.716	-1.664	0.712**	0.13*
ΔEC	-1.568	-3.2	-3.272**	-3.745**	0.376*	0.772
ΔGPC	-7.692***	-8.953***	-8.223***	-15.76***	0.323	0.238***
ΔK	-1.983	-3.743**	-1.492	-1.855	0.479**	0.77
ΔL	-2.686	-1.935	-2.379	-1.853	0.166	0.166**
Ningxia						
EC	-0.145	-1.655	0.182	-0.642	0.366*	0.186**
GPC	2.824	0.522	2.266	-0.655	0.682**	0.164**
K	2.314	0.29	7.148	1.478	0.648**	0.2**
L	-4.723***	-0.645	-5.988***	-0.694	0.674**	0.241**
ΔEC	-3.158***	-3.775**	-3.158**	-3.794**	0.48*	0.935
ΔGPC	-0.97	-3.377*	-3.163**	-3.542*	0.392*	0.864
ΔK	-0.932	-3.632	-1.549	-2.998	0.629**	0.148**
ΔL	-3.263***	-4.984***	-3.169**	-5.349***	0.595**	0.779
Qinghai						
EC	2.185	-0.538	6.843	0.348	0.727**	0.184**
GPC	4.644	0.723	4.196	0.434	0.742***	0.188**
K	2.273	0.982	6.174	-0.523	0.715**	0.224**
L	-2.328	-0.584	-2.825*	-0.887	0.732**	0.188**
ΔEC	-4.182***	-4.858***	-4.114***	-5.797***	0.524**	0.247***
ΔGPC	-3.458***	-3.946**	-3.649**	-4.259**	0.536**	0.127
ΔK	-0.979	-5.667***	-0.766	-2.996	0.772**	0.728
ΔL	-3.198***	-4.327**	-2.934*	-3.111	0.497**	0.668
Shaanxi						
EC	0.786	-1.736	1.294	-0.793	0.723**	0.145*
GPC	3.139	-0.387	2.943	-0.525	0.686**	0.185**
K	1.645	-0.714	2.884	1.961	0.681**	0.165**
L	-3.663***	-2.169	-5.499***	-1.357	0.66**	0.216**
ΔEC	-2.364	-3.288	-2.493	-2.618	0.285	0.958
ΔGPC	-3.766***	-4.791***	-3.742***	-4.813***	0.487**	0.722
ΔK	-1.125	-1.971	-1.115	-1.971	0.438*	0.174**
ΔL	-1.545	-3.364*	-1.545	-3.427*	0.668**	0.997

Table B.1 Unit root test results (Cont.)

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Shandong						
EC	0.15	-1.294	0.542	-1.464	0.747***	0.16**
GPC	-0.146	-5.175***	0.745	-2.663	0.779***	0.723
K	2.982	-2.54	2.3	-1.368	0.781***	0.185**
L	-1.559	-1.9	-1.295	-1.352	0.761***	0.168**
ΔEC	-3.737***	-3.752**	-3.747***	-3.723**	0.128	0.176
ΔGPC	-3.3***	-3.198	-3.628**	-2.925	0.143	0.757
ΔK	-3.484***	-5.377***	-1.995	-2.634	0.372*	0.579
ΔL	-4.888***	-4.386**	-3.247**	-3.513*	0.183	0.687
Shanghai						
EC	0.342	-3.638**	0.187	-1.877	0.771***	0.147**
GPC	-0.953	-2.475	0.898	-2.278	0.775***	0.872
K	-1.625	0.716	-1.594	-0.745	0.778***	0.148**
L	1.917	-0.935	0.828	-1.985	0.655**	0.175**
ΔEC	-1.946	-3.97	-3.625**	-3.621**	0.117	0.867
ΔGPC	-2.533	-2.267	-2.438	-2.397	0.151	0.146*
ΔK	-2.198	-3.119	-1.552	-1.879	0.276	0.922
ΔL	-3.569***	-4.253**	-2.368	-2.54	0.29	0.612
Shanxi						
EC	0.974	-1.664	0.253	-1.834	0.652**	0.155**
GPC	1.193	-1.938	1.594	-1.389	0.678**	0.186**
K	1.323	-1.155	5.653	-0.455	0.672**	0.262**
L	-0.751	-3.138	-1.55	-1.837	0.656**	0.158**
ΔEC	-5.992***	-5.218***	-5.946***	-5.573***	0.114	0.986
ΔGPC	-3.577***	-3.916**	-3.399**	-3.654**	0.491**	0.514
ΔK	-2.144	-2.721	-2.114	-2.664	0.6**	0.856
ΔL	-2.182	-1.811	-2.142	-1.898	0.223	0.129*
Sichuan						
EC	1.17	-0.467	0.617	-0.992	0.645**	0.132*
GPC	3.297	0.948	3.638	0.464	0.668**	0.189**
K	2.383	-0.546	6.788	1.227	0.753***	0.226**
L	-3.121***	-2.656	-5.623***	-1.616	0.666**	0.213**
ΔEC	-3.72***	-3.938**	-3.734***	-3.979**	0.231	0.13
ΔGPC	-2.474	-3.792**	-2.492	-3.853**	0.517**	0.834
ΔK	-1.461	-2.956	-1.398	-3.177	0.638**	0.2
ΔL	-1.382	-1.728	-0.976	-1.876	0.647**	0.125*
Tianjin						
EC	3.425	0.499	3.394	0.445	0.728**	0.196**
GPC	1.796	-3.295*	3.75	-2.333	0.773***	0.188**
K	2.467	0.562	4.686	2.814	0.778***	0.184**
L	0.63	-2.338	2.489	0.628	0.628**	0.149**

Table B.1 Unit root test results (Cont.)

	ADF		PP		KPSS	
Specification	Intercept	Trend	Intercept	Trend	Intercept	Trend
Tianjin						
ΔEC	-3.155***	-4.335**	-3.118**	-4.325**	0.6**	0.114
ΔGPC	-1.426	-6.377***	-1.529	-2.265	0.574**	0.857
ΔK	-0.692	-3.153	-0.692	-2.55	0.518**	0.156**
ΔL	-0.695	-1.725	-0.919	-1.849	0.383*	0.156**
Xinjiang						
EC	1.225	-1.167	1.846	-1.322	0.676**	0.152
GPC	-0.652	-2.166	-0.578	-1.794	0.684**	0.137*
K	0.556	-3.526*	0.964	-1.885	0.686**	0.523
L	0.865	-1.912	0.772	-1.243	0.681**	0.892
ΔEC	-3.515***	-3.825**	-3.523**	-3.857**	0.35	0.918
ΔGPC	-3.479***	-3.38*	-3.537**	-3.444*	0.119	0.143
ΔK	-3.358***	-1.944	-2.213	-2.148	0.143	0.749
ΔL	-1.989	-2.818	-2.254	-2.336	0.171	0.118
Yunnan						
EC	1.814	-3.164	1.544	-3.164	0.665**	0.195**
GPC	1.619	-1.462	1.537	-2.115	0.686**	0.831
K	3.448	1.115	6.555	1.743	0.682**	0.193**
L	1.197	-1.765	-3.249**	-2.535	0.678**	0.194**
ΔEC	-4.135***	-4.486***	-4.199***	-4.368***	0.413*	0.665
ΔGPC	-5.382***	-5.438***	-5.38***	-5.437***	0.254	0.938
ΔK	-1.337	-3.595**	-0.979	-2.638	0.558**	0.129*
ΔL	-2.198	-0.181	-1.586	-1.854	0.438*	0.184**
Zhejiang						
EC	-1.655	-4.719***	-0.827	-1.919	0.776***	0.523
GPC	-3.544***	-3.378*	-0.422	-1.95	0.776***	0.88
K	-2.795***	-2.965	-1.148	-1.285	0.777***	0.136*
L	-0.653	-2.846	0.942	-0.629	0.726**	0.172**
ΔEC	-4.344***	-4.457***	-2.675*	-2.756	0.988	0.676
ΔGPC	-2.355	-6.278***	-2.526	-2.5	0.884	0.787
ΔK	-3.18***	-3.993**	-2.792	-2.125	0.183	0.835
ΔL	-1.594	-2.386	-1.78	-1.858	0.263	0.133*

Note: C stands for model with constant while T stands for model with both intercept and trend. The optimal numbers of lags for ADF tests were selected based on SIC; the bandwidth for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Table B.2 Zivot-Andrews structural break unit root test results

Model		Intercept		Both			Intercept		Both	
		T-stats	lags	T-stats	lags		T-stats	lags	T-stats	lags
Anhui										
	EC	-2.699	1	-3.464	1	ΔEC	-5.290*	0	-5.152*	0
	GPC	-2.932	6	-2.614	6	ΔGPC	-5.423**	0	-5.837**	0
	K	-3.896	6	-3.95	6	ΔK	-4.138	3	-4.538	3
	L	-4.547	5	-5.320*	5	ΔL	-5.092*	0	-5.103*	0
Beijing										
	EC	-4.873*	2	-3.464	1	ΔEC	-5.517**	0	-5.152*	0
	GPC	-4.571	1	-3.585	1	ΔGPC	-5.063*	0	-5.788**	1
	K	-2.23	6	-3.95	6	ΔK	-5.888**	5	-4.538	3
	L	-4.776	1	-18.70**	7	ΔL	-4.832*	1	-11.42**	7
Chongqing										
	EC	-2.89	0	-1.929	0	ΔEC	-4.556	0	-6.049**	0
	GPC	-8.373**	0	-2.734	0	ΔGPC	-3.633	0	-3.476	0
	K	0.744	5	-1.191	0	ΔK	-4.719	0	-6.293**	1
	L	-7.992**	0	-0.172	1	ΔL	-2.663	0	-3.274	0
Fujian										
	EC	-5.665**	0	-3.948	0	ΔEC	-4.556	0	-6.049**	0
	GPC	-4.319	3	-4.939	3	ΔGPC	-5.732**	1	-5.644**	1
	K	-3.842	2	-3.764	2	ΔK	-6.540**	8	-5.652**	8
	L	-3.564	5	-3.16	5	ΔL	-3.43	0	-3.646	0
Gansu										
	EC	-3.372	0	-3.356	0	ΔEC	-4.352	0	-4.386	0
	GPC	-3.29	0	-4.012	0	ΔGPC	-5.793**	5	-6.377**	5
	K	-3.194	0	-3.512	0	ΔK	-4.326	0	-4.153	0
	L	-3.457	0	-2.89	0	ΔL	-2.224	4	-3.663	4
Guangdong										
	EC	-5.966**	6	-5.154*	6	ΔEC	-4.71	0	-4.449	3
	GPC	-8.961**	0	-7.725**	0	ΔGPC	-5.470**	3	-6.218**	3
	K	-14.10**	0	-21.38**	0	ΔK	-3.886	1	-3.623	1
	L	-5.738**	6	-5.796**	6	ΔL	-4.791	1	-4.728	1
Guangxi										
	EC	-4.781	1	-4.415	1	ΔEC	-4.515	0	-4.541	0
	GPC	-3.643	8	-3.747	8	ΔGPC	-4.674	6	-5.072	6
	K	0.17	3	-1.973	3	ΔK	-2.637	0	-3.287	0
	L	-3.176	3	-3.625	3	ΔL	-4.374	2	-3.733	2
Guizhou										
	EC	-4.322	0	-4.294	0	ΔEC	-8.530**	0	-8.871**	0
	GPC	-0.188	6	-1.498	6	ΔGPC	-4.595	1	-5.452*	1
	K	-1.3	1	-2.642	1	ΔK	-2.77	0	-2.761	0

Table B.2 Zivot-Andrews structural break unit root test results (Cont.)

Model		Intercept		Both			Intercept		Both	
		T-stats	lags	T-stats	lags		T-stats	lags	T-stats	lags
Guizhou										
	L	-1.291	5	-1.274	5	ΔL	-4.136	4	-4.557	4
Hebei										
	EC	-1.832	0	-3.448	0	ΔEC	-6.070**	0	-6.206**	0
	GPC	-2.089	0	-8.138**	0	ΔGPC	-3.68	7	-3.929	7
	K	-2.884	1	-3.018	1	ΔK	-4.934*	0	-4.704	0
	L	-1.671	0	-6.728**	0	ΔL	-4.013	0	-4.345	0
Heilongjiang										
	EC	-2.485	0	-4.64	0	ΔEC	-5.962**	0	-5.881**	0
	GPC	-0.083	3	-1.39	3	ΔGPC	-3.969	6	-4.267	6
	K	-2.506	4	-4.821	4	ΔK	-3.051	7	-3.098	7
	L	-5.657**	5	-3.05	5	ΔL	-3.821	4	-4.847	4
Henan										
	EC	-4.59	1	-3.528	1	ΔEC	-4.501	0	-6.175**	0
	GPC	-0.824	6	-1.425	6	ΔGPC	-4.032	7	-5.361*	7
	K	-1.884	8	-4.079	8	ΔK	-3.649	7	-4.1	7
	L	-2.507	2	-3.718	2	ΔL	-4.798	1	-4.72	1
Hubei										
	EC	-5.737**	7	-5.561*	7	ΔEC	-4.696	0	-4.965	0
	GPC	-3.437	1	-3.368	1	ΔGPC	-6.292**	5	-6.145**	5
	K	-4.281	7	-4.561	7	ΔK	-5.773**	3	-5.780**	3
	L	-2.049	0	-3.169	0	ΔL	-5.002*	1	-7.097**	1
Hunan										
	EC	-3.683	1	-4.253	1	ΔEC	-5.666**	7	-4.272	7
	GPC	-3.565	0	-3.949	0	ΔGPC	-5.203*	7	-4.981	7
	K	-2.001	1	-3.016	1	ΔK	-5.019*	2	-5.055	2
	L	-1.703	0	-4.505	0	ΔL	-3.084	1	-4.611	1
Jiangsu										
	EC	-5.903**	6	-5.873**	6	ΔEC	-3.902	0	-3.867	0
	GPC	-27.729**	0	-23.675**	0	ΔGPC	-4.755	6	-5.092*	6
	K	-40.954**	0	-51.589**	0	ΔK	-3.823	0	-3.845	0
	L	-5.013*	5	-4.679	5	ΔL	-5.272*	0	-9.322**	0
Jiangxi										
	EC	-3.64	1	-4.58	1	ΔEC	-6.737**	0	-6.571**	0
	GPC	-6.081**	0	-5.146*	0	ΔGPC	-3.542	2	-3.667	2
	K	-10.98**	0	-9.551**	0	ΔK	-3.62	1	-4.095	1
	L	-2.365	5	-4.004	5	ΔL	-4.506	3	-4.511	3

Table B.2 Zivot-Andrews structural break unit root test results (Cont.)

Model		Intercept		Both			Intercept		Both	
		T-stats	lags	T-stats	lags		T-stats	lags	T-stats	lags
Jilin										
	EC	-2.39	2	-4.045	2	ΔEC	-4.741	1	-4.578	1
	GPC	-1.703	2	-2.857	2	ΔGPC	-6.920**	1	-6.971**	1
	K	-3.714	7	-5.198*	7	ΔK	-6.076**	3	-4.667	3
	L	-4.156	3	-4.067	3	ΔL	-2.956	3	-4.105	3
Liaoning										
	EC	-3.18	0	-4.111	0	ΔEC	-7.798**	0	-8.618**	0
	GPC	0.098	8	-1.107	8	ΔGPC	-5.191*	4	-5.996**	4
	K	-3.927	8	-4.637	8	ΔK	-4.098	1	-3.456	1
	L	-3.736	7	-2.903	7	ΔL	-2.013	6	-3.405	6
Ningxia										
	EC	-3.861	1	-3.917	1	ΔEC	-4.202	0	-4.822	0
	GPC	-0.44	6	-3.52	6	ΔGPC	-8.076**	5	-11.31**	5
	K	-2.395	5	-2.825	5	ΔK	-4.887*	1	-5.153*	1
	L	-1.95	2	-2.274	2	ΔL	-5.550**	1	-6.094**	1
Neimenggu										
	EC	-3.735	0	-3.274	0	ΔEC	-4.387	3	-4.659	3
	GPC	-6.724**	0	-5.506*	0	ΔGPC	-10.95**	0	-12.04**	0
	K	-4.834*	6	-4.742	6	ΔK	-4.312	1	-4.996	1
	L	-39.47**	0	-31.89**	0	ΔL	-4.731	0	-4.773	0
Qinghai										
	EC	-2.937	0	-4.504	0	ΔEC	-5.990**	0	-6.041**	0
	GPC	0.988	7	0.689	7	ΔGPC	-4.836*	5	-4.799	5
	K	-2.963	0	-2.937	0	ΔK	-4.994*	7	-5.334*	7
	L	-6.902**	2	-8.224**	2	ΔL	-5.294*	1	-6.733**	1
Shaanxi										
	EC	-3.143	1	-6.398**	1	ΔEC	-4.851*	3	-4.622	3
	GPC	-2.742	0	-2.662	0	ΔGPC	-6.371**	0	-7.925**	0
	K	-2.114	1	-3.302	1	ΔK	-3.939	0	-3.945	0
	L	-2.772	1	-4.37	1	ΔL	-6.360**	0	-5.861**	0
Shandong										
	EC	-6.560**	0	-5.412*	0	ΔEC	-7.093**	0	-7.117**	0
	GPC	-20.93**	0	-18.56**	0	ΔGPC	-6.727**	6	-6.513**	6
	K	-14.28**	0	-16.64**	0	ΔK	-4.948*	2	-5.440*	2
	L	-31.03**	0	-24.59**	0	ΔL	-6.211**	1	-8.066**	1
Shanghai										
	EC	-4.074	6	-4.011	6	ΔEC	-3.718	6	-4.229	6

Table B.2 Zivot-Andrews structural break unit root test results (Cont.)

Model		Intercept		Both			Intercept		Both	
		T-stats	lags	T-stats	lags		T-stats	lags	T-stats	lags
Shanghai										
	GPC	-35.29**	0	-36.48**	0	ΔGPC	-4.508	4	-6.215**	4
	K	-18.39**	0	-23.51**	0	ΔK	-4.021	5	-3.839	5
	L	-1.947	6	-0.218	6	ΔL	-4.55	3	-6.168**	3
Shanxi										
	EC	-3.345	0	-4.609	0	ΔEC	-5.648**	3	-5.504*	3
	GPC	-2.556	7	-3.349	7	ΔGPC	-5.285*	6	-5.351*	6
	K	-3.513	1	-4.292	1	ΔK	-4.786	6	-5.764**	6
	L	-5.575**	3	-3.706	3	ΔL	-3.288	3	-5.548*	3
Sichuan										
	EC	-0.161	0	-1.775	0	ΔEC	-5.520**	0	-5.639**	0
	GPC	1.116	4	0.088	4	ΔGPC	-6.646**	5	-6.366**	5
	K	1.384	4	0.522	4	ΔK	-4.183	7	-4.813	7
	L	0.332	0	-0.597	0	ΔL	-2.028	0	-1.974	0
Tianjin										
	EC	-3.886	6	-3.549	6	ΔEC	-5.261*	0	-5.487*	0
	GPC	-21.983**	0	-19.697**	0	ΔGPC	-4.127	0	-3.954	0
	K	-10.750**	0	-11.775**	0	ΔK	-4.598	1	-4.872	1
	L	-9.317**	0	-7.292**	0	ΔL	-4.998*	5	-5.005	5
Xinjiang										
	EC	-3.108	8	-3.48	8	ΔEC	-2.666	8	-5.028	8
	GPC	-2.73	7	-2.792	7	ΔGPC	-3.92	0	-6.160**	0
	K	-3.68	1	-4.351	1	ΔK	-3.909	2	-4.234	2
	L	-3.485	1	-5.233*	1	ΔL	-4.64	1	-5.209*	1
Yunnan										
	EC	-4.782	0	-4.362	0	ΔEC	-4.645	5	-5.626**	5
	GPC	-2.355	0	-3.549	0	ΔGPC	-6.184**	0	-6.519**	0
	K	-0.394	8	-3.01	8	ΔK	-2.87	7	-3.085	7
	L	-4.34	5	-4.645	5	ΔL	-2.103	2	-4.454	2
Zhejiang										
	EC	-18.768**	0	-14.451**	0	ΔEC	-5.598**	3	-5.691**	3
	GPC	-28.169**	0	-21.732**	0	ΔGPC	-7.545**	3	-7.542**	3
	K	-17.644**	0	-14.068**	0	ΔK	-4.826*	3	-5.169*	3
	L	-8.661**	0	-7.166**	0	ΔL	-4.372	1	-4.579	1

Note: "Intercept" stands for model with constant while "Both" stands for model with both intercept and trend.*, ** and denote significance at 5% and 1% respectively. The optimal numbers of lags were selected based on AIC.

APPENDIX C: SUPPLEMENTARY RESULTS FOR CHAPTER 6

Table C.1 Unit root test results for the time series (aggregate level)

		ADF test	PP test	KPSS
Variables	Specification	Z(t)	Z(t)	Test statistic
GPC	Intercept	1.735	3.165	0.916***
	Intercept & trend	-3.497*	-3.395*	0.220**
ΔGPC	intercept & trend	-5.166***	-4.956***	0.150**
EC	Intercept	2.000	2.322	0.910***
	Intercept & trend	-1.376	-1.363	0.171**
ΔEC	Intercept & trend	-7.514***	-7.524***	0.070
K	Intercept	3.606	7.123	0.915***
	Intercept & trend	0.825	-0.356	0.241***
ΔK	Intercept & trend	-6.121***	-2.765	0.039
L	Intercept	-1.983	-2.815	0.896***
	Intercept & trend	-0.532	0.058	0.197**
ΔL	Intercept & trend	-3.638**	-3.526**	0.125*

Note: The optimal numbers of lags for ADF tests were selected based on SIC; the bandwidth for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and ***denote significance at 10%, 5% and 1% respectively.

Table C.2 Unit root test results for disaggregated renewable energy consumption

		ADF test	PP test	KPSS
Variables	Specification	Z(t)	Z(t)	Test statistic
Hydro				
EC	Intercept	1.369	1.731	0.911***
	Intercept & trend	-2.274	-2.284	0.161**
ΔEC	Intercept & trend	-7.391***	-7.391***	0.292
Solar				
EC	Intercept	1.232	3.461	0.684**
	Intercept & trend	-0.217	1.209	0.153**
ΔEC	Intercept & trend	-1.952	-2.042	0.145*
Wind				
EC	Intercept	-1.762	-1.713	0.699**
	Intercept & trend	-3.017	-3.082	0.100
ΔEC	Intercept	-3.954***	-3.917***	0.150

Note: The optimal numbers of lags for ADF tests were selected based on SIC; the bandwidth for KPSS and PP tests were chosen based on Newey-West selection procedure using Bartlett kernel. *, ** and ***denote significance at 10%, 5% and 1% respectively.

Table C.3 Zivot and Andrews Test

Variables	Specification	T statistics	Lags
Solar			
EC	Intercept & trend	-5.115**	2008

Note: *, ** and ***denote significance at 10%, 5% and 1% respectively. The optimal numbers of lags were selected based on AIC.