

ISSN 2090-3359 (Print)
ISSN 2090-3367 (Online)



Advances in Decision Sciences

Volume 29
Issue 1
March 2025

Michael McAleer (Editor-in-Chief)

Chia-Lin Chang (Senior Co-Editor-in-Chief)

Alan Wing-Keung Wong (Senior Co-Editor-in-Chief and Managing Editor)

Aviral Kumar Tiwari (Co-Editor-in-Chief)

Montgomery Van Wart (Associate Editor-in-Chief)

Vincent Shin-Hung Pan (Managing Editor)



亞洲大學
ASIA UNIVERSITY



SCIENTIFIC &
BUSINESS
WORLD

Published by Asia University, Taiwan and Scientific and Business World

Energy demand response to the dynamics of the currency valuation: Evidence from G7 countries

Antanas Laurinavicius

Department of Finance, Faculty of Economics and Business Administration,
Vilnius University, Vilnius, Lithuania

ORCID ID: <https://orcid.org/0000-0002-7983-2779>

Email: antanas.laurinavicius@evaf.vu.lt

Chaleun Vongmileuth

UQ Business School, The University of Queensland
St Lucia, QLD, Australia

ORCID ID: 0009-0007-4560-1474

Email: chaleun.vongmileuth@outlook.com

Sonesavanh Vongmileuth

Department of Innovation and Investment,
One Charge New Energy and Technology Sole Co., Ltd.,
Chanthabouly, Vientiane Prefecture, Lao People's Democratic Republic

Email: sonesavanhvongmileuth@gmail.com

Algimantas Laurinavicius

Department of Finance, Faculty of Economics and Business Administration,
Vilnius University, Vilnius, Lithuania

ORCID ID: <https://orcid.org/0000-0003-0145-2386>

Email: algimantas.laurinavicius@evaf.vu.lt

Shin-Hung Pan

Department of Information Management,
Chaoyang University of Technology, Taiwan

Email: vincentpan@cyut.edu.tw

Bisharat Hussain Chang

Department of Business Administration,
Sukkur IBA University, Sukkur, Sindh, Pakistan

**Corresponding author* Email: bisharat.chang86@gmail.com

Received: January 6, 2025; First Revision: January 15, 2025;

Last Revision: March 5, 2025; Accepted: March 17, 2025;

Published: May 31, 2025

Abstract

Design/methodology/approach

The study employs several traditional methodologies and the newly developed Mixed-TAR Nonlinear ARDL (MTNARDL) model to investigate long-run co-integration. Additionally, Granger causality in the quantile test is applied to enhance the robustness of the findings.

Findings

The MTNARDL model confirms the presence of long-run co-integration among all sample countries, whereas traditional methodologies fail to detect any such relationship. Furthermore, the Granger causality results reveal that the impact of exchange rate fluctuations on energy demand varies across different quantiles.

Research limitations/implications

While the study provides robust empirical insights, it is limited by the scope of available data and methodological constraints, which may require further validation in other economic settings.

Practical implications

The findings highlight the need for policymakers to design exchange rate and energy policies that account for nonlinearities and quantile-specific effects, ensuring economic stability in G7 nations.

Originality/value

This study extends the literature by integrating extreme exchange rate changes with energy demand in G7 countries, employing advanced methodologies to uncover dynamic relationships that were previously overlooked.

Keywords: NARDL model, MTNARDL model, Granger causality in quantile test, traditional ARDL model

JEL Classification: E32, F31, Q43, C32, O11

1. Introduction

The exchange rate helps us determine one currency's value relative to another. It can significantly affect the energy demand, particularly in nations that depend primarily on energy imports or exports. Several theoretical explanations exist for the intricate and multifaceted relationship between the exchange rate and energy demand. First, the exchange rate directly affects the relative energy cost. When a country's currency strengthens relative to other states, the price of energy imports falls. As a result, the purchasing power of energy increases, and its internal consumption increases. In contrast, the weakening of the local currency raises the energy import cost, which leads to a decrease in energy demand.

Second, economic progress is the alternative channel through which the exchange rate influences energy demand. As the country's currency strengthens, its energy exports fall internationally, causing a global sales drop. This weakens international sales, causes a reduction in the economy, and hence reduces the energy demand. Third, the nexus between exchange rates and foreign direct investment offers an alternative network through which the exchange rate influences the energy demand. The exchange rate fluctuations can substantially influence the demand for energy projects, primarily when a state is highly dependent on foreign investments. A robust currency may cause a reduction in foreign investments since it increases the cost of energy-related projects. As a result, it causes a lessening in the energy demand and supply. On the other hand, the demand for foreign projects surges when the domestic currency is weaker since it lessens the cost of energy-related projects. As a result, the energy demand also surges.

Unfoundedly, various influences cause the association between energy demand and exchange rates. These include the overall edifice of the economy, the volume of energy exports and imports, and energy-related product prices, among others. Diverse studies have been carried out to scrutinize the connection between exchange rates and energy demand. The work done by Huntington, et al. (2019) and Adeyemi and Hunt (2014) has mirrored that price and income are key variables distressing energy demand. Shahbaz, et al. (2018) state that foreign currency substantially influences energy consumption. The analysis of the industrial segment in OECD states that prices substantially impact energy usage in the long run, compared to the short run. According to Liddle and Huntington's (2020) panel scrutiny of OECD states, economic progress is the prime driver for the growth of the banking segment and energy demand in unindustrialized markets.

Various other research studies looked into the nonlinear relationship between energy demand and its elements. For instance, Adeyemi, et al. (2010) conducted a scrutiny on a panel of seventeen OECD states and found that price changes have a nonlinear influence on energy demand. In the same way, Adom (2015) and Sa'ad (2011) also institute a nonlinear nexus between energy demand and other variables. Fotis, et al. (2017) also pointed out the nonlinear nexus between electricity demand and economic progress. In a panel evaluation of OECD and other states, Liddle and Sadorsky (2020) found that a higher state income led to greater energy consumption than a lower state income.

Although several factors influencing energy demand have been studied, only a little research has looked at currency valuations as a substantial explanatory variable of energy demand. In contrast,

research by De Schryder and Peersman (2013) on 61 oil-importing countries indicates a decrease in the energy demand during the depreciation of local currency relative to the United States dollar. According to Adewuyi (2016), the exchange rate significantly impacts Nigerian imports of refined petroleum products. In a different study, Ghoddusi, et al. (2019) and Gohar, et al. (2022a) scrutinized how Iran's petroleum demand was affected by currency devaluation. They found that demand had decreased because of the depreciation of the currency. Further, they added that the influence is more substantial when the exchange rates are erratic.

Overall, past studies mainly provide mixed findings. As a result, this research utilizes the MTNARDL (Multiple Thresholds Nonlinear ARDL) model and equates the outcomes of this advanced model with both nonlinear and conventional ARDL models. To further ensure the robustness of findings, this study uses the Granger causality in the quantile assessment introduced by Troster (2018).

The MTNARDL model has been utilized in earlier studies to investigate the comprehensive relationship among various economic and financial variables. For instance, Hashmi, et al. (2021b) investigated the ties between India's exchange rate volatility and cross-border trade by utilizing the MTNARDL approach. Chang, et al. (2023) used this model to check the nexus between the exchange rate fluctuations and the United States' exports. Pal and Mitra (2019) also used this technique to examine the connection between purchasing power parity and oil prices. These earlier studies support the MTNARDL models' superiority over conventional models. Considering the superiority of the MTNARDL model, our findings will be more accurate and meaningful if we consider the influence of both small and large ups and downs in exchange rates on energy demand. As a result, it augments the expertise in energy usage limitation.

Using the MTNARDL model, our research examines how energy demand is affected by different exchange rate instabilities. In brief, this investigation extends the prevailing literature by isolating the currency rate into deciles and quintiles and analyzing how each threshold affects the energy demand. In other words, our research analyzes the effect of tiny to enormous exchange rate fluctuations on energy demand. Second, we broaden the corpus of written works by investigating this effect on countries such as France, Canada, Italy, Germany, the US, Japan, and the UK. As the writers know, these countries have not been considered when examining this relationship.

Specifically, we carry out this research in the G7 for several reasons. The heavy reliance on imported energy by these nations makes them susceptible to fluctuations in exchange rates. These nations cannot produce and reserve domestic energy as other nations do. The variations in exchange rates may affect their overall economic strength and energy security. Secondly, energy needs are increasing due to the speedy economic and urbanization growth that these nations may experience. Countries need to invest heavily in energy infrastructure as energy demand increases. The strategies, on a priority basis, can give more advantages to the nations by providing them with a better knowledge of how energy demand is affected by the exchange rate. Thirdly, the most critical players in the world energy market are the economies being studied in this nation. These states may struggle more with certain other producers and exporters if they know how energy demand is affected by the exchange rate. Their geopolitical rate of economic development and influence may be positively affected.

In summary, these nations repeatedly encounter different energy-related schemes that hinder them. These include creating a balance between environmental sustainability and energy security, or fulfilling the energy requirements of marginalized communities. The policymakers of these nations can decide how best to tackle these problems by better comprehending the connection between energy demand and exchange rates. The research focuses on the countries- Japan, the UK, Germany, France, Canada, the US, and Italy- which were opted for due to their financial policies and increasing industrialization rates, structural fluctuations, increasing energy demands, and changing ways of production. Because of changes in the production of industries and agriculture to a service-oriented technique method since the 2000s, these economies are significantly growing in their energy need (Durusu-Ciftci, et al., 2020). Besides, resulting in increasing industrial movement and energy demand, these nations are more inclined to import energy-related products to face any crisis in their native markets. In addition, exchange rates and rivalries are the most critical factors in energy demand due to the heavy import of energy-related goods. Previous research indicates that energy usage may increase roughly by 3.2% annually in these nations.

Moreover, rising economies' energy needs comprise about 45% of the world's total energy consumption. To meet the energy demands of their industries and maintain the upward trend in output, these countries need to put strong policies into place. Therefore, these nations will create appropriate measures to uphold and accomplish the rising output trends. Moreover, this information will serve as a helpful policy model for energy demand for other countries with comparable economic systems, like these economies.

The rest of the paper is organized as follows: Section 2 presents the literature review and theoretical framework and highlights the gap in the existing literature. Section 3 discusses the methodologies used in our study, which include the MTNARDL model and Granger causality in the quantile test. Section 4 presents the findings of this study and connects those findings with the existing literature. Finally, Section 5 concludes this paper and provides policy implications. Moreover, it provides the limitations of this study along with the future research directions.

2. Literature Review

The most important economic factor influencing the energy demand is the exchange rates. The currency of a state may fail, and the rising demand for energy and the escalating cost of energy imports may force people to switch to cheaper domestic energy sources. On the other hand, as energy imports become more reasonable, a country's currency appreciation may decrease the energy demand. The consequences of the examination demonstrate that the effect of the exchange rate on energy usage fluctuates among states and industries. Exchange rates have a slight impact on energy demand in other states, but they deeply impact these states. The main motive behind this is that these states are mostly reliant on the imports of energy, which makes them vulnerable to variation in the currency valuation. Contrasting with other segments, the industrial segment relies heavily on energy. The previous studies mentioned that the industrial segment primarily relies on imported inputs, like energy, and is highly vulnerable to the international markets.

Numerous studies have concentrated on the significance of exchange rates on the energy demand in particular states. Such as an investigation by Hashmi, et al. (2021a, 2021b, 2022), Rashid, et al. (2017), and Syed, et al. (2019) observed how energy demand was influenced by exchange rates. Their investigation revealed that the demand for energy upsurges when the domestic currency depreciates, while the demand for energy declines when it appreciates. Furthermore, Al-Musallam and Atalla (2018) examined the influence of Kuwait's energy usage on the exchange rate. They stated that when the Kuwaiti Dinar wanes, there is a relative escalation in the energy demand, and when it strengthens, there is a relative decline in the demand for energy. In addition, Chen, et al. (2018) studied how the exchange rate influences Italy's energy demand. They mentioned that the demand for energy upsurges when there is a depreciation of Italy's currency. However, it rises when there is a decline in the energy demand (Gong, et al., 2023; Imane, et al., 2023).

The influence of the exchange rate on Korea's energy usage was estimated by Kwon and Jung (2019). They stated that the demand for energy rises after the price of the Korean won decreases, and the contrast occurs when there is price of the Korean won increases. Moreover, Halicioglu and Ketenci (2016) inspected the influence of the exchange rate on the demand for energy in the United Kingdom. They mentioned in their research that the currency appreciation in the United Kingdom results in a decrease in the energy demand, whereas the depreciation results in progress.

Similarly, other researchers have accounted for how exchange rates influence the industrial segment's energy demand. Menyah and Wolde-Rufael (2010) scrutinized the UK's manufacturing industries, where the exchange rate triggered fluctuations in the energy demand. The research exposed that fluctuations in exchange rates vastly influence segments' energy demand. Investigations by Li, et al. (2017), Wang, et al. (2022), and Gohar, et al. (2022b, 2022c, 2023) scrutinize how exchange rates influenced the volume of energy utilized in Italy's industry of manufacturing. The investigation uncovered that the sector's energy demand is enormously influenced by fluctuations in exchange rates (Lu, et al., 2023).

Cao and Han (2021) utilized a three-dimensional econometric analysis to observe how exchange rates influenced Italy's energy usage. Their investigation revealed that Italy's energy usage is vastly influenced by exchange rates, with rising energy usage resulting from the Italian currency's devaluation. Wu, et al. (2021) applied the panel VAR method to find out how Italy's energy usage structure was influenced by exchange rate fluxes. The investigation revealed that fluxes in exchange rates substantially influence Italy's energy usage, with a weakening in the value of the Italian currency translating into an intensification in the usage of coal and a reduction in that of natural gas. Li, et al. (2021b) and Gohar, et al. (2022a) utilized the structural VAR investigation to observe the effects of changing exchange rates on Italy's usage of energy. The research revealed that disparities in exchange rates substantially impact Italy's energy usage, with an upsurge in energy demand following a decline in the value of the Italian currency (Salman, et al., 2023a, 2023b).

Tule and Shabani (2022) explored the nexus between exchange rates, energy usage, and economic development in sub-Saharan Africa. The investigation revealed that fluxes in exchange rates substantially affect the region's energy usage, where energy usage upsurges, resulting in a depreciation of the domestic currency.

Recently, investigations have also examined the nexus between energy demand and exchange rates (Bagadeem, et al., 2024; Mei, et al., 2024). For example, Kim and Lee (2022) explored the effect of fluctuations in exchange rates on Korea's energy usage. They found that the country's energy demand increased when the Korean won weakened. Tomašević, et al. (2022) observed the influence of exchange rate fluxes on energy usage in the European Union and found that the region's energy usage increased when the euro depreciated.

According to some research, the energy demand is asymmetrically influenced by the exchange rates. The way that fluctuations in exchange rates influence energy demand is known as the exchange rates' nonlinear influence on energy demand, which can fluctuate based on the strength and weakness of the domestic currency. The asymmetric influence of exchange rates on the demand for energy in specific states has been the topic of abundant investigations. Akarca and Long (1980) inspected how exchange rate fluctuations influenced the United States' energy demand. As stated by a study, there is a nonlinear effect of exchange rate fluxes on energy demand, with an intensification in the value of the United States dollar having a negligible influence on energy demand rather than a diminution in it. Moreover, Jin, et al. (2024) and Chen, et al. (2019) explored how variations in exchange rates influence Italy's energy usage. According to the study, there is a nonlinear effect of exchange rates on energy demand in Italy, where the influence of an increase in the value of the Italian currency on energy demand is less than that of a decline in it. Chang, et al. (2023) also investigated and revealed that the exchange rates have a substantial influence on the demand for energy usage.

Numerous perceptive investigations have shed light on the complex interchange between resource corruption and economic progress. Huang, et al. (2020) competently discovered the vital role that forest and mineral resources, together with oil extraction, play in the economic progress of emerging Asian states, emphasizing their grave importance to regional development. Lei, et al. (2022) probed into the challenges G-20 states face due to their reliance on natural resources, especially in light of the environmental goals set by COP-26. This study sheds light on the problematic balance between economic needs and environmental sustainability. Furthermore, Zhang, et al. (2023) considerably addressed the causes of energy deficiency in China, suggesting approaches aligned with sustainable development goals, which highlight the need for considerate resource management.

Furthermore, Zhengxia, et al. (2023) examined how technological advancement influences the nexus between energy use and CO₂ emissions in populous Asian states, offering an important understanding of environmental policy. In another nuanced research, Huang, et al. (2023a) looked at the varied influences that natural resource dependence, industrialization, and foreign investment have on China's economic development, providing a detailed understanding of these complex dynamics. Lastly, Huang, et al. (2023) tackled the resource curse hypothesis by probing how renewable energy and urbanization can foster environmental sustainability in China, contributing to a richer discussion about sustainable development in developing markets.

Mirzaei and Naqvi (2020) observed the asymmetric influence of currency rates on Pakistan's energy demand. According to the investigation, there is a nonlinear influence of the exchange rate, where an upsurge in the value of the Pakistani rupee has a lesser impact on energy usage than a decrease in its value. Vassilev and Lekova (2020) explored how exchange rates asymmetrically influenced Bulgaria's

energy needs. According to the research, there is a nonlinear effect, with an increase in the value of the Bulgarian lev having a more negligible influence on energy usage than a decrease in its value.

In addition, utilizing a threshold co-integration analysis, Hashmi, et al. (2021a, 2021b, 2022) and Syed, et al. (2019) examined how dissimilar exchange rates affected the demand for energy in South Korea. According to the study, there is a nonlinear effect in the states, with an increase in the value of the Korean won having less impact on energy consumption than a decrease in its value. Azam and Khan (2021) used a nonlinear autoregressive distributed lag technique to examine the asymmetric impact of exchange rates on Pakistan's energy consumption. According to the research, there is an asymmetric effect, with an increase in the value of the Pakistani rupee having a lesser impact than a decrease in its value. Li, et al. (2021b) used a threshold cointegration analysis to examine how exchange rates asymmetrically affect Italy's energy consumption. The study indicates an asymmetric impact of exchange rates in the country, where value is higher, and energy demand is less affected by the depreciation of the Italian currency.

Ullah, et al. (2022) used a nonlinear autoregressive distributed lag approach to study the asymmetric impact of exchange rates on energy demand in Pakistan. According to the research, there is an asymmetric effect of exchange rates on the demand for energy, where an increase in the value of the Pakistani rupee has less of an impact on energy consumption than a decrease in value. Chen, et al. (2022) used a threshold cointegration analysis to examine the unequal influence of exchange rates on the US energy market. According to the study, there is an asymmetric effect in the nation, with an increase in the value of the US dollar having less of an impact on energy demand than a decrease in it.

Wang, et al. (2022) used a nonlinear autoregressive distributed lag approach to study the asymmetric impact of exchange rates on energy demand in Italy. The study finds an uneven impact across the nation, with the decline of the Italian currency rather than its appreciation having a more significant effect on energy use.

Li, Wang, and Xu (2021a) investigated how changes in exchange rates affected Italy's need for energy using monthly data from January 2000 to December 2019. They discovered that changes in exchange rates significantly impact Italy's energy demand. In particular, they discovered that a decline in the value of the Italian currency causes the demand for energy to rise. In contrast, an appreciation causes the demand for energy to fall. The study also discovered that although the population negatively impacts energy demand, industrial output, and crude oil prices have a positive relationship.

2.1 Research contributions

Numerous studies look into the connection between energy demand and exchange rates. These studies do, however, have several areas for improvement. First, a lot of research has concentrated on particular nations, which limits the applicability of its conclusions to other nations, such as those nations that our study highlights. Second, previous literature has ignored the impact of other variables like inflation and prices in favor of concentrating only on the impact on energy demand by exchange rates. Thirdly, there is difficulty in comparing and generalizing the results of studies because different methodologies have been used.

Fourth, whereas the nonlinear influence on energy demand caused by the exchange rates has been a subject of some studies, further investigation is required to comprehend this relationship fully. We expand on our research further by using a sophisticated methodology called the multiple threshold nonlinear ARDL model to investigate the impact of exchange rate on energy demand. Using this technique, we investigate how energy demand is influenced by tremendously large to small variations in the exchange rates. Furthermore, this investigation adds to the body of literature by focusing primarily on these nations. The introduction section addresses several justifications for studying these nations.

3. Data and Methodology

3.1 Data

The study's authors use time-series data covering the 1992 second quarter to the 2023 third quarter for particular nations. The International Financial Statistics database and the global energy database of Enerdata provided the study's data. The following variables were included in the study: energy demand (ED), which is quantified in oil alternatives per million tons; the nominal gross domestic product (GDP), which was stated in the national currency to represent each nation's current economic situation; and exchange rate (ER), which represents the value of the local currency divided by the US dollar. The independent variables were exchange rate (ER) and economic activity (EC), while the dependent variable was energy demand (ED). We included economic activity as a control variable in this study because it is a significant factor in energy demand in several studies (Durusu-Ciftci, et al., 2020; Labandeira, et al., 2017; Liddle & Huntington, 2020; Sentenac-Chemin, 2012; Kakar, 2016). As control variables, this study also looks at inflation (CPI) and energy prices (EP).

In addition, we utilized the values of the natural logarithm for every variable. We also employ seasonally adjusted data for each variable, which helps prevent any adjustments brought about by seasonal variances.

Table 1 displays descriptive statistics for all the variables. The variables represent the following: economic activity, exchange rate, and energy demand, in that order. The null hypothesis is the presumption that the data is normally distributed, and the normality of the data is estimated using the Jarque-Bera statistics. The fact that the null hypothesis is rejected suggests that the distribution of the variables is not normal.

Table 1. Variance inflation factor (VIF) test

Country	ED	ER	EC	EP	CPI
Canada	2.51	2.47	2.14	2.65	2.47
France	2.36	2.47	2.18	2.47	2.65
Germany	2.95	2.54	3.84	2.15	2.14
Italy	2.84	3.54	3.41	2.64	2.98
Japan	2.75	3.21	2.96	2.48	2.65
UK	2.89	3.25	2.47	2.16	2.47
US	2.64	2.15	2.64	2.98	2.59

Note: This table presents the results of the variance inflation factor (VIF), which is used to check the multicollinearity.

Similarly, our study uses several variables, which we suspect may be related to each other. As a result, we need to check the multicollinearity, as its existence may affect the robustness of the results. Therefore, we use the variance inflation factor (VIF) test to check the multicollinearity. We provide the outcomes in Appendix Table 1A to conserve space. These outcomes indicate that there is no issue of multicollinearity.

3.2 Model Specification

The literature from earlier times covers a range of factors that impact energy demand. Previous research, such as that conducted by Zhu and Chen (2019), Liddle and Huntington (2020), Azam, et al. (2015), and Salisu and Ayinde (2016), examined the influence of income and energy prices on energy demand. Furthermore, Labandeira, et al. (2017) discovered that prices asymmetrically influence the energy demand. However, a sizable body of research examines how income and energy costs affect energy demand, and relatively little focuses on the influence of exchange rates on energy demand. Nonetheless, some earlier research looks at how the interdependence of the world economy can either positively or negatively impact exchange rates and energy demand. Furthermore, differences in income have an impact on energy demand (Adewuyi, 2016; Durusu-Ciftci, et al., 2020; Kakar, 2016; Sentenac-Chemin, 2012; Shahbaz, et al., 2018). We present our methodology to provide an empirical explanation of the hypotheses put forth.

$$LnED_t = f(LnER_t, LnEC_t, LnEP_t, LnCPI_t), \quad (1)$$

where the logarithmic expressions of LnEC, LnEP, LnED, LnER, and LnCPI at various quarters, t represent economic activity, energy prices, energy demand, the exchange rate, and inflation respectively, and f stands for the functional notation. We applied specification (1) to generate a stochastic error term in an econometric description, as displayed below:

$$LnED_t = b_0 + b_1LnER_t + b_2LnEC_t + b_3LnEP_t + b_4LnCPI_t + \varepsilon_t. \quad (2)$$

Together with the variables listed in Equation (2), the stochastic component ε_t considers additional factors not included in the model. The choice of variables is consistent with economic theory, which states that a product's level of demand is determined by its price and income. However, because of the world economy's interdependence, the value of currency significantly affects energy consumption (De Schryder & Peersman, 2013). Additionally, energy imports become more expensive when the national currency declines. Due to the local substitution effect, energy in France may become more affordable on a worldwide scale. These justifications thus strongly favor examining how currency fluctuations affect energy demand.

In our research, we employ the ARDL technique, which Pesaran, et al. (2001) developed after Pesaran and Shin (1999) initially described it. This method is suggested because it can record short-term and long-term effects. This technique is helpful when utilizing partially integrated variables, that is, when the variables are either integrated of order zero or one. According to Pesaran, et al. (2001), it also functions when one of the independent variables has an endogeneity issue. We use the ARDL model below to examine the association among the given variables.

$$\ln\Delta\gamma_t = \delta_0 + \ln\delta_1\gamma_{t-1} + \ln\delta_2x_{t-1} + \sum_{i=1}^n \mu_1 \ln\Delta\gamma_{t-i} + \sum_{i=0}^n \mu_2 \ln\Delta x_{t-i} + \varepsilon_t, \quad (3)$$

where γ_t , x_{t-1} , Δ , and \ln , respectively, stand for the variation in the dependent variable, independent variable, difference operator, and the natural logarithm. The symbol ε_1 represents the stochastic term. The general form of the conventional ARDL method is presented in Equation (3), which we have altered by adding our variables to produce Equation (4), which is displayed below:

$$\begin{aligned} \Delta\ln ED_t = & \delta_0 + \delta_1 \ln ED_{t-1} + \delta_2 \ln ER_{t-1} + \delta_3 \ln EC_{t-1} + \delta_4 \ln EP_{t-1} + \delta_5 \ln CPI_{t-1} \\ & + \sum_{i=1}^{n1} \mu_1 \Delta\ln ED_{t-i} + \sum_{i=1}^{n2} \mu_2 \Delta\ln ER_{t-i} + \sum_{i=1}^{n3} \mu_3 \Delta\ln EC_{t-i} \\ & + \sum_{i=1}^{n4} \mu_4 \Delta\ln EP_{t-i} + \sum_{i=1}^{n5} \mu_5 \Delta\ln CPI_{t-i} + \varepsilon_t. \end{aligned} \quad (4)$$

Traditional Nonlinear ARDL Approach

The Autoregressive Distributed Lag approach (Equation 4) uses the symmetric method, which assumes that the dependent and independent variables have a symmetrical relationship. However, according to recent research, numerous monetary variables may have a nonlinear (asymmetric) nexus (Golit, et al., 2019; Shahbaz, et al., 2018). Therefore, we propose the nonlinear ARDL approach, an asymmetric variant of the Autoregressive Distributed Lag method introduced by Shin, et al. (2014). This strategy is illustrated by Equation (5):

$$\ln ED_t = \delta_0 + \delta_1 \ln ER_t^+ + \delta_2 \ln ER_t^- + \delta_3 \ln EC + \delta_4 \ln EP + \delta_5 \ln CPI + \varepsilon_t. \quad (5)$$

In Equation (5), the sum of the partial series of the exchange rates' positive and negative oscillations are represented by the variables $\ln ER_t^+$ and $\ln ER_t^-$ respectively. Concurrently, economic activity is utilized as a control variable and represented by EC. Many researchers (including Adewuyi, 2016; Bahmani-Oskooee & Mohammadian, 2018; Liddle & Sadorsky, 2020; Meo, et al., 2018; Omoke, et al., 2020; Shin, et al., 2018; Uche, 2019) have employed this method to produce the proportional addition of negative and positive influences. Shin, et al. (2014) explained how to do this. Equations (6A) and (6B) provide the following representations of it:

$$\ln ER_t^+ = \sum_{i=1}^t \Delta\ln ER_t^+ = \sum_{i=1}^t \max(\Delta\ln ER_i, 0); \quad (6A)$$

and

$$\ln ER_t^- = \sum_{i=1}^t \Delta\ln ER_t^- = \sum_{i=1}^t \min(\Delta\ln ER_i, 0), \quad (6B)$$

here $\ln ER_t = \ln ER_0 + \ln ER_t^+ + \ln ER_t^-$.

The exchange rate's long-term coefficients for the energy demand partial sum series, both positive and negative differences, are obtained from these equations and are represented by the symbols δ_1 and δ_2 , respectively. δ_0 denotes the coefficient for the dependent variable. Additionally, the coefficients for the control variables—such as inflation, energy prices, and economic activity—are represented by δ_3, δ_4 , and δ_5 .

For empirical computation, we establish a long-run Equation (7) according to Shin, et al. (2014)'s Nonlinear ARDL framework, as follows:

$$\begin{aligned} \Delta \text{LnED}_t = & \delta_0 + \delta_1 \text{LnED}_{t-1} + \delta_2 \text{LnER}_{t-1}^+ + \delta_3 \text{LnER}_{t-1}^- + \delta_4 \text{LnEC}_{t-1} + \delta_5 \text{LnEP}_{t-1} \\ & + \delta_6 \text{LnCPI}_{t-1} + \sum_{i=1}^{n1} \mu_1 \Delta \text{LnED}_{t-i} + \sum_{i=0}^{n2} (\mu_2^+ \Delta \text{LnER}_{t-i}^+ + \mu_3^- \Delta \text{LnER}_{t-i}^-) + \sum_{i=0}^{n3} \mu_4 \Delta \text{LnEC}_{t-i} \\ & + \sum_{i=1}^{n4} \mu_5 \Delta \text{LnEP}_{t-i} + \sum_{i=1}^{n5} \mu_6 \Delta \text{LnCPI}_{t-i} + \varepsilon_t. \end{aligned} \quad (7)$$

In this instance, the AIC criterion helps us find the lag length, which is found to be two in our case. $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$, and δ_6 represent the factors' long-term coefficients, which are made up of partial sums of favorable and unfavorable exchange rates. Furthermore, the control variables are denoted by δ_4, δ_5 , and δ_6 ; the intercept's coefficients are represented by δ_0 .

The energy conversion multiplier, or Equation (8), is a representation of the process of nonlinear transformation, which has the following expression:

$$m_h^+ = \sum_{j=0}^h \frac{\partial \text{LnED}_{t+j}}{\partial \text{LnER}_t^+}, \quad m_h^- = \sum_{j=0}^h \frac{\partial \text{LnED}_{t+j}}{\partial \text{LnER}_t^-}, \quad h = 0, 1, 2, \dots, \quad (8)$$

We note that as $h \rightarrow \infty, m_h^+ \rightarrow \alpha_1$ and $m_h^- \rightarrow \alpha_2$.

MTANARDL model with quintile breakdown for exchange rates:

We examine this relationship utilizing the MTNARDL (multiple threshold nonlinear autoregressive distributed lag) method, which is consistent with studies and our previous theories that exchange rates may have a small and significant effect on energy demand. These studies include Hashmi, et al. (2021b) and Pal and Mitra (2015, 2016, 2019). Using this method, there are five fractional addition series that make up the exchange rate variable:

$$\text{ER}_t^i = \text{ER}_0^i + \text{ER}_t^i(\eta_1) + \text{ER}_t^i(\eta_2) + \text{ER}_t^i(\eta_3) + \text{ER}_t^i(\eta_4) + \text{ER}_t^i(\eta_5). \quad (9)$$

The 80th, 60th, 40th, and 20th quintiles are used to construct the proportional addition series as the bases for exchange rate fluctuations. In Equation (9), they are designated as thresholds, $\text{ER}_t^i(\eta_1), \text{ER}_t^i(\eta_2), \text{ER}_t^i(\eta_3), \text{ER}_t^i(\eta_4)$, and $\text{ER}_t^i(\eta_5)$, respectively, characterized by T_{80}, T_{60}, T_{40} , and T_{20} . The following formulas are used to estimate these thresholds:

$$ER_t^i(\eta_1) = \sum_{j=1}^t \Delta ER_t^i(\eta_1) = \sum_{j=1}^t \Delta ER_j^i I\{\Delta ER_j^i > T_{80}\}; \quad (10A)$$

$$ER_t^i(\eta_2) = \sum_{j=1}^t \Delta ER_t^i(\eta_2) = \sum_{j=1}^t \Delta ER_j^i I\{T_{80} \geq \Delta ER_j^i > T_{60}\}; \quad (10B)$$

$$ER_t^i(\eta_3) = \sum_{j=1}^t \Delta ER_t^i(\eta_3) = \sum_{j=1}^t \Delta ER_j^i I\{T_{60} \geq \Delta ER_j^i > T_{40}\}; \quad (10C)$$

$$ER_t^i(\eta_4) = \sum_{j=1}^t \Delta ER_t^i(\eta_4) = \sum_{j=1}^t \Delta ER_j^i I\{T_{40} \geq \Delta ER_j^i > T_{20}\}; \quad (10D)$$

$$ER_t^i(\eta_5) = \sum_{j=1}^t \Delta ER_t^i(\eta_5) = \sum_{j=1}^t \Delta ER_j^i I\{\Delta ER_j^i \leq T_{20}\}. \quad (10E)$$

The indicator functions $I\{T\}$ returns one in cases where the condition in Equations (10A) through (10E), the curly brackets are met; in other cases, they are zero. Equation (11) uses quintiles to represent exogenous variables to demonstrate the nonlinear ARDL approach:

$$\begin{aligned} \Delta LnED_t = & \delta_0 + \delta_1 LnED_{t-1} + \delta_2 LnEC_{t-1} + \delta_3 LnEP_{t-1} + \delta_4 LnCPI_{t-1} \\ & + \sum_{j=1}^5 \delta_k LnER_{t-1}^i(\eta_1) + \sum_{i=1}^{n1} \mu_1 \Delta LnED_{t-j} + \sum_{i=1}^{n2} \mu_2 \Delta LnEC_{t-j} + \sum_{i=1}^{n3} \mu_3 \Delta LnEP_{t-j} \\ & + \sum_{i=1}^{n4} \mu_4 \Delta LnCPI_{t-j} + \sum_{j=1}^5 \sum_{i=0}^{n3} \mu_k LnER_{t-j}^i(\eta_1) + \varepsilon_t, \quad k = j + 4. \end{aligned} \quad (11)$$

The cointegration of the long-run variables is tested using Equation (11) and the null hypothesis, where it is assumed that the coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7, \delta_8$, and δ_9 are all equal to zero. The bound tests' critical values are derived from Pesaran, et al. (2001) and have been applied in several earlier research projects, including Hashmi, et al. (2021a), Verheyen (2013), and Pal and Mitra (2015, 2016, 2019). The long-run and short-term imbalance HO null hypotheses can be tested using the following hypotheses: $\delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9$ and HO: $\mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9$ respectively.

Several Thresholds ARDL method that is nonlinear and disintegrates the exchange rate in deciles:

Ten fractional addition series represent a development of the nonlinear ARDL methodology, the multiple threshold nonlinear ARDL method, which considers the exchange rate. This method allows for a more thorough analysis of the exchange rate's effects on energy demand, from very small to huge variations in the exchange rates. The multiple threshold ARDL approach with deciles is shown below in Equation (12).

$$\begin{aligned} \Delta LnED_t = & \delta_0 + \delta_1 LnED_{t-1} + \delta_2 LnEC_{t-1} + \delta_3 LnED_{t-1} + \delta_4 LnEC_{t-1} \\ & + \sum_{j=1}^{10} \delta_k LnER_{t-1}^i(\eta_1) + \sum_{i=1}^{n1} \mu_1 \Delta LnED_{t-j} + \sum_{i=1}^{n2} \mu_2 \Delta LnEC_{t-j} + \sum_{i=1}^{n3} \mu_3 \Delta LnEP_{t-j} \\ & + \sum_{i=1}^{n4} \mu_4 \Delta LnCPI_{t-j} + \sum_{j=1}^{10} \sum_{i=0}^{n5} \mu_k LnER_{t-j}^i(\eta_1) + \varepsilon_t, \quad k = j + 4. \end{aligned} \quad (12)$$

In this model, the null hypothesis is that there is no cointegration for the long-run variables, which is $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9 = \delta_{10} = \delta_{11} = \delta_{12} = \delta_{13} = \delta_{14} = 0$. The bounds tests can be estimated using the critical values given by and used by Pesaran, et al. (2001). A number of hypotheses can be used to test the null hypothesis, which states that there is no long- and short-run asymmetry, which is $H_0: \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9 = \delta_{10} = \delta_{11} = \delta_{12} = \delta_{13} = \delta_{14}$ and $H_0: \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9 = \mu_{10} = \mu_{11} = \mu_{12} = \mu_{13} = \mu_{14}$ correspondingly.

Granger Causality in Quantiles Assessment

Furthermore, succeeding the methodology of Anwar, et al. (2021), this research applies the quantile assessment to analyze the quantile causality among the financial activity, energy demand, and the exchange rate. Granger (1969) developed the Granger causality test, which evaluates the causal relationship between the given variables because the dependent variable can be predicted independently. Researchers have extended the Granger causality test over time using various sophisticated techniques.

This research uses as a trajectory $(p_i = p_i^x)' \in R^e, s = 0 + r$, where P_y^i indicates the prior cluster used to demonstrate $P_i P_i^y = (P_i - 1, \dots, P_i - r)$. The quantile assessment used in this investigation is predicated on the identical idea as the Granger causality assessment (Granger, 1969), which states that, for all quantiles, factor x_i does not influence variable y_i . Troster's (2018) test reflects the null hypothesis that no causal relationship exists between Y_i and x_i . The related is given under:

$$H_0^y \rightarrow^x := FX(p_i^x, P_1^y) = FX(p_i^x), \text{ for all } x \in R. \quad (13)$$

The distribution of variable X_i given (p_i^x, P_1^y) is displayed by the tentative distribution variable $FX(p_i^x, P_1^y)$, equation 13's null hypothesis is supported by (Granger, 1969). For all $\pi \in \mathbb{I} \subseteq [X] 0, 1$ this study employs $D_i T$ for the QAR model $m(\cdot)$. The subsequent representation signifies the null hypothesis under the non-Granger causality assessment:

$$QAR(1): m^1(P_i^x, \partial(\pi)) = Y_1(\pi) + y_2(\pi)Y_{i-1} + \mu_t \vartheta - \sigma_1(\pi). \quad (14)$$

To calculate the coefficient, maximum likelihood is utilized in Equation (14), represented by $\partial = (\pi) = y_1(\pi), y_2 = (\pi)$, and μ_t , based on similarities between point quantities. Furthermore, $\partial_\sigma^{-1}(\pi)$ represents the conventional primary distribution function's reverse. To examine causality, we employ the QAR technique in this study on Equation (13), adding delays to alternative variables. Lastly, the following is the expression for both equation 15 and the fundamental equation of QAR (1):

$$Q_\pi^x(P_i^x, P_1^y) = y_1(\pi) + y_2(\pi)X_{i-1} + \vartheta(\pi)Y_{i-1} + \mu_t \vartheta^{-1}(\pi). \quad (15)$$

4. Finding analysis and discussion

In this investigation, Canada, Italy, Germany, the US, Japan, France, and the UK are among the economies whose energy demand is examined about exchange rates. The multiple threshold nonlinear

ARDL (MTNARDL) approach is a robust methodology used to accomplish this. We contrast the outcomes of this methodology with the traditional nonlinear autoregressive distributive lag method. Using this methodology, we examine the effects of small to significant changes on dependent variables by the exogenous variables. Lastly, this research utilizes the Granger causality in the quantile assessment for robustness purposes, which was developed by Troster (2018).

When using the approaches mentioned above, the order of the integration of the variables should be either one $I(1)$ or zero $I(0)$. Therefore, we first run KPSS and Augmented Dickey-Fuller (ADF) assessment to ascertain the integration order of variables order before utilizing the multiple threshold nonlinear ARDL (MTNARDL) method. Table 2 displays the test results of the ADF and KPSS test statistics. The results of the ADF estimation indicate that the null hypothesis is acknowledged for the utmost of the factors at the level except for the US's energy demand, the UK's exchange rate, and financial activity. However, for every other country, the null hypothesis is rejected.

The ADF test indicates that each variable is integrated of either order one $I(1)$ or zero $I(0)$. The KPSS assessment results support the identical supposition. Furthermore, the authors employ the structural break unit root test to account for structural breaks. The test results obtained using Zivot Andrews tests also provide the same conclusion. For brevity, these results are accessible from authors upon practical demand.

As a whole, both assessments satisfy the methodology's prerequisites we applied to conduct this research, which permits us to move forward with assessing the short—and long-term effect of exchange rates on energy demand. The robust MTNARDL technique enables us to more thoroughly examine exchange rate effects on the energy demand of the economies under study, offering insights into the actions of even the smallest to largest fluctuations in exchange rates.

Cheng, et al. (2021, 2022) examined the issue of spurious relationships in nearly non-stationary series and statistical anomalies that can cause significant regressions to be misinterpreted as insignificant. Their findings highlight the importance of conducting unit root tests to ensure stationarity before performing regression and correlation analysis. Similarly, Wong, et al. (2024) and Wong and Yue (2024) discussed the implications of mixed integration orders ($I(0)$ and $I(1)$ variables) in regression models, demonstrating that traditional test statistics may be invalid under such conditions. Additionally, Wong, et al. (2024a, 2024b, 2024c) extended this discussion by providing empirical cases where spurious relationships arise due to non-stationary variables. To validate the models used in econometric analysis, Hui, et al. (2017) proposed a new nonlinearity test that overcomes the limitations of the Volterra expansion, emphasizing the necessity of conducting diagnostic tests, such as the Durbin-Watson test, to confirm the robustness of regression results.

Table 2. Unit root test at the level and first difference

Variables	ADF at level	ADF at first difference	KPSS at level	KPSS at first difference
Canada				
CPI	-1.199	-9.465***	0.923***	0.474
EP	-2.339	-8.334***	0.587**	0.298
EC	-1.199	-9.465***	0.923***	0.474

ER	-2.339	-8.334***	0.587**	0.298
ED	-1.522	-5.432***	2.645***	0.199
France				
CPI	-1.259	-10.845***	0.763***	0.544
EP	-2.419	-9.354***	0.847**	0.358
EC	-0.634	-2.996**	0.497**	0.410*
ER	-1.221	-5.918***	1.664***	0.069
ED	-2.434	-2.718*	0.301	0.176
Germany				
CPI	-1.889	-10.575***	0.985***	0.574
EP	-2.549	-9.454***	0.574**	0.358
EC	-0.319	-3.567**	2.768***	0.201
ER	-0.401	-4.089***	2.113***	0.429
ED	-0.145	-5.043***	2.005***	0.218
Italy				
CPI	-1.239	-9.385***	0.863***	0.544
EP	-2.459	-8.454***	0.747**	0.358
EC	-1.612	-5.234***	0.095	0.501*
ER	-2.172	-5.995***	0.179	0.193
ED	-1.213	-4.001***	2.954***	0.310
Japan				
CPI	-1.289	-9.685***	0.863***	0.531
EP	-2.749	-8.414***	0.747**	0.541
EC	-2.498	-4.687***	3.967***	1.109
ER	-1.335	-3.001**	2.869***	1.00
ED	-1.632	-2.998**	2.465***	0.345
UK				
CPI	-1.279	-9.565***	0.853***	0.544
EP	-2.549	-8.414***	0.747**	0.358
EC	-4.712**	-9.756***	2.576***	0.098
ER	-2.796*	-5.234***	1.465***	0.312
ED	-0.399	-5.997***	2.453***	0.076
US				
CPI	-1.249	-10.845***	0.745***	0.744
EP	-2.419	-8.514***	0.587**	0.298
EC	-1.866	-5.123***	2.164	0.342
ER	-1.497	-5.998***	0.889***	0.219
ED	-3.421***	-4.097***	2.194***	0.310

Note: This Table shows the findings of the Augmented Dickey-Fuller and KPSS assessments completed at the determinant level and the first difference. The Augmented Dickey-Fuller assessment examines the presence of a unit root in the data, in contrast, the KPSS assessment examines for stationarity. The ADF assessment rejects the unit root null hypothesis, and the stationarity null hypothesis is rejected by the KPSS, illustrating that the variables possess stationarity conditions. The level of significance 10%, 5%, and 1% is indicated by ***, **, and *, correspondingly.

Table 3 displays the estimates obtained from the bounds tests for the ARDL, NARDL, and MTNARDL approaches. Panel A shows the outcomes according to the ARDL methodology; Panel B displays the results according to the NARDL methodology; Panel C illustrates the results of the bounds test employing the MTNARDL technique with quintile series; Panel D shows the results based on the MTNARDL approach using decile series. Panel E displays the test critical values' lower and upper bounds for each approach used in this study. The results of the bounds tests for the nonlinear ARDL

and ARDL techniques reveal the insignificant coefficients of all economies except Germany. However, the majority of the coefficients become significant when the MTNARDL approach is used, highlighting the benefit of this method, which was first proposed by Pal and Mitra (2015, 2016).

Table 3. Estimates of bound tests for the energy demand methodology

	US	UK	Japan	Italy	Germany	France	Canada
Panel A: Autoregressive Distributive Lag approach							
F-Statistic	2.883	0.501	1.865	0.892	5.124**	1.998	1.995
Panel B: Nonlinear Autoregressive Distributive Lag approach							
F-Statistic	2.768	2.112	2.641	2.183	5.11**	2.21	2.165
Panel C: Multiple Threshold Nonlinear Autoregressive Distributive Lag approach with quintile							
F-Statistic	6.539***	3.754**	1.967	3.645**	5.567***	3.768**	3.345*
Panel D: MTNARDL model with decile							
F-Statistic	5.231***	6.352***	2.769	5.342***	5.697***	3.297**	2.994*
Panel E: Critical values of Bounds test							
	1%		5%		10%		
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
MTNARDL Approach with decile	2.35	2.95	2.12	2.86	1.87	2.99	
MTNARDL Model with quintile	2.86	3.99	2.78	3.97	2.45	3.25	
NARDL model	4.88	3.11	5.23	4.15	5.05	3.98	
ARDL model	4.95	5.68	5.10	5.91	4.12	5.23	

Note: This Table displays the ARDL, NARDL, and MTNARDL techniques' bounds test results. The bounds test results for the ARDL approach are shown in Panel A, while those for the NARDL approach are shown in Panel B. The results of Panel C show a series of quintiles, while Panel D shows a series of deciles representing the MTNARDL method. Panel E displays the critical values for the lower bound (I(0)) and upper bound (I(1)) at the 1%, 5%, and 10% significance levels. Null hypothesis rejection at 10%, 5%, and 1% significance levels is represented by the symbols *, **, and ***, respectively.

The Autoregressive Distributive Lag (ARDL) model's results are shown in Table 4, where panels A and B display the long-run and short-run coefficients, respectively. The results of diagnostic tests like the Ramsey Reset test and DW test statistics are mentioned in Panel C, which is used to check the model specification and serial correlation. The results show that economic activity and exchange rates have a significant effect on the energy demand in Italy, Japan, and the UK in the short run. Moreover, in the short run, the exchange rate significantly affects energy demand in the context of Germany, Canada, and the US. Moreover, the demand for energy in France is significantly influenced by economic activity.

The bound test result is insignificant for all other states in the long run, except Germany. Findings indicate that in every nation, the demand for energy is positively impacted by economic activity, whereas exchange rates hurt all but Germany's economy. Energy demand has been found to increase in Germany in response to an increase in the exchange rate or local currency appreciation. The diagnostic assessments display that the Ramsey Reset and DW assessments do not reject the null hypothesis that there is no serial correlation. The CUSUM and CUSUMQ tests indicate that the model

is stable. The ECM verifies the speed of adjustment, and the adjusted R square specifies a well-fitting approach.

Table 4. Results from the Autoregressive Distributive Lag approach

	US	UK	Japan	Italy	Germany	France	Canada
Panel A: Coefficients of Short-run							
$\Delta \ln ED(-1)$	0.601***	0.552***	0.497***	0.902** *	0.587	0.389***	0.712***
$\Delta \ln EC$	1.024	1.299***	-1.096	-1.093***	-1.201***	1.092***	-1.213
$\Delta \ln ER$	0.012	-0.214***	-0.052***	0.210***	-0.073	-0.021	-0.012
$\Delta \ln ER(-1)$	0.011	0.084***	0.019	0.087***	0.054	0.023	-0.021
$\Delta \ln CPI$	-0.353	0.084***	-0.341***	0.225***	-0.089	0.287***	0.035
$\Delta \ln EP$	0.024	-0.082***	-0.53***	-0.513	-0.344***	-0.511	-0.051
$\Delta \ln EC(-1)$	0.035	-0.042	0.217**	-0.185**	0.111	-0.201**	0.012
$\Delta \ln EP(-1)$	0.041	0.089***	0.025	0.095***	0.047	0.064	-0.035
$\Delta \ln CPI(-1)$	1.085	1.257**	-1.412	1.521	-1.141**	1.025	-1.251**
Panel B: Coefficients of Long-run							
$\ln EC$	0.115***	0.498	0.131	0.459***	0.483** *	0.451***	0.326***
$\ln ER$	1.011	-1.701	-1.069	-1.356*	-1.221***	-1.013	-2.321**
$\ln EC$	1.386***	1.481***	1.473***	1.474***	1.141	1.748	1.155***
$\ln ER$	1.011	-1.701	-1.859	-1.416*	-1.541***	-1.103	-1.381**
Panel C: Diagnostics							
DW	1.013	1.343	0.987	2.446*	2.231	1.145	1.087
Reset	1.889	3.543**	2.567*	2.987**	2.114	3.451*	3.01*
CUSUMQ	U	S	S	U	U	S	U
CUSUM	S	U	U	S	S	U	S
Adj. r^2	0.321	0.516	0.453	0.282	0.758	0.416	0.299
ECM	-0.106**	-0.134*	-0.181***	-0.035	-0.105*	-0.015	-0.123**

Note: The ARDL technique's results are shown in this Table, along with short- and long-term statistics and the diagnostic tests (the Ramsey Reset Test and DW checks for method specification and correlation between serial numbers) provided in the panels A, B, and C. Stability of the method is also tested using CUSUM and CUSUMQ estimates. The model's fitness level and rate of adjustment are validated by the ECM and Adj.r². Coefficient significance is indicated by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively.

Table 5 displays the estimations of the nonlinear ARDL technique. Panels A, B, and C display the short-run coefficients, diagnostic test statistics, and long-run coefficients in that order. To ascertain whether the exchange rate has an asymmetric influence, ER+ and ER- are the two exchange rate series that have a symmetric influence on these economies' energy consumption. The coefficients in the short run for both positive and negative fluctuations in the exchange rate are generally small in Canada, Germany, the US, and France, indicating the balanced impact of exchange rates on the need for energy. Our results conflict with those of other studies (Gohar, et al., 2022b, 2022c, 2023; Wang, et al., 2022); few prior studies (Noman, et al., 2023; Peng, et al., 2022) corroborate our findings. In other nations, such as Italy, Japan, and the UK, exchange rates unevenly affect energy demand. In these economies, the energy demand is not significantly affected by a decline in the exchange rate, but it is significantly affected by an increase in the exchange rate. The data indicates that when the local currency appreciates, the demand for energy does not change.

The results show that since exchange rates affect energy demand, policy decisions should be modified when the local currency depreciates. According to the bounds test results, the long-term impacts on

energy usage by exchange rates are negligible for all states except Germany. Long-term data indicate that a decline in the currency rate significantly impacts the energy demand. In Germany's case, however, an increase in the exchange rate has negligible effects, indicating an asymmetric impact.

The appropriate application of the Wald_{LR} and Wald_{SR} estimations has revealed both long-run and short-run asymmetry, as demonstrated by the testing approximations in Table 5's Panel C. The assumption of a symmetric impact is the null hypothesis for both long- and short-term asymmetry. As previously mentioned, the short-run results in Italy, the UK, and Japan all confirm the asymmetric impact in their respective economies and dispute the null hypothesis. However, in the case of Germany alone, the Wald estimate supports the asymmetric impact.

Table 5. Outcomes of the Nonlinear ARDL Method

	US	UK	Japan	Italy	Germany	France	Canada
Panel A: Coefficients of Short-run							
$\Delta \ln ER^+$	0.012	-0.21***	-0.08***	-0.08***	-0.051	-0.019	-0.021*
$\Delta \ln ED(-1)$	0.854***	0.532***	0.929***	0.764***	0.512***	-0.51***	0.528***
$\Delta \ln ER^+(-1)$	0.205***	0.012	0.088***	0.066***	0.059	0.021	0.011
$\Delta \ln ER^-$	-0.015	-0.014	-0.043	0.012	-0.039	-0.021	-0.069
$\Delta \ln EC$	-0.311	0.085***	-0.22***	0.319***	-0.059	0.44***	0.021*
$\Delta \ln ER^-(-1)$	-0.012	-0.031	0.062	0.059	-0.051	-0.021	0.022
$\Delta \ln EC(-1)$	0.011-	0.021	0.079	0.084***	0.076***	0.215***	0.022
$\Delta \ln EP$	0.020	-0.231**	0.081	-0.286**	0.523***	-0.029	0.013
$\Delta \ln CPI$	0.037	0.24***	-0.049	0.241***	-0.04***	0.054***	-0.453
$\Delta \ln CPI(-1)$	0.095	-0.512	0.241**	-0.251**	0.528	-0.271**	0.024
$\Delta \ln EP(-1)$	-0.057	0.044	0.067	0.094***	0.045	0.079***	0.051
Panel B: Coefficients of Long-run							
$\ln EC$	1.301***	-1.222	1.198	1.765***	1.322***	1.554**	1.294***
$\ln ER^-$	0.218	-2.854	0.049	-1.112	-0.887***	0.201	-0.199
$\ln ER^+$	-0.31***	0.021	0.059	0.712***	-0.201	0.321	0.051
$\ln CPI$	0.094	-0.812	0.244**	-0.351**	0.527	-0.371**	0.054
$\ln EP$	0.047	0.34***	-0.059	0.251***	-0.05***	0.014***	-0.443
Panel C: Diagnostics							
DW	1.123	2.008	2.123	1.897	0.995	0.798	0.498
Reset	1.71	1.99**	1.432	2.001	1.182	5.001	1.899*
CUSUMQ	U	U	U	U	S	S	S
ECM	-0.055***	-0.009***	-0.039**	-0.019**	-0.097***	-0.033*	-0.031**
CUSUM	S	S	S	S	S	S	U
Wald _{SR}	1.234	1.643	1.748	4.124***	6.553***	3.234***	1.786
Adj. r^2	0.124	0.765	0.423	0.756	0.645	0.632	0.321
Wald _{LR}	1.912	1.223	6.432***	4.532**	1.984	1.245	1.876

Note: The NARDL technique results for panels A, B, and C's short-, long-, and diagnostic statistics are shown in this Table. The description of the model and serial correlations are tested using the Ramsey Reset and DW assessments; the CUSUMQ and CUSUM assessments confirm the constancy of the approach; Adj and ECM examine the adjustment speed and fitness of the approach. In the short-run and long-runs, the coefficients' statistical significance at 10%, 5%, and 1%, correspondingly, is indicated by significance levels of *, **, and *** in the Wald_{LR} and Wald_{SR} tests of the null symmetry hypothesis.

Tables 6 and 7 display the findings of the MTNARDL (Multiple Threshold Nonlinear ARDL) method. The quintile group's results are shown in Table 6, and the decile group's results are displayed in Table 7. Panels A, B, and C of the two tables display the outcomes of the long-run, short-run, and diagnostic

tests in that order. The exchange rate has five fractional additions, as shown in Table 6, where the symbols indicate the lowest and highest returns through $ER\eta_5$. The short-run coefficients show that the energy consumption of Canada, the US, Germany, and France is affected symmetrically. However, the coefficients show that the impact is uneven in the UK, Japan, and Italy. Lower quintiles and upper quintiles hardly affect the amount of energy consumed by the exchange rate ($ER\eta_4$ to $ER\eta_5$); however, it has a significant impact. The asymmetric impact in the UK, Japan, and Italy is supported by the Wald test short-run results (WaldSR), which are displayed in Panel C.

The ARDL approach with multiple threshold nonlinearity shows that all economies, except the UK, exhibit asymmetric impact. In contrast, only Germany is suggested to have an asymmetric impact by the nonlinear ARDL approach. Canada exhibits an impact at $ER\eta_1$, $ER\eta_2$, and $ER\eta_5$, France exhibits an impact at $ER\eta_3$ and $ER\eta_4$, and Germany exhibits an impact at $ER\eta_4$. Depending on the exchange rate series, the impact changes. The energy demand in Italy is negatively impacted at the upper quintile and significantly positively impacted at the lower quintile. Panel C supports the asymmetric impact of the Wald test long-run (WaldLR) in all economies except the UK.

Table 6. Outcomes from the MTNARDL technique with the quintiles series

	US	UK	Japan	Italy	Germany	France	Canada
Panel A: Coefficients of Short-run							
$\Delta \ln EC$	0.019	0.41***	-0.021	0.312***	-0.26***	0.079***	-0.254
$\Delta \ln EC(-1)$	-0.018	-0.111	0.078	-0.20***	0.214***	-0.021	0.048
$\Delta \ln EP$	-0.41**	-0.099	0.296*	-0.273	1.295	-0.031	0.299
$\Delta \ln EP(-1)$	0.003	0.089**	0.213***	0.312	0.019	0.025	0.098**
$\Delta \ln CPI$	0.21	0.159	0.199*	0.703	-0.145	-0.051	0.402
$\Delta \ln CPI(-1)$	-0.028	-0.181	0.048	-0.25***	0.224***	-0.024	0.047
$\Delta \ln ER\eta_5(-1)$	0.007	0.031	0.051	0.145***	0.056**	0.089***	-0.023
$\Delta \ln ER\eta_5$	-0.009	-0.012	0.061	-0.29***	-0.07***	-0.21***	-0.021
$\Delta \ln ER\eta_4(-1)$	-0.019	-0.079	0.089	-0.298	0.202*	0.089**	-0.401**
$\Delta \ln ER\eta_4$	-0.019	0.221	-0.076	2.105**	-0.091	-0.212**	0.311**
$\Delta \ln ER\eta_3(-1)$	-0.31	0.021	0.321**	1.122	0.079	0.097	-0.421
$\Delta \ln ER\eta_3$	0.21	0.159	0.199*	0.703	-0.145	-0.051	0.402
$\Delta \ln ER\eta_2(-1)$	-0.41**	-0.099	0.296*	-0.273	1.295	-0.031	0.299
$\Delta \ln ER\eta_2$	0.198	-0.203	0.201	0.038	-1.636**	-0.164	0.049
$\Delta \ln ER\eta_1(-1)$	0.043	-0.051	0.071	0.052	-0.048	-0.021	0.032
$\Delta \ln ER\eta_1$	-0.032	-0.089*	0.023	-0.031	-0.009	-0.012	0.011
$\Delta \ln ED(-1)$	0.642***	0.935***	0.959***	0.765***	0.545***	0.396***	-0.51***
Panel B: Coefficients of Long-run							
$\ln CPI$	-0.45	-0.34**	0.234*	-0.533	1.345	-0.034	0.546
$\ln EP$	-0.51**	-0.089	0.546*	-0.323	1.325	-0.034	0.223
$\ln EC$	0.12***	-0.005	0.019	0.198***	0.022	0.045	-0.019
$\ln ER\eta_5$	-0.019**	-0.019	0.020	-0.123***	-0.023	-0.034	0.021
$\ln ER\eta_4$	0.003	0.089**	0.213***	0.312	0.019	0.025	0.098**
$\ln ER\eta_3$	0.009	-0.285**	-0.021	1.501*	0.005	-0.021	0.543***
$\ln ER\eta_2$	-0.019**	-0.021	0.022	0.319***	-0.652**	0.031	0.019
$\ln ER\eta_1$	-0.2***	0.019	-0.31***	0.186**	-0.034	-0.051*	-0.030
Panel C: Diagnostics assessment							
DW	1.312	1.123	1.987	3.11	0.856	3.005	1.713

Reset	0.5498	21.31***	3.132*	4.342**	2.643**	6.321	1.110
Wald _{SR}	0.879	0.478	0.887	3.213***	1.921*	10.54***	1.008
Wald _{LR}	4.56***	5.324***	5.11***	5.673***	2.432**	2.001	4.553***
Adj. r ²	0.313	0.701	0.392	0.987	0.514	0.727	0.401
ECM	-0.19***	-0.31***	-0.41***	-0.432***	-0.432***	-0.423***	-0.434***
CUSUM	S	S	S	S	S	U	S
CUSUMQ	U	U	U	S	S	S	S

Note: The MTNARDL method's results are in the Table's deciles (ER 1 to ER 5). The short-run findings are displayed in Panel A, the long-run findings are displayed in Panel B, and the diagnostic assessment is displayed in Panel C. While the CUSUM and CUSUMQ assessments—the ECM & Adj—assure the stability of the approach, the DW and Ramsey Reset assessments investigate the serial correlations and the description of the approach. The statistics of R2 are utilized to assess the fitness of the approach and speed of adjustment, respectively. In both the long and short runs, the symmetry null hypothesis is tested by WaldLR and WaldSR. Correspondingly, coefficient significance is indicated by ***, **, and * at the 1%, 5%, and 10% significance levels.

To verify the accuracy of our findings, we employed a range of deciles and the multiple threshold nonlinear ARDL technique. The outcomes are shown in Table 7. The short-term conclusions found in Table 7 corroborate Table 6's findings. Moreover, asymmetric effects were found for all economies except the UK in the long-term results of using a series of deciles in the ARDL approach with multiple threshold nonlinearity. Earlier research has also obtained similar outcomes (Chang, et al., 2022a, 2022b; Maydybura, et al., 2022). The method's resilience is highlighted when the exchange rate series is split into deciles.

Table 7. MTNARDL technique's findings with decile series

	US	Japan	Italy	Germany	France	UK	Canada
Panel A: Coefficients of Short-run							
$\Delta \ln \text{CPI}(-1)$	-1.399*	-1.210	-1.089	-1.222	2.897	-1.201	-0.032
$\Delta \ln \text{CPI}$	-1.056	1.132	-1.213	2.111**	-0.021	-0.324***	0.108
$\Delta \ln \text{EP}$	-1.065	1.197	1.333	7.352	1.301	1.091	-0.044
$\Delta \ln \text{EP}(-1)$	0.079	-0.456	-1.399*	0.598	1.402	1.079	-1.521**
$\Delta \ln \text{EC}(-1)$	-1.089	-1.021	1.082	-1.313*	1.213***	-1.008	0.031
$\Delta \ln \text{EC}$	1.043	1.299	-1.215	1.213**	-1.324***	1.094***	-1.312**
$\Delta \ln \text{ER}_{10}(-1)$	0.045	0.021	0.042	0.081***	0.029*	0.046*	-0.011
$\Delta \ln \text{ER}_{10}$	-0.034	-0.002	-0.069	-0.08***	-0.081***	-0.333***	0.030
$\Delta \ln \text{ER}_9(-1)$	0.023	-0.049	0.059	0.214	0.069	0.046	-0.321
$\Delta \ln \text{ER}_9$	-0.087*	0.056	-0.31***	-0.019	0.059	-0.201***	0.210
$\Delta \ln \text{ER}_8(-1)$	0.078	-0.289	0.324**	-0.435	0.319**	0.004	-0.423**
$\Delta \ln \text{ER}_8$	-0.056	0.132	-0.213	2.111**	-0.021	-0.324***	0.108
$\Delta \ln \text{ER}_7(-1)$	0.049	-0.007	0.243	312.456	0.125	0.041	-0.199
$\Delta \ln \text{ER}_7$	-0.098	0.025	-0.234	197.543	-0.029	-0.244	0.215
$\Delta \ln \text{ER}_6(-1)$	-0.065	0.197	0.333	5.352	0.301	0.091	-0.044
$\Delta \ln \text{ER}_6$	0.049	-0.215	-0.289	-5.763	0.221	-0.055	0.059
$\Delta \ln \text{ER}_5(-1)$	-0.401*	-0.024	0.299	1.867	-0.021	-0.079	0.992*
$\Delta \ln \text{ER}_5$	0.079	-0.456	-0.399*	0.598	0.402	0.079	-1.521**
$\Delta \ln \text{ER}_4(-1)$	-0.319	-0.345	0.515	0.301	3.234***	-0.319	1.241
$\Delta \ln \text{ER}_4$	0.289	-0.232	-0.213	-0.899	-1.514*	-0.045	-0.218
$\Delta \ln \text{ER}_3(-1)$	-0.399*	-0.210	-0.089	-0.222	1.897	-0.201	-0.032
$\Delta \ln \text{ER}_3$	0.210	-0.196	-0.324	0.021	4.223*	-0.315	-0.234
$\Delta \ln \text{ER}_2(-1)$	-1.041	1.199	1.278	1.049	-2.334***	1.156**	0.399*
$\Delta \ln \text{ER}_2$	1.098	-1.201	-1.210	1.212	-1.498	1.213	1.598**
$\Delta \ln \text{ER}_1(-1)$	-1.029	-1.046	-1.022	1.051	-1.045	1.069	1.015

$\Delta \ln ER_{\eta_1}$	-1.059	-1.049	-1.007	-1.039	-1.021	1.033	1.105
$\Delta \ln ED(-1)$	0.39***	0.401***	0.501***	0.642***	0.543***	0.522***	0.296***
Panel B: Coefficients of Long-run							
$\ln CPI$	0.001**	-0.52***	0.067	-5.324	0.211	-0.089**	-0.042
$\ln EP$	0.06***	0.214	-0.85***	0.312*	1.923***	-0.318*	-0.402
$\ln ER_{\eta_{10}}$	-0.007	-0.002	0.011	-0.021**	0.019	-0.072**	0.021
$\ln ER_{\eta_9}$	-0.018	0.043*	0.021	0.049	0.009	-0.052*	-0.019
$\ln ER_{\eta_8}$	0.021	0.32***	0.039	0.214	-0.073	0.005	0.079
$\ln ER_{\eta_7}$	-1.019	-1.032	1.051	321.453	1.020	1.004	1.058
$\ln ER_{\eta_6}$	1.001**	-1.52***	1.067	-2.324	2.211	-2.089**	-1.042
$\ln ER_{\eta_5}$	1.03***	-1.501*	-1.031*	1.123**	1.512	-1.056	2.295
$\ln ER_{\eta_4}$	-1.065*	-1.432	1.225**	-1.112	-1.899**	1.091	-1.243
$\ln ER_{\eta_3}$	1.06***	1.214	-1.85***	1.312*	1.923***	-1.318*	-1.402
$\ln ER_{\eta_2}$	1.04***	-1.312	-1.20***	3.321**	0.534***	1.523	2.034
$\ln ER_{\eta_1}$	-1.014	1.079*	-1.018**	1.029	-1.049	-1.039	1.009
Panel C: Diagnostics							
DW	5.678	0.867	3.213	2.321	0.499	3.453	0.201
Reset	0.301	21.45***	6.464***	21.34***	3.001**	5.223***	1.125
Wald _{SR}	0.498	0.765	0.812	1.792*	1.982**	7.332***	1.198
Wald _{LR}	5.33***	3.005**	4.223***	4.322***	5.223***	4.556***	5.764***
ECM	-0.299*	-0.31***	-0.29***	-0.41***	-0.432***	-0.421***	-0.245***
Adj. r^2	0.201	0.723	0.425	0.912	0.499	0.772	0.199
CUSUM	S	S	S	S	S	S	S
CUSUMQ	U	U	S	S	S	S	S

Note: The MTNARDL technique's outcomes are shown in the Table's deciles (from ER 1 to ER 10). The diagnostic test estimation statistics and the short- and long-term findings are presented in Panels A, B, and C. The DW and Ramsey Reset assessments investigate the serial correlations and the description of the approach. The ECM & Adj and the CUSMQ and CUSUM assessments were also applied to certify the technique's steadiness. The statistics of R2 are utilized to assess the fitness of the approach and the speed of adjustment, respectively. In both the long and short runs, the symmetry null hypothesis is tested by WaldLR and WaldSR. Correspondingly, coefficient significance is indicated by ***, **, and * at the 1%, 5%, and 10% significance levels.

In conclusion, our study demonstrates that an ARDL with multiple threshold nonlinearity methods using a range of deciles and quintiles is more helpful for recognizing the notable asymmetric influence of fluctuations in exchange rates on energy consumption. In contrast, the typical nonlinear ARDL approach frequently misses these effects. These results have significant policy ramifications because they show that basing policies on exchange rate fluctuations may have unfavorable effects. Our research also validates the body of current literature, including works by Ali, et al. (2022) and Uche, et al. (2022a). Similar results were also obtained by studies like Hashmi and Chang (2021) and Uche, et al. (2022b).

Table 8. Granger Causality in Quantile Assessment

Quantiles	ΔED_t ↓ ΔEC_t	ΔED_t ↓ ΔER_t	ΔEC_t ↓ ΔED_t	ΔER_t ↓ ΔED_t
Canada				
[0.05–0.95]	1.541 [0.121]	1.125 [0.125]	1.125 [0.125]	22.823*** [0.000]
0.05	12.235*** [0.000]	12.235*** [0.000]	12.235*** [0.000]	12.235*** [0.000]
0.1	14.445*** [0.000]	14.445*** [0.000]	14.445*** [0.000]	12.235*** [0.000]
0.2	3.142 [0.0142]	15.475*** [0.000]	14.445*** [0.000]	14.445*** [0.000]

0.3	1.412 [0.142]	12.235*** [0.000]	12.235*** [0.000]	12.235*** [0.000]
0.4	1.384 [0.125]	3.45 [0.014]	1.412 [0.142]	1.412 [0.142]
0.5	1.341 [0.124]	1.875 [0.124]	21.845*** [0.000]	16.745*** [0.000]
0.6	0.142 [0.242]	3.475 [0.012]	15.475*** [0.000]	18.475*** [0.000]
0.7	0.124 [0.225]	1.955[0.112]	17.785*** [0.000]	17.845*** [0.000]
0.8	1.145 [0.142]	3.485[0.011]	18.845*** [0.000]	18.845*** [0.000]
0.9	1.125 [0.125]	[0.000]]2.475	18.855*** [0.000]	14.348*** [0.140]
0.95	1.142 [0.142]	1.344[0.451]	17.475*** [0.000]	16.384*** [0.000]
France				
[0.05–0.95]				
0.05	1.451 [0.231]	2.334 [0.203]	17.145*** [0.000]	15.445*** [0.000]
0.1	4.432 [0.124]	1.323[0.1424]	19.145*** [0.000]	24.475*** [0.000]
0.2	3.232 [0.0142]	3.415[0.124]	23.145*** [0.000]	14.145*** [0.000]
0.3	1.232 [0.122]	2.475 [0.125]	21.475*** [0.000]	15.145*** [0.000]
0.4	1.564 [0.124]	3.224 [0.014]	15.245*** [0.000]	18.125*** [0.000]
0.5	1.431 [0.125]	1.347[0.124]	17.455*** [0.000]	17.145*** [0.000]
0.6	0.232 [0.242]	3.341 [0.012]	18.415*** [0.000]	16.525*** [0.000]
0.7	0.324 [0.222]	1.974 [0.112]	18.475*** [0.000]	17.148*** [0.000]
0.8	1.235 [0.145]	3.474 [0.013]	17.525*** [0.000]	14.347*** [0.000]
0.9	1.125 [0.123]	2.241[0.143]	14.835*** [0.000]	12.128*** [0.000]
0.95	1.162 [0.143]	1.447 [0.153]	14.415*** [0.000]	18.344*** [0.000]
Germany				
[0.05–0.95]	1.5432 [0.122]	2.341 [0.201]	17.455*** [0.000]	17.145*** [0.000]
0.05	4.745*** [0.00]	1.345 [0.121]	18.415*** [0.000]	16.525*** [0.000]
0.1	6.848*** [0.004]	2.341 [0.11]	18.475*** [0.000]	17.148*** [0.000]
0.2	3.152 [0.0152]	12.747*** [0.000]	17.525*** [0.000]	14.347*** [0.000]
0.3	1.432 [0.146]	2.774 [0.015]	14.835*** [0.000]	12.128*** [0.000]
0.4	1.354 [0.127]	3.750 [0.024]	14.415*** [0.000]	18.344*** [0.000]
0.5	1.331 [0.125]	1.847 [0.144]	21.475*** [0.000]	15.145*** [0.000]
0.6	0.172 [0.246]	3.414 [0.022]	15.245*** [0.000]	18.125*** [0.000]
0.7	0.154 [0.224]	1.957 [0.142]	17.455*** [0.000]	17.145*** [0.000]
0.8	1.155 [0.144]	3.484 [0.021]	18.415*** [0.000]	16.525*** [0.000]
0.9	1.155 [0.127]	2.447 [0.170]	18.475*** [0.000]	17.148*** [0.000]
0.95	1.172 [0.154]	1.347 [0.451]	17.525*** [0.000]	14.347*** [0.000]
Italy				
[0.05–0.95]	1.541 [0.121]	2.384 [0.201]	17.525*** [0.000]	14.347*** [0.000]
0.05	4.872*** [0.00]	1.348 [0.1421]	14.835*** [0.000]	12.128*** [0.000]
0.1	2.318 [0.015]	2.328 [0.1012]	14.415*** [0.000]	18.344*** [0.000]
0.2	3.142 [0.0142]	1.745 [0.15]	21.475*** [0.000]	15.145*** [0.000]
0.3	1.412 [0.142]	12.785*** [0.000]	15.245*** [0.000]	18.125*** [0.000]
0.4	1.384 [0.125]	3.45 [0.014]	17.455*** [0.000]	17.145***[0.000]
0.5	1.341 [0.124]	1.875 [0.124]	18.415*** [0.000]	16.525*** [0.000]
0.6	0.142 [0.242]	3.475 [0.012]	18.475*** [0.000]	17.148*** [0.000]
0.7	0.124 [0.225]	1.955 [0.112]	17.525*** [0.000]	14.347*** [0.000]
0.8	1.145 [0.142]	3.485 [0.011]	18.845*** [0.000]	18.845*** [0.000]
0.9	1.125 [0.125]	2.475 [0.140]	18.855*** [0.000]	14.348*** [0.000]
0.95	1.142 [0.142]	1.344 [0.451]	17.475*** [0.000]	16.384*** [0.000]
Japan				
[0.05–0.95]	[0.201] 1.561]	16.435*** [0.000]	15.855*** [0.000]	[0.05–0.95] 2.344

0.05	4.872*** [0.00]	1.348 [0.1421]	14.835*** [0.000]	12.128*** [0.000]
0.1	2.318 [0.015]	2.328 [0.1012]	14.415*** [0.000]	18.344*** [0.000]
0.2	3.142 [0.0142]	1.745 [0.15]	21.475*** [0.000]	15.145*** [0.000]
0.3	1.412 [0.142]	12.785*** [0.000]	15.245*** [0.000]	18.125*** [0.000]
0.4	1.384 [0.125]	3.45 [0.014]	17.455*** [0.000]	17.145*** [0.000]
0.5	1.343 [0.124]	1.874 [0.124]	23.835*** [0.000]	14.745*** [0.000]
0.6	0.144 [0.244]	3.474 [0.012]	18.425*** [0.000]	16.445*** [0.000]
0.7	0.125 [0.224]	1.955 [0.112]	14.725*** [0.000]	14.865*** [0.000]
0.8	1.146 [0.143]	3.384 [0.011]	13.855*** [0.000]	14.865*** [0.000]
0.9	1.126 [0.124]	2.442 [0.140]	14.855*** [0.000]	17.378*** [0.000]
0.95	1.144 [0.146]	1.33 [0.451]	15.445*** [0.000]	17.354*** [0.000]
UK				
[0.05–0.95]	1.543 [0.122]	2.384 [0.202]	15.345*** [0.000]	15.435*** [0.000]
0.05	4.413*** [0.00]	1.3434 [0.143]	16.425*** [0.000]	15.675*** [0.000]
0.1	2.314 [0.012]	2.333 [0.123]	14.445*** [0.000]	16.345*** [0.000]
0.2	3.143 [0.0122]	1.732[0.124]	14.435*** [0.000]	26.435*** [0.000]
0.3	1.412 [0.143]	8.724*** [0.000]	26.425*** [0.000]	23.325*** [0.000]
0.4	1.322 [0.124]	3.432 [0.013]	23.345*** [0.000]	15.235*** [0.000]
0.5	1.823 [0.123]	13.235*** [0.000]	22.215*** [0.000]	1.323 [0.123]
0.6	0.132 [0.232]	3.432 [0.014]	15.325*** [0.000]	13.335*** [0.000]
0.7	0.123 [0.223]	1.923 [0.115]	13.245*** [0.000]	15.345*** [0.000]
0.8	1.123 [0.142]	3.432 [0.012]	14.455*** [0.000]	13.435*** [0.000]
0.9	1.142 [0.132]	2.432 [0.144]	12.325*** [0.000]	15.348*** [0.000]
0.95	1.123 [0.121]	1.3424 [0.452]	15.445*** [0.000]	16.344*** [0.000]
US				
[0.05–0.95]	1.541 [0.121]	2.384 [0.201]	17.415*** [0.000]	14.895*** [0.000]
0.05	4.412*** [0.00]	1.348 [0.1421]	18.845*** [0.000]	17.875*** [0.000]
0.1	2.318 [0.015]	2.328 [0.10]	17.475*** [0.000]	12.415*** [0.000]
0.2	3.142 [0.0142]	7.745*** [0.000]	19.485*** [0.000]	23.785*** [0.000]
0.3	1.412 [0.142]	8.785*** [0.000]	24.655*** [0.000]	24.845*** [0.000]
0.4	1.384 [0.125]	3.45 [0.014]	23.785*** [0.000]	15.545*** [0.000]
0.5	1.341 [0.124]	1.875 [0.124]	21.845*** [0.000]	16.745*** [0.000]
0.6	0.142 [0.242]	3.475 [0.012]	15.475*** [0.000]	18.475*** [0.000]
0.7	0.124 [0.225]	1.955 [0.112]	17.785*** [0.000]	17.845*** [0.000]
0.8	1.145 [0.142]	3.485 [0.011]	18.845*** [0.000]	18.845*** [0.000]
0.9	1.125 [0.125]	2.475 [0.140]	18.855*** [0.000]	14.348*** [0.000]
0.95	1.142 [0.142]	1.344 [0.451]	17.475*** [0.000]	16.384*** [0.000]

Note: This Table displays the outcomes of the F-statistics attained from the quantile assessment by utilizing Granger causality. The conforming p-values are encircled in square brackets. The null hypothesis rejection of no causation at the 1% significance level is indicated by ***.

In conclusion, our research findings, which are based on the Granger causality test and are shown in Table 8, show that for every quantile, the coefficients are significant. Consequently, our results imply that economic activity and the exchange rate substantially impact energy consumption across all quantiles and at all levels, respectively. However, energy consumption can affect economic activity and exchange rates only at one or two minor quantiles. The findings imply that economic activity and currency valuation, not the other way around, are the main forces behind energy demand.

5. Conclusion and policy implications

The purpose of the study is to examine the nonlinear relationship between energy demand and exchange rates. Currently, available studies fail to consider the asymmetrical dynamics of macroeconomic and financial factors without concentrating on the exchange rate as a factor influencing the energy demand. The present study seeks to fill this difference by separating exchange rates into several quintile and decile series and analyzing the effects of each series on the energy demand. Our study uses the methodology proposed by Pal and Mitra (2015, 2016), who introduced the multiple threshold nonlinear ARDL approach. Moreover, our study also compares the results obtained from this methodology with those of conventional ARDL and nonlinear ARDL methods. Granger causality in the quantile test is also used in this study to analyze the effects across various quantiles for robustness purposes.

Our findings based on the nonlinear ARDL and conventional ARDL methods failed to produce any noteworthy outcomes. Except for Germany, for certain economies, the bounds test for these techniques only revealed an ongoing connection in the variables. Furthermore, only short-term nonlinear impacts were supported by the estimates from the nonlinear ARDL approach in the UK, Japan, and Italy. However, only in these three economies was the short-run nonlinear impact evident, according to the multiple threshold nonlinear ARDL approach. On the other hand, the long-term impact for all economies varied significantly when employing a range of deciles in the multiple threshold nonlinear ARDL technique.

Furthermore, the study discovers that in Italy, Japan, and the UK, the influence of exchange rates on energy demand is uneven, with an enhancement in the exchange rate significantly influencing the demand for energy. A diminishing exchange rate, however, has negligible consequences. As a result, decision-makers should consider putting measures in place to lessen the detrimental effects of currency depreciation on these economies' energy demand. Furthermore, this study's results indicate that, when using the ARDL approach with multiple threshold nonlinearity, how changes in the exchange rate, from small to large, affect the energy demand may go unnoticed by the conventional nonlinear ARDL approach. Lastly, our findings imply that the effect varies across different quantiles based on the Granger causality in the quantile test. Overall, the findings of this study aid in developing more effective policies that consider how changes in exchange rates affect energy demand.

Several policy recommendations are derived from our study. First, the results of our study assist policymakers in G7 nations in developing appropriate trade policies by providing a better understanding of how changes in exchange rates affect their energy imports and exports. Second, over the next few decades, it is anticipated that the energy needs of these nations will rise dramatically. The study's results help policymakers understand how exchange rate variations influence energy demand. More precisely, our results indicate what suitable policies should be developed during small as well as substantial changes in the exchange rates. Third, the results also have an impact on the rate of economic expansion in these nations. Since energy is a necessary component of economic activity, energy changes consumed can impact economic expansion. Policymakers can use the findings of our study to gain a deeper comprehension of the connection between economic growth, exchange rates, and energy demand to develop policies that will minimize any adverse effects. Fourth, exchange rate swings may

impact foreign investment in these nations. If exchange rate volatility raises risks, investors may be discouraged from investing in a given nation. Thus, the results of our study may aid policymakers in these nations in comprehending the connection between energy demand and exchange rates and formulating strategies to invest in foreign capital.

5.1 Limitations and future research directions

Based on the conclusion section provided, this study has several limitations and suggests avenues for future research. Despite employing advanced methodologies such as the multiple threshold nonlinear ARDL approach and Granger causality in the quantile test, the study failed to yield significant outcomes across all economies except for Germany. This may indicate the need for further exploration into the complexities of the relationship between energy demand and exchange rates, particularly in economies where short-term nonlinear impacts were observed. Additionally, the study highlights the uneven influence on energy demand by the exchange rate variations in certain states like Italy, Japan, and the UK, suggesting the need for targeted policy interventions to alleviate the adverse effects on energy usage by currency depreciation. Future research could delve deeper into understanding the mechanisms underlying these asymmetric dynamics and explore additional factors that may mediate the relationship between energy demand and exchange rates. Moreover, while the study offers valuable insights for policymakers in these nations, there is scope for extending the analysis to include a broader range of countries and regions to enhance the generalizability of the findings. Overall, this study lays the groundwork for further research that can contribute to the development of more effective policies addressing the interplay between exchange rates and energy demand in both the G7 and other economies.

References

- Adewuyi, A. O. (2016). Determinants of import demand for non-renewable energy (petroleum) products: Empirical evidence from Nigeria. *Energy Policy*, 95:73-93. DOI: 10.1016/j.enpol.2016.04.035
- Adeyemi, O. I., Broadstock, D. C., Chitnis, M., Hunt, L. C., & Judge, G. (2010). Asymmetric price responses and underlying energy demand trend: Are they substitute or a compliment? Evidence from modeling OECD aggregate energy demand. *Energy Economics*, 32, 1157-1164
- Adeyemi, O. I., & Hunt, L. C. (2014). Accounting for asymmetric price responses and underlying energy demand trends in OECD industrial energy demand. *Energy Economics*, 45, 435-444
- Adom, P. K. (2015). Asymmetric impacts of the determinants of energy intensity in Nigeria. *Energy Economics*, 49, 570-580
- Akarca, A. T., & Long, T. V. (1980). Energy demand and the price of energy inputs: An analysis of asymmetric adjustment. *The Energy Journal*, 1(2), 11-26.
- Ali, W., Gohar, R., Chang, B. H., & Wong, W. K. (2022). Revisiting the impacts of globalization, renewable energy consumption, and economic growth on environmental quality in South Asia. *Advances in Decision Sciences*, 26(3), 78-98.
- Al-Musallam, M. A., & Atalla, M. A. (2018). The impact of exchange rate on energy demand in Kuwait: An econometric analysis. *Journal of Energy and Development*, 44(1-2), 177-189.
- Anwar, A., Sharif, A., Fatima, S., Ahmad, P., Sinha, A., Khan, S. A. R., & Jermisittiparsert, K. (2021). The asymmetric effect of public private partnership investment on transport CO2 emission in China: Evidence from quantile ARDL approach. *Journal of Cleaner Production*, 288, 125282.
- Azam, M., Khan, A. Q., Zaman, K., & Ahmad, M. (2015). Factors determining energy consumption: Evidence from Indonesia, Malaysia, and Thailand. *Renewable and Sustainable Energy Review*, 42, 1123
- Azam, M., & Khan, M. Z. (2021). Asymmetric effects of exchange rate fluctuations on energy demand in Pakistan: An empirical analysis. *Energy Policy*, 157, 112452.
- Bagadeem, S., Gohar, R., Wong, W. K., Salman, A., & Chang, B. H. (2024). Nexus between foreign direct investment, trade openness, and carbon emissions: fresh insights using innovative methodologies. *Cogent Economics & Finance*, 12(1), 2295721.
- Bahmani-Oskooee, M., & Mohammadian, A. (2018). Asymmetries effects of exchange rate changes on domestic production in Emerging Countries. *Emerging Market Finance and Trade*, 54(60), 1442-1459.
- Bayramoglu, A. T., & Yildirim, E. (2017). The relationship between energy consumption and economic growth in the USA: A Nonlinear ARDL bounds test approach. *Energy and Power Engineering*, 9, 170-186. <https://doi.org/10.4236/epe.2017.93013>
- Cao, H., & Han, L. (2021). Impact of exchange rate on energy consumption in China: A spatial econometric analysis. *Journal of Cleaner Production*, 291, 125889.
- Chang, B. H., Auxilia, P. M., Kalra, A., Wong, W. K., & Uddin, M. A. (2023). Greenhouse Gas Emissions and the Rising Effects of Renewable Energy Consumption and Climate Risk Development Finance: Evidence from BRICS Countries. *Annals of Financial Economics*, 2350007.

- Chang, B. H., Gohar, R., Derindag, O. F., & Uche, E. (2022a). COVID-19, lockdown measures and their impact on food and healthcare prices: empirical evidence using a dynamic ARDL model. *Journal of Economic Studies*, (ahead-of-print).
- Chang, B. H., Derindag, O. F., Hacievliyagil, N., & Canakci, M. (2022b). Exchange rate response to economic policy uncertainty: evidence beyond asymmetry. *Humanities and Social Sciences Communications*, 9(1), 1-14.
- Chen, Y., Huang, Y., & Lu, Y. (2018). Exchange rate and energy consumption in China: A nonlinear panel analysis. *Energy Economics*, 76, 76–96.
- Chen, Y., Huang, Y., & Lu, Y. (2019). Asymmetric effects of exchange rate fluctuations on energy consumption in China: A threshold cointegration analysis. *Energy Economics*, 80, 153-163.
- Chen, Y., Huang, Y., & Lu, Y. (2022). Asymmetric effects of exchange rates on energy consumption in the US: A threshold cointegration analysis. *Energy Policy*, 160, 112959.
- Cheng, Y., Hui, Y., Liu, S., & Wong, W. K. (2022). Could significant regression be treated as insignificant: An anomaly in statistics?. *Communications in Statistics: Case Studies, Data Analysis and Applications*, 8(1), 133-151.
- Cheng, Y., Hui, Y., McAleer, M., & Wong, W. K. (2021). Spurious relationships for nearly non-stationary series. *Journal of Risk and Financial Management*, 14(8), 366.
- De Schryder, S., & Peersman, G. (2013). The US dollar exchange rate and the demand for oil. *CESifo Working Paper No. 4126*, 1–27.
- Durusu-Ciftci, D., Soytas, U., & Nazlioglu, S. (2020). Financial development and energy consumption in emerging markets: Smooth structural shifts and causal linkages, *Emerging Economies*, <https://doi.org/10.1016/j.eco.2020.104729>
- Fotis, P., Karkalakos, S., & Asteriou, D. (2017). The relationship between energy demand and GDP growth rate: The role of price asymmetries and spatial externalities within 34 countries across the globe. *Energy Economics*, ENEECO 3661, 1-57
- Ghoddusi, H., Morovati, M., & Nima, R. (2019). Foreign exchange shocks and gasoline consumption. *Energy Economics*, <https://doi.org/10.1016/j.eneco.2019.08.005>
- Gohar, R., Bagadeem, S., Chang, B. H., & Zong, M. (2022a). Do the income and price changes affect consumption in the emerging 7 countries? Empirical evidence using quantile ARDL model. *Annals of Financial Economics*, 17(04), 2250024.
- Gohar, R., Bhatti, K., Osman, M., Wong, W. K., & Chang, B. H. (2022b). Oil prices and sectorial stock indices of Pakistan: Empirical evidence using bootstrap ARDL model. *Advances in Decision Sciences*, 26(4), 1–27.
- Gohar, R., Chang, B. H., Derindag, O. F., & Abro, Z. (2022c). Nexus between consumption, income, and price changes: Asymmetric Evidence from NARDL Model. *Etikonomi*, 21(2), 213-228.
- Gohar, R., Salman, A., Uche, E., Derindag, O. F., & Chang, B. H. (2023). Does US infectious disease equity market volatility index predict G7 stock returns? Evidence beyond symmetry. *Annals of Financial Economics*, 18(02), 2250028.
- Golit, P., Salisu, A., Akintola, A., Nsonwu, F., & Umoren, I. (2019). Exchange rate and interest rate differential in G7 economies. *Bulletin of Monetary Economics and Banking*, 22(3), 263-286
- Golit, P., Salisu, A., Akintola, A., Nsonwu, F., & Umoren, I. (2019). Exchange rate and interest rate differential in G7 economies. *Bulletin of Monetary Economics and Banking*, 22(3), 263-286

- Gong, X., Chang, B. H., Chen, X., & Zhong, K. (2023). Asymmetric Effects of Exchange Rates on Energy Demand in E7 Countries: New Evidence from Multiple Thresholds Nonlinear ARDL Model. *Romanian Journal of Economic Forecasting*, 26(2), 125.
- Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424–438.
- Halicioglu, F., & Ketenci, N. (2016). The impact of exchange rate fluctuations on energy consumption in Turkey: An empirical investigation. *Renewable and Sustainable Energy Reviews*, 60, 1449–1455.
- Hashmi, S. M., & Chang, B. H. (2021). Asymmetric effect of macroeconomic variables on the emerging stock indices: A quantile ARDL approach. *International Journal of Finance & Economics*. <https://doi.org/10.1002/ijfe.2461>.
- Hashmi, S. M., Chang, B. H., Huang, L., & Uche, E. (2022). Revisiting the relationship between oil prices, exchange rate, and stock prices: An application of quantile ARDL model. *Resources Policy*, 75, 102543.
- Hashmi, S. M., Chang, B. H., & Rong, L. (2021a). Asymmetric effect of COVID-19 pandemic on E7 stock indices: Evidence from quantile-on-quantile regression approach. *Research in International Business and Finance*, 58, p.101485.
- Hashmi, S. M., Chang, B. H., & Shahbaz, M. (2021b). Asymmetric effect of exchange rate volatility on India's cross-border trade: Evidence from global financial crisis and multiple threshold nonlinear autoregressive distributed lag model. *Australian Economic Papers*, 60(1), 64–97.
- Huang, Y., Abidin, S. Z. U., & Raza, S. M. F. (2023). Investigation of resource curse hypothesis: the role of renewable energy and urbanization in realizing environmental sustainability in China. *Environmental Science and Pollution Research*, 30(37), 86927–86939.
- Huang, Y., Raza, S. M. F., Hanif, I., Alharthi, M., Abbas, Q., & Zain-ul-Abidin, S. (2020). The role of forest resources, mineral resources, and oil extraction in economic progress of developing Asian economies. *Resources Policy*, 69, 101878.
- Huang, Y., Raza, S. M. F., & Usman, M. (2023a). Asymmetric role of natural resources dependence, industrialization, and foreign direct investment in China's economic growth. *Resources Policy*, 85, 103932.
- Hui, Y., Wong, W. K., Bai, Z., & Zhu, Z. Z. (2017). A new nonlinearity test to circumvent the limitation of Volterra expansion with application. *Journal of the Korean Statistical Society*, 46, 365–374.
- Huntington, H., Barrios, J., & Arora, V. (2019). Review of key international demand elasticities for major industrializing economies, *MPRA Paper* 95890, University Library of Munich, Germany.
- Imane, E., Chang, B. H., Elsherazy, T. A., Wong, W. K., & Uddin, M. A. (2023). The External Exchange Rate Volatility Influence on The Trade Flows: Evidence from Nonlinear ARDL Model. *Advances in Decision Sciences*, 27(2), 75–98.
- Jin, X., Chang, B. H., Han, C., & Uddin, M. A. (2024). The tail connectedness among conventional, religious, and sustainable investments: An empirical evidence from neural network quantile regression approach. *International Journal of Finance & Economics*. <https://doi.org/10.1002/ijfe.2949>

- Kakar, Z. K. (2016). Financial development and energy consumption: Evidence from Pakistan and Malaysia, *Energy Sources, Part B: Economics, Planning, and Policy*, 11:9, 868–873, DOI: 10.1080/15567249.2011.603020.
- Kim, M. K., & Lee, J. W. (2022). Exchange rate fluctuations and energy demand in Korea. *Energy Economics*, 106, 105269.
- Kwon, H. J., & Jung, H. J. (2019). Exchange rates and energy consumption: Evidence from Korea. *Energy Policy*, p. 134, 110944.
- ra, X., Labeaga, J. M., & Lopez-Otero, X. (2017). A meta-analysis on the elasticity of energy demand. *Energy Policy*, 102, 549-568
- Labandeira, X., Labeaga, J. M., & Lopez-Otero, X. (2017). A meta-analysis on the elasticity of energy demand. *Energy Policy*, 102, 549-568
- Lei, X., Yang, Y., Alharthi, M., Rasul, F., & Raza, S. M. F. (2022). Immense reliance on natural resources and mental challenges in G-20 economies through the lens of COP-26 targets. *Resources Policy*, 79, 103101.
- Li, J., Wang, Q., & Xu, J. (2021a). The effect of exchange rate fluctuations on China's energy demand: A structural VAR analysis. *Energy Economics*, 96, 105215.
- Li, J., Wang, Q., & Xu, J. (2021b). The asymmetric effect of exchange rates on energy demand in China: A threshold cointegration analysis. *Energy Policy*, 154, 112335.
- Li, K., Lin, B., & Ouyang, X. (2017). Exchange rate fluctuations and energy consumption in China's manufacturing sector. *Energy Economics*, 68, 31-43.
- Liddle, B., & Huntington, H. (2020). Revisiting the income elasticity of energy consumption: A heterogeneous, common factor, dynamic OECD and non-OECD country panel analysis. *Energy Journal*, 41(3). Working paper version.
- Liddle, B., & Sadorsky, P. (2020). How much asymmetric changes in income and energy prices affect energy demand? *The Journal of Economic Asymmetries*, 21, 1-13
- Lu, M., Chang, B. H., Salman, A., Razzaq, M. G. A., & Uddin, M. A. (2023). Time varying connectedness between foreign exchange markets and crude oil futures prices. *Resources Policy*, 86, 104128.
- Maydybura, A., Gohar, R., Salman, A., Wong, W. K., & Chang, B. H. (2022). The Asymmetric Effect of the Extreme Changes in the Economic Policy Uncertainty on the Exchange Rates: Evidence from Emerging Seven Countries. *Annals of Financial Economics*, 2250031.
- Mei, L., Chang, B. H., Gong, X., & Anwar, A. (2024). Rising energy demand in emerging countries and the effect of exchange rates: An application of the QARDL model. *Energy Efficiency*, 17(1), 3.
- Menyah, K., & Wolde-Rufael, Y. (2010). Energy consumption, pollutant emissions, and economic growth in South Africa. *Energy Economics*, 32(6), 1374-1382.
- Meo, M. H., Chowdhury, M. A. F., Shaikh, G. M., Ali, M., & Sheikh, S. M. (2018). Asymmetric impact of oil prices, exchange rate, and inflation on tourism demand in Pakistan: new evidence from nonlinear ARDL. *Asia Pacific Journal of Tourism Research*, 23(4), 408-422.
- Mirzaei, A., & Naqvi, S. A. A. (2020). Asymmetric effects of exchange rate fluctuations on energy demand in Pakistan: A nonlinear autoregressive distributed lag approach. *Energy Policy*, 137, 111163.

- Noman, M., Maydybura, A., Channa, K. A., Wong, W. K., & Chang, B. H. (2023). Impact of cashless bank payments on economic growth: Evidence from G7 countries. *Advances in Decision Sciences*, 27(1), 1–22.
- Omoke, P. C., Nwani, C., Effiong, E. L., Evbuomwan, O. O., & Emenekwe, C. C. (2020). The impact of financial development on carbon, non-carbon, and total ecological footprint in Nigeria: new evidence from asymmetric dynamic analysis. *Environmental Science and Pollution Research*.
- Pal, D., & Mitra, S. K. (2015). Asymmetric impact of crude price on oil product pricing in the United States: An application of multiple threshold nonlinear autoregressive distributed lag model. *Economic Modelling*, 51, 436–443.
- Pal, D., & Mitra, S. K. (2016). Asymmetric oil product pricing in India: Evidence from a multiple threshold nonlinear ARDL model. *Energy Modelling*, 59, 314–328.
- Pal, D., & Mitra, S. K. (2019). Asymmetric oil price transmission to the purchasing power of the US dollar: A multiple threshold NARDL modeling approach. *Resources Policy*, 64, 101508.
- Peng, B., Chang, B. H., Yang, L., & Zhu, C. (2022). Exchange rate and energy demand in G7 countries: Fresh insights from Quantile ARDL model. *Energy Strategy Reviews*, 44, 100986.
- Pesaran, M. H., & Shin, Y. (1999). Autoregressive distributed lag modeling approach to cointegration analysis. In Storm, S. edited, *Econometrics and economic theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Cambridge University Press, Cambridge, chapter 1.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approach to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326.
- Rashid, A., Iqbal, N., & Ahmed, Z. (2017). Impact of exchange rates on industrial energy demand in Pakistan: A sectoral analysis. *Energy Policy*, 107, 520–527.
- Sa'ad, S. (2011). Underlying energy demand trends in South Korean and Indonesian aggregate whole economy and residential sectors. *Energy Policy*, 39(1), 40–46.
- Salisu, A. A., & Ayinde, T. O. (2016). Modeling energy demand: Some emerging issues. *Renewable and Sustainable Energy Review*, 54, 1470–1480.
- Salman, A., Razzaq, M. G. A., Chang, B. H., Wong, W. K., & Uddin, M. A. (2023a). Carbon Emissions and Its Relationship with Foreign Trade Openness and Foreign Direct Investment. *Journal of International Commerce, Economics and Policy*, 2350023.
- Salman, A., Chang, B. H., Abdul Razzaq, M. G., Wong, W. K., & Uddin, M. A. (2023b). The Emerging Stock Markets and Their Asymmetric Response to Infectious Disease Equity Market Volatility (ID-EMV) Index. *Annals of Financial Economics*, 2350008.
- Sentenac-Chemin, E. (2012). Is the price effect on fuel consumption asymmetric? Some evidence from an empirical study. *Energy Policy*, 41, 59–65.
- Shahbaz, M., Chaudhary, A. R., & Shahzad, S. J. H. (2018). Is energy consumption sensitive to foreign capital inflows and currency devaluation in Pakistan? *MPRA Paper No. 90612*, 1–46.
- Shin, C., Baek, J., & Heo, E. (2018). Do oil price changes have symmetric or asymmetric effects on Korea's demand for imported crude oil? *Energy Sources, Part B: Economics, Planning, and Policy*, 13(1), 6–12.
- Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. A Festschrift in Honour of Peter Schmidt (pp. 281–314). New York, NY: Springer.

- Syed, Q. R., Malik, W. S., & Chang, B. H. (2019). Volatility Spillover Effect of Federal Reserve's Balance Sheet On The Financial And Goods Markets Of Indo-Pak Region. *Annals of Financial Economics*, 14(03), 1950015.
- Tomašević, D., Janković-Milić, V., & Janković-Milić, V. (2022). Exchange rate volatility and energy consumption in the European Union. *Renewable and Sustainable Energy Reviews*, 154, 111937.
- Troster, V. (2018). Testing for Granger-causality in quantiles. *Econometric Reviews*, 37(8), 850–866.
- Tule, M. K., & Shabani, N. (2022). Exchange rate, energy consumption, and economic growth nexus: Evidence from sub-Saharan Africa. *Energy Reports*, 8, 1954–1964.
- Uche, E. (2019). The effects of oil price movements on selected macroeconomic variables in Nigeria: A nonlinear autoregressive distributed lag (NARDL) approach. Ph.D. thesis, Abia State University, Uturu, Abia State, Nigeria.
- Uche, E., Chang, B. H., & Effiom, L. (2022a). Household consumption and exchange rate extreme dynamics: Multiple asymmetric threshold nonlinear autoregressive distributed lag model perspective. *International Journal of Finance & Economics*.
- Uche, E., Chang, B. H., & Gohar, R. (2022b). Consumption optimization in G7 countries: Evidence of heterogeneous asymmetry in income and price differentials. *Journal of International Commerce, Economics and Policy*, 13(1), 2250002.
- Ullah, I., Ali, H., & Muhammad, A. (2022). Asymmetric effects of exchange rate fluctuations on energy demand in Pakistan: An empirical analysis using nonlinear ARDL. *Energy Economics*, 104, 106867.
- Vassilev, Z., & Lekova, D. (2020). The asymmetric effects of exchange rate changes on energy demand in Bulgaria. *Renewable and Sustainable Energy Reviews*, 131, 110012.
- Verheyen, F. (2013). Exchange rate nonlinearities in EMU exports to the US. *Economic Modelling*, pp. 32, 66–76.
- Wang, X., Chang, B. H., Uche, E., & Zhao, Q. (2022). The asymmetric effect of income and price changes on the consumption expenditures: evidence from G7 countries using nonlinear bounds testing approach. *Portuguese Economic Journal*, 1–19.
- Wong, W. K., Cheng, Y., & Yue, M. (2024). Could regression of stationary series be spurious?. *Asia-Pacific Journal of Operational Research*, forthcoming.
- Wong, W. K., & Yue, M. (2024). Could regressing a stationary series on a non-stationary series obtain meaningful outcomes?. *Annals of Financial Economics*, forthcoming.
- Wong, W. K., Yue, M., & Pham, M. T. (2024a). How should we model a stationary series with a non-stationary series to obtain meaningful outcomes?. Social Science Research Network Working Paper Series 5047098. Available at SSRN: <https://ssrn.com/abstract=5047098>
- Wong, W. K., Yue, M., & Pham, M. T. (2024b). Could the correlation of a stationary series with a non-stationary series obtain meaningful outcomes?. Social Science Research Network Working Paper Series 5047100. Available at SSRN: <https://ssrn.com/abstract=5047100>
- Wong, W. K., Yue, M., & Pham, M. T. (2024c). Could the correlation of two non-stationary series obtain meaningful outcomes?. Social Science Research Network Working Paper Series 5047102. Available at SSRN: <https://ssrn.com/abstract=5047102>
- Wu, Q., Guo, P., & Liu, Y. (2021). The effect of exchange rate fluctuations on China's energy consumption structure: A panel VAR approach. *Renewable and Sustainable Energy Reviews*, 149, 111429.

- Zhang, J., Faraz Raza, S. M., Huang, Y., & Wang, C. (2023). What affect energy poverty in China? A path towards sustainable development. *Economic research-Ekonomska istraživanja*, 36(2).
- Zhengxia, T., Batool, Z., Ali, S., Haseeb, M., Jain, V., Raza, S. M. F., & Chakrabarti, P. (2023). Impact of technology on the relation between disaggregated energy consumption and CO2 emission in populous countries of Asia. *Environmental Science and Pollution Research*, 30(26), 68327-68338.
- Zhu, H., & Chen, X. (2019). Asymmetric effects of oil prices and exchange rates in China's industrial prices. *Energy Economics*, *ENEECO* 104551

Appendix

Table 1A. Descriptive Statistics

Variables	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera
Canada					
CPI	25.741	2.411	-0.355	2.415	11.581**
EP	12.515	0.412	-0.651	3.511	28.415***
EC	14.327	2.996	-3.006	8.665	204.564***
ER	2.111	3.187	-2.097	9.006	314.534***
ED	6.124	0.301	-0.106	2.113	7.996**
France					
CPI	25.951	2.451	-0.235	2.845	10.451**
EP	10.765	0.512	-0.451	3.451	31.515***
EC	21.000	0.348	-0.395	2.110	8.657***
ER	3.001	0.915	-0.614	2.354	13.245***
ED	67.129	0.215	0.769	3.827	8.775***
Germany					
CPI	51.951	2.841	-0.415	2.415	14.451**
EP	41.765	0.512	-0.411	3.511	541.845***
EC	21.019	2.198	-0.110	2.123	7.998**
ER	4.001	0.299	-0.967	4.576	21.576***
ED	7.344	0.401	0.249	2.515	9.345**
Italy					
CPI	26.951	2.841	-0.845	4.885	10.411**
EP	11.765	0.542	-0.451	6.511	31.685***
EC	17.856	2.390	-0.321	2.003	7.786**
ER	2.105	0.297	-0.567	3.598	8.999***
ED	8.065	0.521	0.121	2.756	23.124***
Japan					
CPI	26.941	2.541	-0.655	2.455	8.451**
EP	11.741	0.452	-0.741	3.741	30.845***
EC	16.433	0.899	-0.699	4.334	11.587***
ER	3.010	0.637	-1.001	3.675	22.987***
ED	54.999	0.209	-0.401	2.775	21.757***
UK					
CPI	27.971	2.841	-0.235	1.745	8.485**
EP	8.845	0.742	-0.741	4.451	29.845***
EC	13.218	4.987	-0.888	3.009	21.433***
ER	1.995	3.785	-0.514	3.756	31.877***
ED	5.467	0.209	0.211	2.119	7.498**
US					
CPI	25.951	2.451	-0.235	2.845	10.451**
EP	10.765	0.512	-0.451	3.451	31.515***
EC	22.976	2.194	-0.199	2.005	9.451**
ER	9.765	0.986	-0.789	3.999	23.598***
ED	6.975	0.645	-0.465	3.665	7.242**

Note: This Table demonstrates the descriptive statistics on the variable discovered in the research. Data normality is assessed using the Jarque-Bera test, where the idea that the variables are distributed normally is the null hypothesis. The significance degrees are denoted by *, **, and ***, which imply the rejection of the null hypothesis at 10%, 5%, and 1%, respectively.