THE DYNAMIC RELATIONSHIP BETWEEN UNCERTAINTY IN CLIMATE CHANGE POLICY AND ENERGY DEPLOYMENT IN THE UNITED STATES

SYED QASIM RAZA

UNIVERSITI SAINS MALAYSIA

2025

THE DYNAMIC RELATIONSHIP BETWEEN UNCERTAINTY IN CLIMATE CHANGE POLICY AND ENERGY DEPLOYMENT IN THE UNITED STATES

by

SYED QASIM RAZA

Thesis submitted in fulfilment of the requirements
for the degree of
Doctor of Philosophy

October 2025

ACKNOWLEDGEMENT

I would like to thank Almighty Allah and Ahl-e-Bait for everything I have, including this achievement. Thereafter, I am immensely thankful to my Supervisor, Dr. Soo Khoon Goh, for her financial and non-financial support throughout my Ph.D. journey. She always remained available to guide me. Similarly, I am grateful to my co-supervisor, Dr. Nicholas Apergis, for his invaluable guidance in shaping my Ph.D. thesis. With the help of both supervisors, I managed to extract four research papers from my thesis. I am thankful to my parents, brother, sister, wife, daughter, son, grandparents, and other family members for their endless support. Undoubtedly, I am obliged to Miss. Nusrat (my schoolteacher), Sir Rana (my schoolteacher), and Dr. Waseem Shahid Malik for being the role models in my life and for their valuable contribution to my academic progress. I am also thankful to my office colleagues/seniors for their support, since they helped me focus on my Ph.D. thesis. Finally, I am thankful to the reviewers from USM, other peer reviewers, and editors from the journals where I submitted my Ph.D. papers, since their comments are imperative in improving the study. Not only this, but I am also grateful to all academics, administration, and staff members of the Centre for Policy Research for helping and supporting me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Full Form
AARDL	Augmented ARDL
ARDL	Autoregressive distributed lags
CC	Coal consumption
CCp	Per capita coal consumption
CH4	Methane
CO2	Carbon dioxide emissions
COP26	United Nations Climate Conference
CPI	Consumer price index
CPU	Climate policy uncertainty
ECT	Error correction term
EG	Economic growth
EIA	Energy Information Administration
EPU	Economic policy uncertainty
FAARDL	Fourier augmented autoregressive distributed lags
FRED	Federal Reserve Economic Data
GC	Natural gas consumption
GCp	Per capita natural gas consumption
GLS test	Elliot et al. (1992) unit root test
IPI	Industrial production index
KRLS	Kernel-Based Regularized Least Squares
NRE	Non-renewable energy
NREC	Non-renewable energy consumption
NRECp	Per capita non-renewable energy consumption
NREP	Non-renewable energy production
NREPP	Per capita non-renewable energy production

Abbreviation	Full Form
OIL	Oil prices
PC	Petroleum consumption
PCp	Per capita petroleum consumption
PSS	Pesaran et al. (2001)
QC	Quantile Correlation
QQKRLS	Quantile-on-Quantile Kernel-Based Regularized Least Squares
RE	Renewable energy
REN	Renewable energy consumption
REP	Renewable energy production
REPP	Per capita renewable energy production
SDGs	Sustainable Development Goals
SOR	Smooth and sharp structural breaks unit root test
TEP	Total energy production
TEPP	Per capita total energy production
US	United States of America
WQC	Wavelet quantile correlation
WTI	West Texas Intermediate
ZA test	Zivot and Andrew (1992) unit root test

HUBUNGAN DINAMIK ANTARA KETIDAKPASTIAN POLISI PERUBAHAN IKLIM DAN PENGGUNAAN TENAGA DI AMERIKA SYARIKAT

ABSTRAK

Amerika Syarikat *(AS)* telah menyaksikan kemerosotan alam sekitar akibat aktiviti antropogenik yang berlebihan terutamanya disebabkan oleh penggunaan tenaga yang tidak terkawal. Untuk memulihkan kelestarian alam sekitar, *AS* telah memperkenalkan pelbagai dasar iklim. Namun, dasar-dasar ini tidak stabil dan dikaitkan dengan ketidakpastian. Oleh itu, tahap ketidakpastian dasar iklim *AS (CPU)* juga telah meningkat sejak awal abad ke-21, memberi kesan yang ketara kepada ekonomi, sektor tenaga, dan alam sekitar. Setakat ini, kajian mengenai hubungan antara *CPU* dan tenaga adalah agak terhad dan menghasilkan penemuan yang tidak konsisten. Tambahan pula, aspek teori mengenai hubungan *CPU*-tenaga adalah terhad. Memandangkan latar belakang ini, kajian ini mempunyai tiga objektif utama: 1) untuk menyiasat kesan *CPU* terhadap penggunaan tenaga boleh diperbaharui (*REN*); 2) untuk menyiasat kesan *CPU* terhadap penggunaan tenaga tidak boleh diperbaharui (*NREC*); dan 3) untuk menyiasat kesan *CPU* terhadap pengeluaran tenaga boleh diperbaharui (*REP*) dan pengeluaran tenaga tidak boleh diperbaharui (*NREP*) di *AS*. Hasil daripada pendekatan *novel Fourier augmented autoregressive distributed lags (FAARDL)* menggambarkan bahawa *CPU* mengurangkan *REN* dalam jangka pendek dan panjang. Untuk menyiasat kesan *CPU* ke atas *NREC*, pendekatan baru *wavelet quantile correlation (WQC)* digunakan. Keputusannya menunjukkan bahawa *CPU* mengurangkan *NREC* dan penggunaan gas asli *(Pesaran, Shin, & Smith)* dalam jangka pendek. Namun, ia juga mempunyai kesan positif dalam jangka sederhana dan jangka panjang. Sebaliknya, *CPU* mengurangkan penggunaan arang

batu *(Corsatea, Giaccaria, & Arántegui)* dan petroleum *(PC)* dalam jangka pendek dan jangka panjang tetapi meningkatkan penggunaannya dalam jangka sederhana. Selanjutnya, pendekatan baru *Quantile-on-Quantile Kernel-Based Regularized Least Squares (QQKRLS)* digunakan untuk meneroka kesan *CPU* terhadap pengeluaran tenaga keseluruhan *(Fried, Novan, & Peterman), NREP,* dan *REP*, dan hasilnya menunjukkan bahawa *CPU* bertanggungjawab terhadap peningkatan *TEP, NREP*, dan *REP* sepanjang kuantil. Analisis kepekaan juga digunakan dalam kajian ini untuk menilai ketahanan hasil. Hasil utama daripada analisis kepekaan adalah selaras dengan hasil asas, menunjukkan bahawa keputusan itu boleh dipercayai. Berdasarkan hasil ini, kajian mencadangkan beberapa implikasi dasar untuk mengurus penggunaan/pengeluaran tenaga boleh diperbaharui dan tidak boleh diperbaharui. Selain itu, beberapa garis panduan dasar untuk merancang *CPU* telah dicadangkan.

THE DYNAMIC RELATIONSHIP BETWEEN UNCERTAINTY IN CLIMATE CHANGE POLICY AND ENERGY DEPLOYMENT IN THE UNITED STATES

ABSTRACT

In the current epoch, the United States of America (US) has been witnessing environmental degradation due to excessive anthropogenic activities mainly derived from intemperate energy consumption. To replenish environmental sustainability, the US has introduced several climate policies. However, these policies are unstable, and the uncertainty factor is associated with them. Hence, the US climate policy uncertainty (CPU) level has also been on the rise since the turn of the 21st century, significantly impacting the economy, energy sector, and environment. The existing literature on the CPU-energy nexus is relatively sparse and renders inconsistent findings. Also, the theoretical aspects of the CPU-energy nexus are vague. Based on the discourse mentioned above, the primary aim of this thesis is to scrutinize the influence of CPU on (non)-renewable energy deployment (i.e., energy production and consumption). In particular, the study has three core objectives. The first objective involves investigating the impact of CPU on renewable energy consumption (REN). In contrast, the second objective examines the effect of CPU on different sources of non-renewable energy consumption (NREC). The third objective of this thesis is to investigate the impact of CPU on renewable energy production (REP) and non-renewable energy production (NREP) in the US. To accomplish its first objective (i.e., investigating the impact of CPU on REN), this study adopts a monthly time series dataset covering the period 2000M1-2020M12. The outcomes from the novel Fourier augmented autoregressive distributed lags (FAARDL) approach delineate that CPU plunges REN across the long- and short-run. For achieving its second objective, this study makes use of monthly time series data on CPU and non-renewable energy sources for the period 1990M1-2019M12. The empirical findings from the novel wavelet quantile correlation (WQC) approach report that CPU initially decreases NREC and natural gas consumption (Pesaran et al.) in the short run. However, it also has a positive effect in the medium and long run. Conversely, CPU reduces coal (Corsatea et al.) and petroleum consumption (PC) in the short and long run but increases their consumption in the medium run. A monthly dataset from 2000M1 to 2020M12 is used for estimating the novel Quantile-on-Quantile Kernel-Based Regularized Least Squares (QQKRLS) approach, addressing the third objective of the study (i.e., investigating the impact of CPU on energy production). The results elucidate that the CPU is responsible for an upsurge in total energy production (Fried et al.), NREP, and REP across quantiles. While attempting to achieve all objectives, this study also conducts sensitivity analyses in addition to the baseline methodologies/methods. The core outcomes from the sensitivity analysis are consistent with baseline results, indicating the reliability of the results. Based on these results, the study proposes several policy implications for managing (non)-renewable energy consumption/production. The key policy suggestions include reforms to maintain CPU stability. It is also suggested to adopt measures to facilitate REN during periods of high CPU. Similarly, it is proposed to adopt time and energy-source specific policies since CPU has a heterogeneous impact across different energy sources and periods.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Although energy is defined in several ways, one of its most straightforward definitions explains that energy is the ability to perform work. Scientific developments are responsible for transforming energy from one form to another, which is essential for performing different activities. For instance, energy is converted from one form to another to cook food, light homes, drive a car, freeze food, produce goods, and fly an airplane, among others. It is worth noting that energy comes in various forms, including gravitational, electrical, heat, light, motion, and chemical energy. However, these aforementioned forms of energy can be grouped into two broader forms: 1) potential or stored energy and 2) kinetic or working energy. As highlighted earlier, energy is converted from one form to another to perform work. For instance, to produce electrical energy for heating, lighting, cooking, and other purposes, the chemical energy stored in coal or natural gas is converted into electrical energy. Similarly, kinetic energy from water is converted into electrical energy to produce electricity for consumers and producers. Parallel to this, energy is divided into two broader categories: non-renewable and renewable.

It is a repeatedly cited point that energy is a basic input for several consumption and production activities (Rahman et al., 2022). For instance, energy is required to produce industrial output (Ewing, Sari, & Soytas, 2007). Furthermore, the energy-led growth hypothesis posits that energy plays a significant role in driving economic growth (Apergis & Tang, 2013). On the contrary, energy influences environmental quality based on whether non-renewable or renewable energy is being used (Shafiei &

Salim, 2014). Non-renewable energy (NRE) is a significant contributor to greenhouse gas emissions, exacerbating acute environmental issues. Conversely, renewable energy (RE) is considered green energy because it has a lesser adverse environmental impact (Midilli, Dincer, & Ay, 2006). Therefore, energy is closely linked to the economy and the environment, and efforts to achieve high economic growth (EG) may exacerbate environmental degradation.

Similar to other countries of the world, the United States of America (US) has also been confronting the economic-environmental dilemma associated with energy. As the world's largest economy, the US significantly depends on energy. It is worth noting that the US is the second-largest energy producer and consumer worldwide, reflecting its reliance on energy resources.[1,2] Due to this, the US is also one of the leading carbon emitters and, hence, is responsible for environmental degradation at both national and global scales. Particularly, the production and consumption of NRE are greater than that of RE. As a result, EG is being achieved at the cost of environmental damage.

It is worth noting that the US has also endeavored to expedite the energy transition, i.e., moving from NRE to RE sources to establish a green economy where EG is achievable with either no environmental cost or a minimum environmental cost. In line with this aim, the US is also a part of the international efforts to limit climate change, such as the Kyoto Protocol, the Paris Agreement, and a series of COP agreements. The US has adopted several energy policies to manage energy to improve environmental quality.[3] For instance, energy efficiency-related policies, such as building energy codes, retro-commissioning, and appliance standards, aim to improve

[1] https://yearbook.enerdata.net/total-energy/world-energy-production.html
[2] https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html
[3] https://www.energy.gov/scep/slsc/policies-and-programs

energy efficiency. Similarly, policies such as the third-party ownership program and community renewables programs are energy policies that aim to increase RE generation. Further, the renewable fuel standards policy is an energy policy in the transport sector.

Additionally, the US has numerous environmental regulations and laws in place to protect the environment and address climate change. The National Environmental Policy Act of 1969 marked the first step by the US to protect the environment, advocating for the conduct of a detailed environmental impact assessment before constructing roads, railways, bridges, military bases, and airports, among others.[4] Thereafter, the US introduced a series of environmental laws and regulations to protect the environment. For instance, the Clean Air Act, the Clean Water Act, the Resource Conservation and Recovery Act, and the Comprehensive Environmental Response, Compensation, and Liability Act are significant climate policies adopted by the US.[5]

1.2 Problem Statement

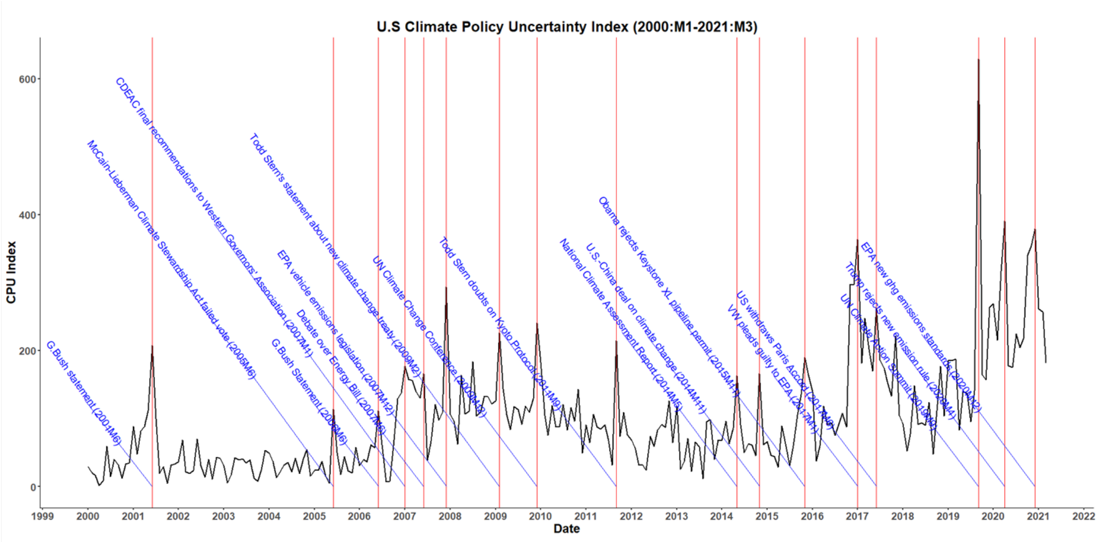
For at least two decades, the adoption of RE has achieved considerable growth in the US due to innovation, a decrease in installation cost, and RE supporting policies such as tax credit schemes and feed-in-tariffs. In addition to these factors, supply chain constraints, grid integration costs, and uncertainty surrounding future policies (i.e., energy and environmental policies) pose significant challenges to the adoption of RE in the US. The uncertainty surrounding future policies may alter the investment landscape and impact business cycle fluctuations.

[4] https://www.epa.gov/laws-regulations/summary-national-environmental-policy-act
[5] https://guides.loc.gov/environmental-law/federal-laws

On the other hand, NRE supports the US economy by providing a stable energy supply due to its well-established infrastructure. This reliance restricts the energy system to carbon-intensive pathways, obstructing the achievement of net-zero goals. The interplay between these two categories—RE serving as a driver for decarbonization and NRE providing a basis for energy stability—forms a crucial backdrop for this research.

Given this discourse, the energy transition in the US is heavily reliant on climate change mitigation policies. Additionally, climate policy uncertainty (CPU) is also worth mentioning in the context of the US energy landscape, given its multifaceted impacts. The CPU can be characterized by the uncertainty associated with the content, timing, scope, and enforcement of policies related to climate change (Wei, Xianjun, & Khan, 2024). In the US, CPU arises due to several factors, including changes in federal or state administration, preferences of different lobbies, economic incentives, the international climate change agenda, and climate-related regulations, among others.

Given the critical role of the CPU in energy, environmental, and economic contexts, researchers recognized the need to measure/calculate CPU for empirical investigations to restructure policy reforms. Hence, Gavriilidis (2021) measured/calculated the CPU index from textual analysis. Using the dataset of daily newspapers published in the US, Gavriilidis (2021) notes/calculates the frequency of the newspaper articles that contain the terms related to “climate”, “policy”, and “uncertainty” at the same time. This seminal CPU experienced a high value in 2017 (when the US announced its withdrawal from the Paris Agreement) and 2021 (when the US rejoined the same agreement), demonstrating the robustness/reliability of this index. Other key events related to the CPU in the US are portrayed in Figure 1.1. It is worth noting that, in the US, high CPU events not only transform political chatter but also significantly impact investment dynamics, restructuring the market environment, consumer preferences, and producers' decision-making in energy markets.



Source: Gavriilidis (2021)

Figure 1.1: CPU in the US

The multifaceted nature of the CPU makes it cyclical in some cases and anticyclical in others. For instance, a high CPU may promote investment in climate change mitigation technologies if firms anticipate stringent climate policies in the coming years. Consequently, energy demand and supply may witness an upsurge in an economy. Contrarily, a rise in CPU can discourage investment (mainly in the case of capital-intensive projects such as large-scale wind farms and gas pipelines), leading to low energy deployment.

Moreover, the distinct nature of RE and NRE sources in the context of environmental degradation, energy insecurity, energy price volatility, energy infrastructure, and vulnerability to policy shocks further complicates the CPU-energy nexus in the case of the US energy system. In addition, the connectedness between

NRE and RE, whether they are substitutes or complements, makes this scenario more interesting and complex. It is essential to note that in the US, the relationship between NRE and RE has long-term implications for the energy transition. Therefore, a separate analysis of both energy sources is indispensable for the detailed insights.

Furthermore, the heterogeneous theoretical arguments related to CPU-energy also motivated researchers to investigate the relationship between CPU and energy consumption. Despite mounting interest in the CPU-energy nexus in the US, the literature remains scant, with contrasting outcomes. For instance, Zhou, Siddik, Guo, and Li (2023) note that CPU increases REN during the short and long run, while the study by Shang, Han, Gozgor, Mahalik, and Sahoo (2022) highlighted that CPU impacts REN neither in the long run nor the short run. These inconsistencies pointed out the differences in methodologies, selected period, energy sources, time horizon, and market conditions, among others.

Given the existing sparse literature on the CPU-energy nexus, several areas remain unaddressed. For instance, the dynamic impact of the CPU on REN remains unclear, and the theoretical connection between the CPU and REN remains unexplained. Similarly, the effect of CPU on NREC is unclear. It is also unknown whether this relationship varies across energy sources. The theoretical foundation related to the CPU-NREC nexus is underdeveloped and not yet empirically tested. The CPU-energy nexus across different market conditions (i.e., high, moderate, or low energy consumption episodes) is also missing. Finally, the nexus between CPU and REP/NREP is disregarded. These research directions are essential to be addressed for transforming energy and climate change policies in the US.

1.3 Research Questions

This study attempts to explore the answers to the following research questions:

1. What is the long and short-run impact of CPU on REN?
2. What is the time- and quantile-based impact of CPU on consumption of non-renewable energy sources, and how is CPU theoretically interlinked with NREC?
3. Does CPU impact TEP, NREP, and REP?

1.4 Research Objectives

This thesis aims to understand the relationship between CPU and energy deployment in the US. That is, the thesis aims to investigate whether the CPU impacts (non)-renewable energy consumption and production. Based on the aforementioned debate, the core objectives of this research are:

1. To examine the long- and short-run impact of CPU on REN.

2. To explore the time- and quantile-varying impact of CPU on consumption of non-renewable energy sources and empirically examine the theoretical interlinkages between CPU and NREC.

3. To determine the impact of CPU on TEP, NREP, and REP.

1.5 Significance of the Study

This study makes a significant contribution to existing literature in several dimensions. Since the study is segmented into three core chapters, the significance of each chapter is reported separately.

Considering the second chapter, it is worth noting that the current literature on the dynamic impact of CPU on REN remains scant and yields contradictory findings.

For instance, Zhou et al. (2023) probe the impact of CPU on REN using the time-varying structural vector autoregressive model. The study highlights that the CPU escalates REN in the short and long run, whereas it mitigates REN in the medium run. Similarly, Shang et al. (2022) employ the autoregressive distributed lag (ARDL) model to explore the impact of CPU on REN. Their findings report that CPU does not affect REN in the short and long run. Hence, this analysis reinvestigates the impact of CPU on REN to provide complementary findings, which will help to reach a more definitive conclusion. Next, previous studies on the CPU-REN nexus have overlooked a detailed discussion of the theoretical linkages between CPU and REN; however, our work aims to fill this gap by examining the theoretical aspects that connect CPU with REN. Third, we use the novel Fourier augmented ARDL approach (FAARDL) that outperforms the contemporary methods in two aspects: i) it makes use of the augmented ARDL (AARDL) of Sam, McNown, and Goh (2019), which probes cointegration by applying three tests (see the methodology section for more details); ii) it applies the Fourier transformation to cover multiple structural breaks of different dynamic natures.

Focusing on the third chapter, it is worth highlighting that, in contrast to previous studies that only include NREC when examining the relationship between CPU and energy, our study incorporates aggregate and disaggregated NREC to analyze the CPU-energy relationship. In this study, we investigated the influence of CPU on NREC, coal (CC), petroleum (PC), and natural gas consumption (GC). The existing literature on the CPU-NREC nexus either employs quantile-based models or adopts time-varying models, failing to capture quantile- and time-varying fluctuations simultaneously. Hence, we utilize the novel wavelet quantile correlation (WQC) method recently introduced by Kumar and Padakandla (2022). This methodology surpasses other traditional methods, such as the VAR and quantile regression models, by effectively capturing the influence of an independent variable on the dependent variable at various quantiles over several periods, including the short, medium, and long run. Therefore, this method simultaneously assesses the influence of the CPU on NREC across several quantiles and periods. Next, we contribute to the existing literature by testing the transmission channels that link the CPU with NREC. In particular, we test whether energy prices and technological innovation are the factors through which CPU impacts NREC.

Considering the fourth chapter, the study is significant since it is the earliest attempt to explore the impact of CPU on TEP, REP, and NREP. Not only this, but the study adopts the novel quantile-on-quantile kernel-based regularized least squares (QQKRLS) approach developed by Adebayo, Özkan, and Eweade (2024). This method outperforms others by explaining the impact of independent variables on dependent variables across the quantiles of both variables.

This study will be beneficial for policymakers, as it will help them develop and implement energy and environmental policies to achieve several Sustainable Development Goals (SDGs). In particular, this thesis helps policymakers revise policies to achieve SDG 7 and SDG 13. It will help researchers to understand and expand this line of research. Finally, this study is significant for investors and managers since it also discerns the impact of CPU on energy markets across different time horizons (i.e., the short- and long-run).

While summarizing the significance of this thesis for the US, it is worth reporting that this study provides empirical evidence on whether CPU should be considered an indispensable factor that can influence energy markets. Furthermore, this study also provides a yardstick for understanding whether the CPU can facilitate the process of energy transition in the US. Finally, this thesis also gives recommendations about the nature of future climate policies.

1.6 Organization of the Study

While discussing the organization of the study, it is worth noting that the study is divided into five chapters. Chapter 1 provides an overview of the study's background, followed by a statement of the problem. Thereafter, research questions and objectives are established. Also, Chapter 1 explains the significance of the study.

Chapter 2 explores the impact of the CPU on REN in the US. After probing the order of integration, this study explores the cointegration between CPU and REN. Furthermore, the impact of the CPU on REN across the short- and long-run is examined using a novel FAARDL approach. Additionally, several sensitivity checks are applied to ensure robustness. The results help us to understand whether there is any relationship between CPU and REN. Additionally, the magnitude and direction (i.e., positive or negative) of the CPU's impact on REN are discussed. It is also discussed whether the relationship between CPU and REN varies across the long and short run.

Chapter 3 examines the impact of CPU on aggregated and disaggregated non-renewable energy consumption in the US. After evaluating the order of integration and cointegration, the study applies a novel WQC approach. Thereafter, a sensitivity analysis is performed to ensure robust outcomes. This chapter scrutinizes whether the CPU has an impact on aggregated and non-aggregated non-renewable energy consumption. Next, it is explored whether the relationship between the aforementioned variables varies across quantiles and time. Further, it is examined whether the relationship between CPU and NRE varies across the energy sources.

Similarly, Chapter 4 explores the impact of CPU on TEP, NREP, and REP in the US. The study adopts the novel QQKRLS method to examine the aforementioned relationships. The results help to understand whether the CPU impacts TEP. Does the relationship between CPU and energy production vary across different energy sources? Finally, the results also help us to understand whether the relationship varies across the quantiles of CPU and energy production.

Chapter 5 summarizes the results obtained in chapters 2, 3, and 4. Additionally, it proposes several policy implications and highlights the limitations of this thesis. Finally, it suggests future research directions.

CHAPTER 2

THE DYNAMIC IMPACT OF CLIMATE POLICY UNCERTAINTY ON RENEWABLE ENERGY CONSUMPTION[6]

2.1 Introduction

It is a well-established fact that renewable energy (RE) is crucial for both the economy and the environment. RE reduces the dependence on fossil fuels, such as petroleum, gas, and coal. Likewise, it enhances energy security and stability, which are crucial issues today. It contributes to economic growth (EG) and employment opportunities (Inglesi-Lotz, 2016; Lambert & Silva, 2012). RE yields a cost-effective solution to increased energy demand. On top of this, it helps to curb greenhouse gas emissions and, hence, aids in mitigating climate change (Hashmi, Bhowmik, Inglesi-Lotz, & Syed, 2022; Li, Wang, Liu, & Jiang, 2021; Wang, Wang, & Li, 2023a). Hence, RE could be the right choice for escalating EG without affecting environmental quality. Therefore, the world strives to increase renewable energy consumption (REN). However, the high installation cost of renewables, combined with social, economic, and political factors, discourages REN. According to the World Energy Outlook Report of 2020,[7] the proportion of REN in global energy consumption has been about 19%, which is still very low, with non-renewable energy consumption (NREC) still being very high. Therefore, discerning the drivers for REN is inevitable. This investigation would help policymakers devise policies to achieve Sustainable Development Goals (SDGs), thereby increasing the well-being of the human race.

[6] This core chapter has been published as a journal article in ENERGY (Elsevier). https://doi.org/10.1016/j.energy.2023.127383
[7] https://gotcp.net/wp-content/uploads/2021/10/WEO2021_Launch_Presentation-1.pdf.

The current literature identifies several factors affecting REN, such as EG (Sadorsky, 2009a), energy prices (Troster, Shahbaz, & Uddin, 2018), and environmental degradation (Dogan, Inglesi-Lotz, & Altinoz, 2016; Omri & Nguyen, 2014), among others. However, the literature remains relatively scarce about the nexus between uncertainty in environmental/climate policies (CPU) and REN. For instance, Zhou et al. (2023) probe the impact of CPU on REN using the time-varying structural vector autoregressive model. The study highlights that the CPU escalates REN in the short and long run, whereas it mitigates REN in the medium run. Similarly, Shang et al. (2022) employ the ARDL to explore the impact of CPU on REN. Their findings report that CPU does not affect REN in the short and long run.[8]

The contrasting outcomes indicate that more than one theoretical channel connects the CPU with REN. Hence, this chapter discusses the three channels that link the CPU with REN. First, the 'positive channel/effect' suggests that CPU compels investors to invest in clean technologies since CPU escalates the risk of using NREC (Fried et al., 2021). As a result, REN will increase (Alam, 2021; Khan, 2020). In contrast, the 'negative channel/effect' suggests that the CPU impedes the level of investments in green technologies, R&D, and innovation (Fuss, 2008; Ren, 2022a). Hence, REN is expected to decrease (Li & Ullah, 2022). The third channel is the 'energy prices channel,' which points out that CPU decreases oil prices (Guo, Long, & Luo, 2022a). Thereby, the demand for NREC will experience an increase, and hence, REN will witness a reduction over time (Guo, Yu, Zhang, & Cheng, 2021).

[8] Although Shang et al. (2022) reported a positive long-run relationship between CPU and REN in the abstract of their paper, the authors reported an insignificant relationship between CPU and REN in the result section, as shown in Table 6, p. 662.

Overall, it is crucial to explore the CPU-REN nexus to confirm the net impact of the CPU on REN. The inevitability of investigating the CPU-REN nexus can be based on the fact that at the United Nations Climate Conference (COP26), the primary objective of member nations has been to accelerate REN and explore the factors essential for the energy transition process. It was also discussed that governance, through environmental policies, can help economies accelerate the pace of energy transition. However, the CPU could be the critical factor that affects REN. Thus, probing the nexus between CPU-REN will help to achieve COP26 targets (i.e., upsurge REN to curb carbon emissions).

Given the above-mentioned points, this chapter aims to test whether CPU affects REN in the US. The US is relevant for this analysis because it is the largest economy and the second-largest carbon emitter (Syed & Bouri, 2021). Furthermore, according to a recent report by the Energy Information Administration,[9] the US is among the top countries that use REN. Moreover, regarding renewable installed capacity, the US is among the top three countries. Considering the US carbon emissions level, REN is indispensable to achieving sustainable development. There are various environmental policies in the US. However, the risk factor is associated with them. For instance, federal carbon taxes have not yet been levied in the US, but the higher growth in emissions has created the likelihood of carbon taxation soon, escalating CPU in the US. In addition, the announcement to withdraw from the Paris Agreement has upsurged CPU in the US. Similarly, the variations in tariffs and other taxes (i.e., levied on renewables) create uncertainty in environmental policies in the US. Thus, it is essential to explore the impact of CPU as one of the determinants of REN.

[9] https://www.eia.gov/pressroom/presentations/capuano_01292020.pdf

The contribution of this chapter is as follows. First, the current literature on the dynamic impact of CPU on REN is still scant and provides contradictory findings. Hence, this analysis reinvestigates the impact of CPU on REN to provide complementary findings, which will help to reach a more definitive conclusion. Second, previous studies on the CPU-REN nexus have overlooked a detailed discussion of the theoretical linkages between CPU and REN; however, this work aims to fill this gap by examining the theoretical aspects that connect CPU with REN. Third, this work performs a novel smooth and sharp structural breaks unit root test recommended by (Shahbaz, Omay, & Roubaud, 2018) (henceforth, the SOR test) to investigate the order of integration. The SOR unit root test accommodates more than one structural break of various dynamic natures, yielding more reliable results. Fourth, this study uses the novel Fourier augmented ARDL approach (FAARDL) that outperforms the contemporary methods in two aspects: i) it makes use of the AARDL of (Sam et al., 2019), which probes cointegration by applying three tests (see the methodology section for more details); ii) it applies the Fourier transformation to cover multiple structural breaks of different dynamic natures.

2.2 Review of Related Literature

The existing literature reports several drivers of REN while modelling REN. In general, literature broadly segregates the drivers of REN into economic and environmental indicators. Factors such as EG, inflation, and energy prices are key economic indicators that affect the demand for renewables, whereas CO_2 emissions are the most inevitable environmental factor that impacts REN.

It is worth noting that EG is the most widely used economic indicator while modelling REN. Empirical studies have found that EG leads to higher income levels, making RE more affordable. As a result, EG promotes REN. Several research outlets have reached this conclusion. For instance, Soytas & Sari (2009) investigate the causal relationships between REN and EG in the case of G7 countries. Their results document that REN and EG are positively associated. Sadorsky (2009b) notes that EG is an influencing factor of REN. For Ghana, Gyimah, Yao, Tachega, Hayford, and Opoku-Mensah (2022) test the causal relationship between REN and EG. The study claims that EG contributes to REN. Likewise, Yi, Raghutla, Chittedi, and Fareed (2023) note that EG, financial development, and globalization enhance REN. Parallel to this, Van Hoang, Shahzad, and Czudaj (2020) probe the REN-industrial production nexus. They report that bidirectional causality exists between REN and industrial production.

Another line of research suggests that EG has a detrimental effect on REN. As economies grow, there may be greater demand for energy from fossil fuels, which are cheaper and more readily available than RE. Next, governments may reduce subsidies for RE, making it less economically viable. Moreover, in some countries, there may be a lack of infrastructure to support the growth of RE, hindering its development and consumption. Based on these aforementioned arguments, certain studies justify the adverse impact of EG on REN. For instance, Yildirim, Saraç, and Aslan (2012) and Uzar (2020) explore the causal impact of various sources of renewables and EG in the US. They report that EG has a detrimental impact on a few renewable energy sources. Additionally, several empirical studies have noted that EG has an insignificant impact on REN. For instance, Cevik, Yıldırım, and Dibooglu (2021) employ the VAR model to examine the connectedness between REN and EG. Their study concludes that EG does not affect REN in the US. Similarly, Shafiullah, Miah, Alam, and Atif (2021) report that IPI has an insignificant impact on REN in the case of the US.

The level of prices is another essential determinant of REN. Theoretically, a higher general price level (inflation) plummets the cost of buying/purchasing, and hence, REN is expected to decrease over time. In the case of Turkey, Mukhtarov, Mikayilov, Maharramov, Aliyev, and Suleymanov (2022a) conclude that inflation (CPI) hurts REN in the long run. In the case of African countries, Akpanke, Deka, Ozdeser, and Seraj (2023) note that CPI impedes REN in the long run. In contrast, several researchers claim that CPI escalates REN. For instance, in the case of the European Union countries, Anton and Nucu (2020) illustrate that CPI upsurges REN. Li, Su, Umar, and Shao (2022) highlight that CPI has a positive impact on REN at lower quantiles, whereas CPI and REN are negatively linked at higher quantiles.

In addition to CPI, the oil price (OIL) has also been incorporated as a key independent variable in the modelling of REN. Higher OIL plunges NREC. Since NRE and RE are substitutes for each other, a decline in NRE leads to an increase in RE. Atems, Mette, Lin, and Madraki (2023) investigate whether non-renewable energy prices affect REN in the US. The authors report that a shock in non-renewable energy prices enhances REN. Chen, Pinar, and Stengos (2021) explore the impact of OIL on REN for 97 selected countries. The authors report that higher OIL promotes REN. In the case of the US, Sahu, Solarin, Al-Mulali, and Ozturk (2022) report the positive impact of OIL on REN. Brini, Amara, and Jemmali (2017) conclude that a positive shock in OIL enhances REN in Tunisia. For selected Asian economies, Murshed and Tanha (2021) show that OIL raises REN.

Parallel to this, many researchers confirm that OIL decreases REN. For instance, Omri and Nguyen (2014) examine the determining factors of REN across various countries with different income levels. Their findings indicate that OIL reduces REN, suggesting a complementary relationship between NREC and REN. Omri, Daly, and Nguyen (2015) investigate the dynamic influence of OIL on REN in 64 chosen countries. The authors indicate that OIL has no impact on REN, suggesting that NREC and REN function as complements. Karacan, Mukhtarov, Barış, İşleyen, and Yardımcı (2021) observe that in the Russian context, CPI negatively affects REN. Mukhtarov, Humbatova, Hajiyev, and Aliyev (2020) indicate that OIL leads to a decrease in REN in the context of Azerbaijan. In the case of Iran, Mukhtarov, Yüksel, and Dinçer (2022b) arrived at a similar conclusion.

It is worth noting that carbon emissions are a critical environmental indicator that affects REN. A strand of literature claims that CO_2 decreases REN. For instance, Akintande, Olubusoye, Adenikinju, and Olanrewaju (2020) reveal that emissions plunge REN in selected African countries. Similar conclusions have been made by Olanrewaju, Olubusoye, Adenikinju, and Akintande (2019), who note that carbon emissions impede REN in the African region. In contrast, the existing literature also explains the positive impact of CO_2 emissions on REN. For instance, Gozgor, Mahalik, Demir, and Padhan (2020) report that emissions escalate REN in the OECD countries, while a few studies claim that emissions do not impact REN. Lin and Moubarak (2014) conclude that emissions have an insignificant impact on REN in China.

Recently, studies have been conducted to explore the relationship between CPU and REN. Shang et al. (2022) seek to analyze the dynamic effects of CPU on REN and NREC. The authors employ the ARDL method to examine both short-term and long-term estimates. The findings indicate that CPU has no impact on REN in both the short and long term. Zhou et al. (2023) aim to investigate the impact of a CPU shock on REN across short, medium, and long-term periods. The analysis indicates a positive correlation between CPU and REN in both the short and long term, whereas a negative correlation is observed in the medium term. While the investigations conducted by Shang et al. (2022) and Zhou et al. (2023) explore the CPU-REN relationship, they exhibit certain limitations. For example, Shang et al. (2022) utilize the ARDL method proposed by Pesaran et al. (2001), which exclusively implements the overall F-test across all lagged variables.[10] However, in this chapter, the AARDL bounds test of Sam et al. (2019) is applied, covering three tests. In addition, Shang et al. (2022) use dummies to capture structural breaks, whereas we employ the Fourier transformation, which outperforms the dummy approach. Zhou et al. (2023) do not cover structural breaks nor develop their analysis based on economic theory. However, we use the neoclassical demand function (which has an economic basis) to counter the structural breaks.

While concluding the literature review of the determinants of REN, it is apparent that the existing literature explores various factors as determinants of REN. However, the literature on the dynamic impact of CPU on REN is scanty. Furthermore, the existing line of research on the CPU-REN nexus yields inconclusive outcomes. Thus, we aim to reinvestigate the CPU-REN relationship with a robust methodology as described below. The network plot displayed below summarizes the determinants of REN, which also highlights contrasting results related to the CPU-REN nexus.

[10] There are two tests in the ARDL test by Pesaran et al.(2001) to determine the status of cointegration. These two tests are the overall F- test for all lagged variables and the t-test for the lagged of dependent variable. McNown et al. (2018) show that performing only one of the tests may create a spurious cointegration status.

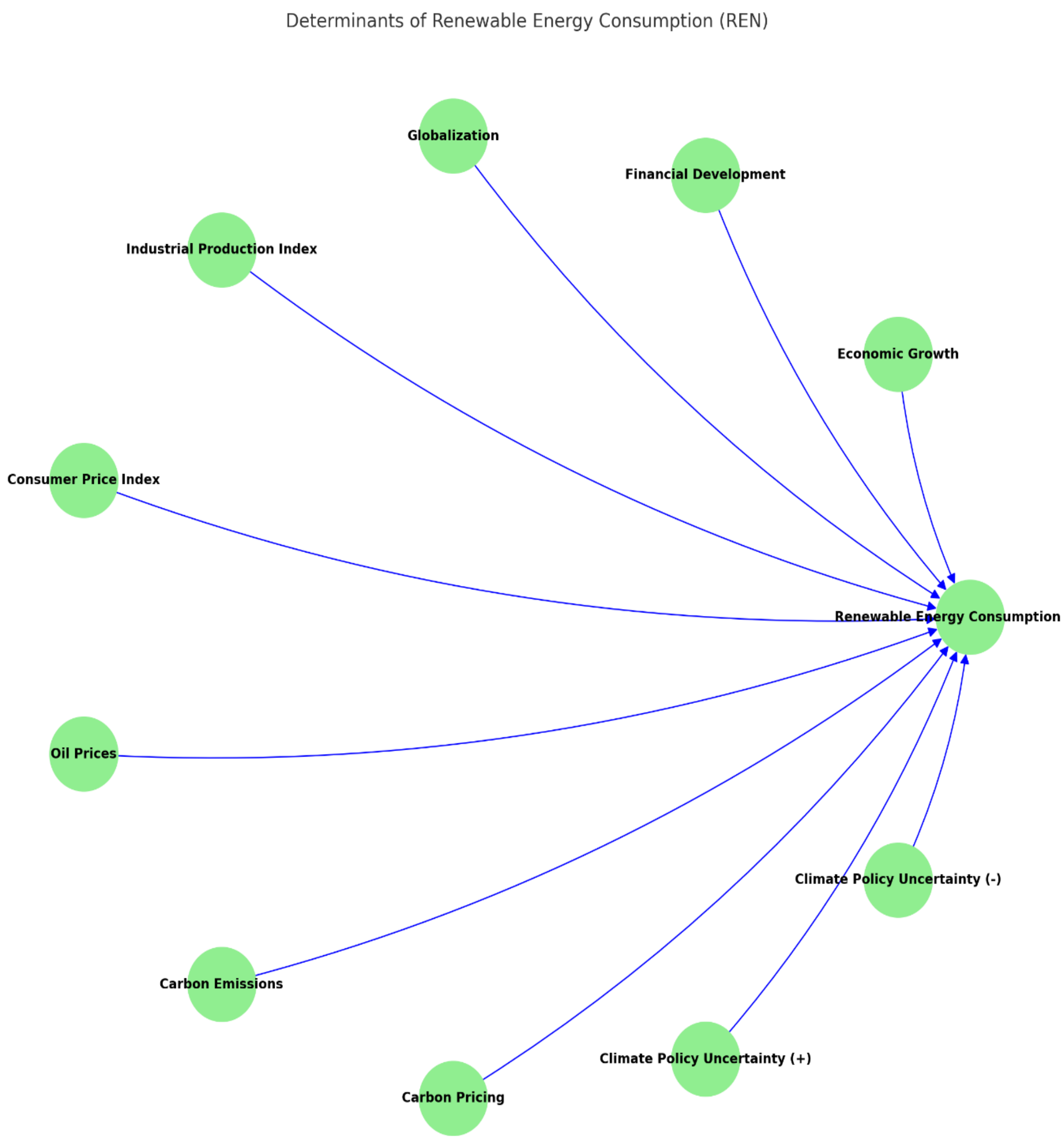


Figure 2.1: Network Plot on the Determinants of REN

2.3 Model, Methodology, and Data

2.3.1 Model

To explore the CPU-REN nexus, the neoclassical demand function is employed. The empirical model is reported as follows:

$$REN_t = \alpha + \beta_1 CPU_t + \beta_2 IPI_t + \beta_3 OIL_t + \beta_4 CO2_t + \varepsilon_t \tag{2.1}$$

In Eq. (2.1), REN, CPU, IPI, OIL, and CO2 denote renewable energy consumption, climate policy uncertainty, industrial production index, oil price, and CO_2 emissions, respectively.[11] β_i (i=1, 2, 3, 4) represents the coefficient of the estimates, α represents the intercept, and ε_t is the error term. Since the neoclassical demand function is used, it is necessary to incorporate income and prices as independent variables. IPI is used to capture the impact of income due to the unavailability of data on monthly GDP. As highlighted by Omri and Nguyen (2014), existing studies incorporate OIL as a proxy for prices when estimating the energy demand function. Therefore, this analysis used OIL as one of the explanatory variables, which is a surrogate for prices. Since environmental quality profoundly impacts the preferences/decisions of economic agents regarding an upsurge/plunge in REN, we include CO2 (i.e., a proxy for environmental quality) as another explanatory variable.

Dogan et al. (2021) and Shafiullah et al. (2021) adopt these explanatory variables (i.e., IPI, OIL, and CO2) while modelling REN. The CPU can be either positive or negative based on the magnitude of the proposed channels. The 'positive channel' points out that CPU leads to higher investments in clean energy, R&D, and innovations, with REN witnessing an increase. Meanwhile, the 'negative channel' notes that the CPU hinders R&D, innovation, and investments in clean energy, thereby decreasing REN. In addition, the 'energy prices channel' indicates that a decline in CPU prices leads to a decrease in oil prices, thereby enhancing NREC. As a result, REN experiences a decline over time. The theoretical linkages between CPU and REN are displayed in Figure 2.2.

[11] Each variable of Eq. 2.1 is taken in its natural logarithmic form.

Next, if the IPI is positive, it suggests that IPI ameliorates REN Van Hoang et al. (2020). If the OIL is positive, it implies that higher energy prices increase REN. Finally, suppose the coefficient of CO2 is negative. In that case, it suggests that environmental degradation transmits a signal in the market, indicating that policymakers have not prioritized the environment, and there are still odds of using non-renewables.

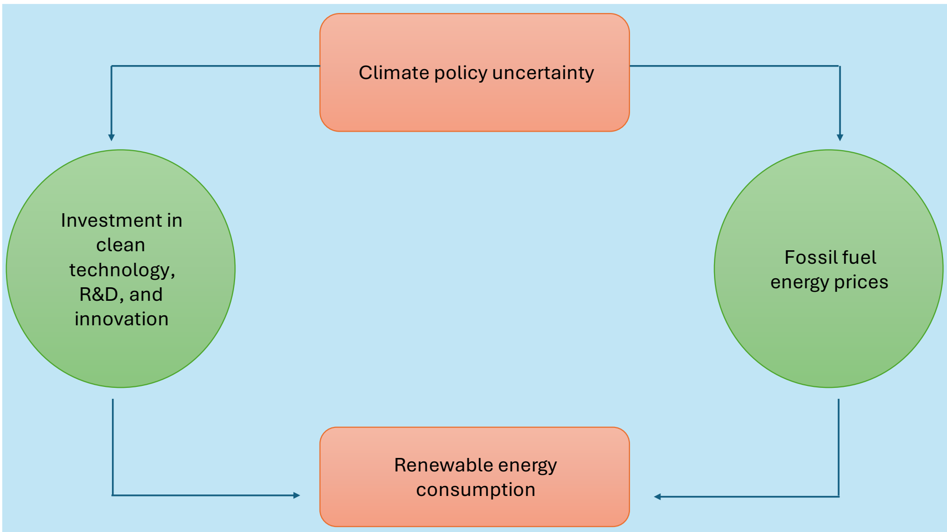


Figure 2.2: Theoretical Linkages Between CPU and REN

2.3.2 SOR Unit Root Test

Examining stationarity is essential in time series datasets. To identify the stationarity condition, various unit root tests are frequently employed in empirical studies, including Augmented Dickey Fuller (ADF) based tests, Lagrange Multiplier (LM) based tests, and Fourier-based tests, such as Fourier-ADF and Fourier-LM tests. Nonetheless, these tests exhibit specific limitations, leading to a significant probability of erroneous conclusions (Enders and Lee, 2012). The ADF test, for example, does not account for structural breaks. Furthermore, this test exhibits limited explanatory power, rendering it inappropriate for small datasets (Ng & Perron, 2001). In contrast, Shahbaz et al. (2018) introduce a two-step procedure in the sharp and smooth structural breaks (Anton & Nucu, 2020) unit root tests, effectively addressing state-dependent nonlinearity and both sharp and smooth breaks while avoiding issues related to over-fitting. Consequently, this chapter employs the SOR unit root test alongside various traditional unit root tests, such as the generalized least squares (GLS) unit root test and the Zivot and Andrews (ZA) test. The SOR test demonstrates superior performance compared to traditional tests (such as the ADF test) by effectively addressing both sharp and smooth structural breaks in the data, thereby yielding more reliable estimates.

While concluding the methodological discussion on the unit root testing approach, this chapter employs three types of unit root procedures: the GLS test, the ZA test, and the SOR test. The motivation behind using three tests is to portray the methodological rigor and robustness in unit root testing. However, the primary unit root test used in this chapter is the SOR test. As highlighted above, the key advantages of the SOR test are its ability to handle nonlinearities and sharp/smooth structural breaks. Further, unlike other tests, the SOR test can handle many structural breaks without prior knowledge of the nature, date, and frequency of breaks (Shahbaz et al., 2018).

2.3.3 Fourier Augmented ARDL Approach

This chapter employs the novel Fourier augmented autoregressive distributed lags (FAARDL) approach to examine whether CPU affects REN. This section initially explains the methodology of the augmented ARDL (AARDL) model, while the latter part expounds on how we transform the AARDL model into the FAARDL model.

To investigate cointegration across variables, Pesaran et al. (2001) (PSS hereafter) proposed the ARDL bounds test. According to the relevant literature, it is believed that the abovementioned bounds testing procedure is superior to other methods (e.g., fully modified ordinary least squares) due to its ability to provide reliable findings when the dataset has mixed ordering (Narayan, 2004). In the ARDL specification, Equation (1.2) can be specified as follows:

$$\Delta \mathrm{REN}_t = \alpha + \sum_{i=1}^{y} \varphi_i \Delta REN_{t-i} + \sum_{i=0}^{p} \beta_i \Delta CO_{2t-i} + \sum_{i=0}^{q} \gamma_i \Delta CPU_{t-i} + \sum_{i=0}^{m} \omega_i \Delta IPI_{t-i}$$
$$+ \sum_{i=0}^{n} \partial_i \Delta OIL_{t-i} + \pi_1 REN_{t-1} + \pi_2 CO2_{t-1} + \pi_3 CPU_{t-1} + \pi_4 IPI_{t-1}$$
$$+ \pi_5 OIL_{t-1} + \; v_t \tag{2.2}$$

In Equation (2.2), α is the intercept, while φ_i, β_i, γ_i, ω_i, and ∂_i are short-run coefficients. Furthermore, π_i delineates estimates retrieved in the long run. Next, y, p, q, m, and n denote the lag order, and v_t is the error term. A critical assumption of the ARDL bounds test is that there does not exist any impact of the dependent variable on the independent variable(s), implying that the considered variables are (weakly) exogenous. Nonetheless, the likelihood of this assumption being fulfilled is low. Thus, if the assumption of weak exogeneity does not hold, the distribution of the ARDL bounds test will not be valid (McNown, Sam, & Goh, 2018).

Next, PSS suggested two tests to confirm the cointegration. That is, the F-test (Ho: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = \pi_5 = 0$) on all lagged-level variables (henceforth F-test*(1)*) and the t-test (Ho: π_1= 0) on the lagged-level dependent variable (t-test*(1)*). Nevertheless, in the AARDL procedure, supplementary F-tests (henceforth F-test*(2)*) on the lagged level independent variables (Ho : $\pi_2 = \pi_3 = \pi_4 = \pi_5 = 0$) is proposed by McNown et al. (2018) and Sam et al. (2019), which is complementary to