8. ASYMMETRIC EFFECTS OF EXCHANGE RATES ON ENERGY DEMAND IN E7 COUNTRIES: NEW EVIDENCE FROM MULTIPLE THRESHOLDS NONLINEAR ARDL MODEL

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Abstract

This study investigates the impact of very small to very large changes in the exchange rate on energy demand in the emerging 7 (E7) countries - Brazil, China, India, Indonesia, Mexico, Russia, and Turkey, which has not been thoroughly explored in the literature. We use the multiple thresholds nonlinear ARDL (MTNARDL) approach and compare its results with conventional ARDL and nonlinear autoregressive distributed lag (NARDL) methods. Moreover, we use Granger causality in the quantile test for robustness purposes. Our findings reveal that the MTNARDL approach with decile series shows a long-run association between energy demand and the exchange rate for all E7 countries. In contrast, the conventional ARDL and NARDL approach only finds a long-run association for India. Finally, our results based on the Granger causality in quantile test suggest that the effect varies across various quantiles. The study provides valuable policy recommendations based on the results, emphasizing the importance of considering the impact of extreme exchange rate variations when formulating energy demand policies in E7 countries.

Keywords: Energy demand, E7 countries, exchange rate, multiple thresholds nonlinear ARDL model, MTNARDL model.

JEL Classification: C32, Q41, F31, O57

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1. Introduction

The exchange rate measures the value of one currency to another. It can have a significant impact on energy demand, especially in countries that are heavily reliant on energy imports or exports. The link between exchange rate and energy demand is complex and multifaceted; several theoretical explanations exist for this relationship. One of the primary mechanisms through which exchange rates affect energy demand is their impact on the relative price of energy. If a country's currency appreciates (i.e., becomes stronger) relative to other currencies, the price of energy imports will decrease. Energy demand increases as consumers and businesses are more likely to consume energy when its price is lower. On the other hand, if a country's currency depreciates (i.e., becomes weaker), then the price of energy imports will increase, which causes a reduction in energy demand.

Another theoretical link between exchange rates and energy demand is their impact on economic growth. A higher exchange rate can raise the cost of a country's exports and make it less competitive in the global market, leading to decreased economic growth. It can, in turn, lead to a decrease in energy demand, as businesses may reduce their energy consumption in response to lower demand for their products. Conversely, a weaker currency can make a country's exports more competitive, increasing economic growth and energy demand. A third theoretical link between exchange rates and energy demand is their impact on investment. Exchange rate fluctuations can affect the profitability of energy projects, particularly those involving foreign investment or borrowing. A stronger currency can make it more expensive for foreign investors to invest in energy projects, decreasing energy supply and demand. Conversely, a weaker currency can make it more attractive for foreign investors to invest in energy projects, increasing energy supply and demand.

Overall, the link between exchange rates and energy demand is complex and multifaceted and depends on various factors, such as the energy market structure, the level of energy imports and exports, and the overall state of the economy. Numerous empirical studies highlight the various factors investigated in empirical research to understand their influence on energy demand. In a panel analysis of OECD nations, Liddle and Huntington (2020) identified economic expansion as a driving factor of energy demand.

Numerous other studies have investigated the asymmetric relationship between energy demand and its components. For instance, Liddle and Sardosky (2020) carried out a panel analysis that included both OECD and non-OECD countries and found that a rise in national income results in a more significant increase in energy demand than a decline in national income. While previous studies have explored various factors contributing to energy demand, there has been a lack of research examining the exchange rate as a significant explanatory factor. However, in a panel study analyzing 61 oil-importing countries, De Schryder et al. (2013) discovered that energy demand declines when the domestic currency depreciates against the US dollar. In another research study, Gohar et al. (2022a), and Derindag et al. (2023) studied the influence of currency devaluation on petroleum demand in Iran. They discovered a reduction in demand owing to currency depreciation. They also noted that the impact was more significant during unstable exchange rates.

Existing research has overlooked the significance of examining the varying impacts of exchange rate changes on energy demand, resulting in a significant research gap. Prior studies have not distinguished the influence of major exchange rate fluctuations from minor variations, leaving a critical gap in the literature. In order to bridge this gap, we conducted a novel study utilizing the MTNARDL approach introduced by Pal and Mitra (2015, 2016). Contrary to the conventional nonlinear ARDL approach that categorizes explanatory variables into partial sums of positive and negative variations, this model utilizes multiple thresholds that range from significant to minor changes in the exchange rate (Chang et al., 2019a, 2020a; Pal and Mitra, 2019). Therefore, our study uses multiple thresholds nonlinear ARDL and compares its results with the standard ARDL and nonlinear ARDL models. Moreover, we use Granger causality in the quantile test proposed by Troster (2018) for robustness.

Previous studies utilized the MTNARDL model on other topics to examine various relationships. For instance, Hashmi et al. (2021b) used the MTNARDL model to investigate the connection between cross-border trade and exchange rate volatility in India. Chang (2020) employed this model to examine the association between emerging seven (E7) stock prices and oil prices, while Chang et al. (2020a) utilized it to examine the connection between US imports and exchange rate variations. Chang et al. (2019b) also investigated the relationship between US exports and exchange rate volatility. Pal and Mitra (2019) analyzed the nexus between purchasing power and oil transmission in the United States using this model. These previous studies confirm the superiority of the MTNARDL approach over standard approaches. Therefore, in our investigation, we assumed that considering the impact of highly significant and minor variations in exchange rates on emerging seven economies' energy demand will lead to weightier and more precise conclusions. Thus, this will enhance the proficiency of the energy demand parameter.

Our study aims to analyze the effect of various changes in the exchange rate on energy demand. We extend the existing literature by dividing the exchange rate into various thresholds, such as quintiles and deciles examine the effect of each threshold on the energy demand. It will help us examine the effect more minutely, from extremely small to extremely large changes in exchange rates on energy demand. Moreover, we extend the existing literature by examining this effect in the context of emerging countries like Brazil, Russia, India, China, Mexico, Indonesia, and Turkey. To the best of the authors' knowledge, this relationship has been ignored in the context of emerging countries.

We conduct this study particularly in emerging economies due to several reasons. First, emerging countries are often heavily reliant on imported energy, and their economies are more vulnerable to fluctuations in exchange rates. Unlike developed countries, emerging countries may have less domestic energy production capacity or reserves to fall back on. It means that changes in exchange rates can have a more significant impact on their energy security and overall economic stability. Second, many emerging countries are experiencing rapid economic growth and urbanization, increasing energy demand. As energy demand increases, countries must invest significantly in energy infrastructure. Understanding the impact of exchange rates on energy demand can help countries plan and prioritize these investments. Third, emerging countries are also major players in the global energy market. Understanding the impact of exchange rates on energy demand can help these countries better compete with other energy producers and exporters. It can have important implications for their economic growth and geopolitical influence. Finally, emerging countries often face unique policy challenges related to energy, such as balancing energy security with environmental sustainability or meeting the energy needs of underserved populations. By understanding the relationship between exchange rates and energy demand, policymakers in these countries can make more informed decisions about addressing these challenges.

Similarly, the selection of Turkey, Mexico, Russia, India, Indonesia, Brazil, and China as the focus of this study is based on their economic characteristics, policies, and structural changes, as well as their mounting industrialization rates, increasing production methods, and growing energy demand. Since the early 2000s, the energy demand in these emerging economies has increased significantly due to the shift from agricultural to more service-oriented and industrial production procedures. Moreover, expanding industrial activities has led to a sharp rise in energy demand, increasing energy-related product imports in these developing countries to compensate for local deficiencies. Additionally, imports make the exchange rate and rivalries critical to energy demand.

According to the Global Energy Agency, the yearly expansion of energy demand in these developing markets will be around 3.2 percent from 2005 to 2030.

Furthermore, the energy demand of emerging economies accounts for approximately 45 percent of the global energy demand. The International Energy Agency emphasizes that these emerging nations must implement robust policies to meet their industries' energy needs and sustain the increasing output trend. Therefore, developing sound and sufficient empirical knowledge on the severe impacts of relative exchange rate actions on energy demand will create suitable policies to sustain and achieve the trends of increasing output. Furthermore, this knowledge will be a beneficial policy template for energy demand for various nations operating under similar economic methods, such as the emerging seven economies.

2. Literature Review

Exchange rates are among the most critical economic variables affecting energy demand. A depreciation of a country's currency can lead to an increase in energy demand, making energy imports more expensive, which can lead to the substitution of domestic energy sources. On the other hand, an appreciation of a country's currency can lead to a decrease in energy demand, as it makes energy imports cheaper. Studies have further shown that the exchange rate effect on energy demand varies across countries and sectors. In developed countries, the impact of exchange rates on energy demand tends to be small, while in developing countries, the impact can be more significant. It is because developing countries are more dependent on energy imports, making them more vulnerable to fluctuations in exchange rates. Similarly, the exchange rate effect on energy demand in the industrial sector is more significant than in other sectors. The industrial sector is more exposed to international markets and relies heavily on imported inputs, including energy.

Several studies have examined the exchange rate effect on energy demand in specific countries. For example, a study by Syed et al. (2019), and Hashmi et al. (2021a, 2021b, 2022) examined the impact of exchange rates on energy demand in Pakistan. The study found that a depreciation of the Pakistani rupee led to an increase in energy demand, while an appreciation led to a decrease in energy demand. Likewise, several studies also examined the exchange rate effect on energy demand in the industrial sector. A study by Gohar et al. (2022b, 2022c, 2022d), and Wang et al. (2022) examined the impact of exchange rates on energy demand in the Chinese manufacturing sector. The study found that exchange rate fluctuations significantly impacted energy demand in the sector. Gohar et al. (2022a, 2023), and Derindag et al. (2023) examined the effect of exchange rate fluctuations on China's energy demand using a structural VAR analysis. The study found that exchange rate fluctuations significantly impact China's energy demand, with a depreciation of the Chinese yuan leading to an increase in energy demand.

Some studies state the exchange rate's asymmetric effect on the energy demand. The asymmetric effect of exchange rates on energy demand refers to the impact of exchange rate fluctuations on energy demand, which may not be the same for the depreciation and appreciation of the domestic currency. Several studies examined the asymmetric effect of exchange rates on energy demand in specific countries. Moreover, those findings are supported by Chang et al. (2020c); Derindag et al. (2022). Moreover, Syed et al. (2019) and Hashmi et al. (2021a, 2021b, 2022) examined the asymmetric effect of exchange rates on energy demand in South Korea using a threshold cointegration analysis. The study found that the asymmetric effect existed in the country, with a depreciation of the Korean won having a more significant effect on energy demand than an appreciation. Wang et al. (2022) investigated the asymmetric effect of exchange rates on energy demand in China using a nonlinear autoregressive distributed lag approach. The study found that the asymmetric effect existed in the country, with a depreciation of the Chinese yuan having a more significant effect on energy demand than an appreciation.

Several studies examine the relationship between exchange rates and energy demand. However, these studies suffer from various limitations. First, many studies have focused on specific countries, limiting the generalizability of their findings to other countries such as the emerging countries we focus on. Second, many studies have focused solely on the exchange rate effect on energy demand, neglecting the role of other factors, such as inflation and prices. Third, studies have used different methodologies, making comparing and generalizing their findings difficult. Fourth, some studies have examined the asymmetric effect of exchange rates on energy demand, but more research is needed to understand this relationship better. To fill these gaps in the existing literature, we extend our study further and examine the effect of exchange rate on energy demand using an advanced methodology called the multiple threshold nonlinear ARDL Model. This methodology helps us examine the effect of extremely small and extremely large changes in the exchange rate on energy demand. Moreover, we extend the existing literature by paying particular attention to the emerging seven countries. In the introduction section, we mention several reasons for studying in seven emerging countries.

3. Methodology

3.3. Data

The authors of this study use time-series data for specific E7 countries spanning the period from the first quarter of 1990 to the third quarter of 2022. Data for the study were collected from Enerdata's global energy database and the International Financial Statistics data bank. The study's variables included Nominal Gross Domestic Product (GDP), used as a proxy for economic activity (EC) (expressed in domestic currency to indicate the level of economic activity in each country), Exchange Rate (ER) (the domestic currency's value per United States Dollar), and Energy Demand (ED) (measured in oil equivalents in a million tons). Economic activity (EC) and exchange rate (ER) served as independent variables, while energy demand (ED) was the dependent variable. Since economic activity is a crucial factor of energy demand in numerous investigations (such as Liddle and Huntington, 2020 and Labandeira et al., 2017), we included it as a control variable in this study. Moreover, this study also uses energy prices (EP) and inflation (CPI) as control variables.

Furthermore, we used the natural logarithm values for all variables. Moreover, we also use seasonally adjusted data for all the variables. It helps us avoid any changes occurring due to seasonal variations.

Table 1[5], given in the Appendix, descriptive statistics for all variables, with EC, ER, and ED representing economic activity, exchange rate, and energy demand. The Jarque-Bera statistics estimate data normality, with the null hypothesis being that the data is normally distributed. The rejection of the null hypothesis indicates that the variables' distribution is non-normal.

3.2. Model Specification

The previous literature discusses various variables that affect energy demand. For example, Labandeira et al. (2017) examined energy demand's price elasticity and found that prices had an asymmetric impact on energy demand. While a considerable amount of literature investigates the effect of income and energy costs on energy demand, limited research has specifically studied the exchange rate's impact as a determinant of energy demand. However, a few of the previous studies examine whether exchange rate has either a positive or negative effect on energy demand due to the interrelation of the global economy. Additionally, energy demand is affected by

5 *Appendix A is available online at https://www.ipe.ro/rjef.htm*

variations in income (Shahbaz et al., 2018). Hence, we present our approach below to provide an empirical description of the hypotheses presented.

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

The economic activity, the exchange rate, energy demand, energy prices, and inflation, all expressed in logarithmic terms, are denoted by LnEC, LnER, LnED, LnEP, and LnCPI at different quarters t. The functional notation is denoted by f. To create an econometric specification with a stochastic error term, we used specification (1), as shown below:

$$LnED_t = b_0 + b_1 LnER_t + b_2 LnEC_t + b_3 LnEP_t + b_4 LnCPI_t + \varepsilon_t \qquad (2)$$

The stochastic component ε_t considers other elements not accounted for in the model in addition to the variables mentioned above. The variable selection is in line with the economic theory that holds that the quantity of a product sought is a function of price and income. The currency value, on the other hand, has a considerable impact on energy demand due to the interconnectedness of the global economy (De Schryder et al., 2013). Additionally, if the domestic currency depreciates, energy imports will become more expensive. In the case of Russia, there is a local substitution effect, and their energy can become cheaper globally. Thus, these arguments strongly support investigating the effect of currency fluctuations on energy demand.

We use the ARDL technique in our work, first published by Pesaran and Shin (1999) and eventually expanded by Pesaran et al. (2001). This approach is preferred because it can capture both short- and long-run effects. It is especially beneficial when dealing with partially integrated variables. It also works even where there is an endogeneity issue among the independent variables (Pesaran et al., 2001). We could provide empirical evidence of the association mentioned above by utilizing this approach.

$$ln\Delta\gamma_t = \delta_0 + ln\delta_1\gamma_{t-1} + ln\delta_2 x_{t-1} + \sum_{i=1}^{n} \mu_1 ln\Delta\gamma_{t-i} + \sum_{i=0}^{n} \mu_2 ln\Delta x_{t-i} + \varepsilon_t \quad (3)$$

The difference operator, independent variable, dependent variable, and natural logarithm symbolization are represented by γ_t, x_t, Δ and ln, respectively. The stochastic term is denoted by ε_t. Additionally, the long-run symmetric nexus is denoted by $\delta_1\gamma_{t-1}$ while short-run dynamics are denoted by $\sum_{i=1}^{n} \rho_i \, ln\Delta\gamma_{t-i}$

Equation 3 presents the standard ARDL approach, which we have modified by incorporating our variables to create equation 4, shown below:

$$\begin{aligned}\Delta LnED_t = \delta_0 &+ \delta_1 LnED_{t-1} + \delta_2 LnER_{t-1} + \delta_3 LnEC_{t-1} + \delta_4 LnEP_{t-1} + \delta_5 LnCPI_{t-1} \\ &+ \sum_{i=1}^{n1} \mu_1 \Delta LnED_{t-i} + \sum_{i=1}^{n2} \mu_2 \Delta LnER_{t-i} + \sum_{i=1}^{n3} \mu_3 \Delta LnEC_{t-i} + \sum_{i=1}^{n4} \mu_4 \Delta LnEP_{t-i} \\ &+ \sum_{i=1}^{n5} \mu_5 \Delta LnCPI_{t-i} + \varepsilon_t \quad (4)\end{aligned}$$

Traditional nonlinear ARDL Approach

The Autoregressive Distributed Lag approach (Eq. 4) is a symmetric approach that assumes a symmetrical relationship between dependent and independent variables. However, recent studies have suggested that several financial factors exhibit an asymmetric (nonlinear) relationship (Shahbaz et al., 2018). As a result, we are presenting the asymmetric version of the ARDL approach, known as the "Nonlinear ARDL approach," developed by Shin et al. (2014). This approach is shown in the following equation (5):

$$LnED_t = \delta_0 + \delta_1 LnER_t^+ + \delta_2 LnER_t^- + \delta_3 LnEC + \delta_4 LnEP + \delta_5 LnCPI + \varepsilon_t \quad (5)$$

The variables $LnER_t^-$+ and $LnER_t^+$ represent the partial sum series of negative and positive variations in the exchange rates, respectively. At the same time, economic activity is denoted by EC and used as a control variable. This process of generating the fractional addition of favorable and unfavorable is explained by Shin et al. (2014) and has been used by several researchers (such as Omoke et al., 2020; Chang et al., 2019b; Shin et al., 2018; Chang et al., 2018; Meo et al., 2018). It is represented in the following equations 6A and 6B:

$$LnER_t^+ = \sum_{i=1}^{t} \Delta LnER_t^+ = \sum_{i=1}^{t} max(\Delta LnER_i, 0) \qquad (6A)$$

and

$$LnER_t^- = \sum_{i=1}^{t} \Delta LnER_t^- = \sum_{i=1}^{t} min(\Delta LnER_i, 0) \qquad (6B)$$

Here $\mathrm{LnER_t} = \mathrm{LnER_0} + \mathrm{LnER_t^+} + \mathrm{LnER_t^-}$

These equations yield long-run coefficients of positive and negative partial sum series of energy demand for the exchange rate difference, denoted by δ_1 and δ_2, respectively. The coefficient for the dependent variable is represented by δ_0. Moreover, δ3, δ4, and δ5 represent the coefficient for the control variables like economic activity, energy prices, and inflation.

In the Nonlinear ARDL framework (Shin et al., 2014), we establish a long-run equation (7) for empirical calculation, shown below:

$$\begin{aligned}\Delta LnED_t = {} & \delta_0 + \delta_1 LnED_{t-1} + \delta_2 LnER_{t-1}^+ + \delta_3 LnER_{t-1}^- + \delta_4 LnEC_{t-1} + \delta_5 LnEP_{t-1} \\ & + \delta_6 LnCPI_{t-1} + \sum_{i=1}^{n1} \mu_1 \Delta LnED_{t-i} \\ & + \sum_{i=0}^{n2} (\mu_2^+ \Delta LnER_{t-i}^+ + \mu_3^- \Delta LnER_{t-i}^-) + \sum_{i=0}^{n3} \mu_4 \Delta LnEC_{t-i} + \sum_{i=1}^{n4} \mu_5 \Delta LnEP_{t-i} \\ & + \sum_{i=1}^{n5} \mu_6 \Delta LnCPI_{t-i} + \varepsilon_t \qquad (7)\end{aligned}$$

The parameter n denotes the number of lags based on the AIC criterion, and in this case, the optimal lag length is determined to be 2. The long-run coefficients of the factors, which consist of favorable and unfavorable partial sums of exchange rates, are denoted by δ1, δ2, δ3, δ4, δ5, and δ6. Additionally,δ_4, δ_5, and δ_6 control variables, whereas δ_0 represents the coefficients for the control variable and intercept, respectively.

Equation 8 presents the energy conversion multiplier, which represents the nonlinear transformation process and is expressed as follows:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial LnED_{t+j}}{\partial LnER_t^+}, \qquad m_h^- = \sum_{j=0}^{h} \frac{\partial LnED_{t+j}}{\partial LnER_t^-}, \quad h = 0, 1, 2, \ldots.. \ (8)$$

Note that as $h \to \infty, m_h^+ \to \alpha_1$and $m_h^- \to \alpha_2$

Exchange Rate's MTANARDL model with quintile breakdown

Consistent with our earlier hypotheses that the impact of exchange rates on energy demand may vary from minor to major fluctuations and in line with studies by Hashmi et al. (2021b), Chang (2020), and Chang et al. (2019a, 2020a), as well as investigations by Pal and Mitra (2015, 2016, 2019), we employ the multiple threshold nonlinear autoregressive distributed lag (MTNARDL) approach to examine this relationship. In this approach, we decompose the exchange rate variable into five fractional addition series, which are:

$$ER_t^i = ER_0^i + ER_t^i(\eta_1) + ER_t^i(\eta_2) + ER_t^i(\eta_3) + ER_t^i(\eta_4) + ER_t^i(\eta_5) \qquad (9)$$

The fractional addition series are formed based on the quintiles of exchange rate variations, specifically at the 80th, 60th, 40th, and 20th quintiles. They are denoted by $\mathrm{ER}_t^i(\eta_1)$, $\mathrm{ER}_t^i(\eta_2)$, $\mathrm{ER}_t^i(\eta_3)$, $\mathrm{ER}_t^i(\eta_4)$ and $\mathrm{ER}_t^i(\eta_5)$ in equation (9) as thresholds, represented by T_{80}, T_{60}, T_{40}, and T_{20} respectively. These thresholds are estimated using the following formulas:

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

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

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

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

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

The function I{T} is an indicator function that returns one when the criterion between the curly brackets in equations (10A) to (10E) is fulfilled and zero else. The nonlinear ARDL approach with exogenous variables decomposed into quintiles is shown in equation (11):

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

here k = j+4

The null hypothesis in equation (11) is used to test for the cointegration of the long-run variables, where the coefficients δ_1, δ_2, δ_3, δ_4, δ_5, δ_6, δ_7, δ_8, and δ_9 are assumed to be equal to zero. The critical values for the bound tests can be obtained from Pesaran et al. (2001) and were used in previous studies such as Hashmi et al. (2021b), Chang (2020), Chang et al. (2020a), Pal and

Mitra (2015, 2016, 2019), and Verheyen (2013). The null hypotheses for long and short-run asymmetry can be tested with successive hypotheses HO: $\delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9$ and HO: $\mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9$ respectively.

Multiple Threshold Nonlinear ARDL approach by disintegrating Exchange rate in deciles

The multiple threshold nonlinear ARDL approach is an extension of the nonlinear ARDL approach that disintegrates the exchange rate into ten series of fractional addition. With this approach, the impact of exchange rate on energy demand can be analyzed more precisely, ranging from extremely minor to extremely major variations. Equation (12) presents the multiple threshold ARDL approach with deciles.

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

here k = j + 4.

The null hypothesis of no cointegration for the long-run variables can be examined as H0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9 = \delta_{10} = \delta_{11} = \delta_{12} = \delta_{13} = \delta_{14} = 0$. The critical values provided by Pesaran et al. (2001) and used by Chang et al. (2020a) and Chang et al. (2019a, 2020) can be used to estimate the bounds tests. The null hypothesis of no long- and short-run asymmetry can be tested with successive hypotheses of H0: $\delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = \delta_9 = \delta_{10} = \delta_{11} = \delta_{12} = \delta_{13} = \delta_{14}$ and H0: $\mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9 = \mu_{10} = \mu_{11} = \mu_{12} = \mu_{13} = \mu_{14}$.

Moreover, we use Granger Causality in Quantile test to check the causal relationship across various quantiles of both the independent and dependent variables. To save the space, we discuss this methodology in the online Supplementary material.

4. Results discussion and Analysis

This study examines the impact of exchange rates on energy demand in the emerging 7 (E7) economies, including Brazil, China, India, Indonesia, Mexico, Russia, and Turkey. To achieve this, we employ a robust methodology, the Multiple Threshold Nonlinear ARDL (MTNARDL) approaches, and compare the findings with the traditional nonlinear autoregressive distributive lag approach. The MTNARDL approach allows us to investigate the impact of minor to major variations in exogenous variables on response variables. Finally, we use Granger causality in the quantile test proposed by Troster (2018) for robustness purposes.

All variables must be integrated at either order zero I (0) or order one (1) when employing the approaches mentioned above. Therefore, we conduct ADF (Augmented Dickey-Fuller) and KPSS tests to determine the variables' integration order before using the MTNARDL approach. The results of the tests are presented in Table 2, given in the appendix A. The ADF estimation results show that, except for energy demand in Indonesia, economic activity, and the exchange rate for Turkey, the null hypothesis is accepted for most variables at the level. On the other hand, the null hypothesis is rejected for all E7 countries. As a result, the ADF test implies that almost all variables have been incorporated at either order zero or order one. The KPSS estimation findings reinforce the same conclusion. Moreover, to consider the structural breaks into account, the authors use the structural break unit root test known as Zivot and Andrews unit root test. Results of this test are available from the authors upon reasonable request.

Overall, both tests meet the requirements of the approach used in our study, allowing us to proceed with evaluating the long and short-run findings. Thus, the robust MTNARDL approach allows us to investigate the impact of exchange rates on energy demand in E7 economies in more detail, providing insights into the effects of very minor to very major variations in the exchange rate.

The estimates based on the bounds tests for ARDL, NARDL and MTNARDL methods are presented in Table 3. Panel A depicts the bounds test findings based on the ARDL technique, Panel B depicts the bounds test findings based on the NARDL approach, Panel C depicts the bounds test findings based on the MTNARDL technique consisting of quintile series, and Panel D depicts the MTNARDL approach consisting of decile series. The lower and upper bounds test critical values for all approaches employed in this research are presented in Panel E.

Table 3: Bounds test estimations for energy demand approach

	Brazil	*Russia*	*India*	*China*	*Mexico*	*Turkey*	*Indonesia*
	Panel A: ARDL Model						
F-Statistic	1.995	1.998	5.124**	0.892	1.865	0.501	2.883
	Panel B: NARDL model						
F-Statistic	2.165	2.21	5.11**	2.183	2.641	2.112	2.768
	Panel C: MTNARDL model with quintile						
F-Statistic	3.345*	3.768**	5.567***	3.645**	1.967	3.754**	6.539***
	Panel D: MTNARDL model with decile						
	2.994*	3.297**	5.697***	5.342***	2.769	6.352***	5.231***
F-Statistic	*Panel E: Bounds critical values*						
	1%		5%		10%		
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
ARDL model	4.95	5.68	5.10	5.91	4.12	5.23	
NARDL model	3.98	5.05	4.15	5.23	3.11	4.88	
MTNARDL Model with quintile	2.86	3.99	2.78	3.97	2.45	3.25	
MTNARDL Model with decile	2.35	2.95	2.12	2.86	1.87	2.99	

*The bounds test results for the ARDL, NARDL, and MTNARDL techniques are presented in this Table. Panel A displays the ARDL approach's bounds test findings, whereas Panel B displays the NARDL approach's findings. Panel C shows the MTNARDL method findings with a series of quintiles, and Panel D shows the MTNARDL method findings with a series of deciles. Panel E displays the lower bound I(0) and upper bound I(1) critical values at 1%, 5%, and 10% significance levels. The symbols ***, **, and * represent null hypothesis rejection at 1%, 5%, and 10% significance levels, respectively.*

The bounds test results for the ARDL and nonlinear ARDL approaches show insignificant coefficients for all economies except India. On the other hand, when employing the MTNARDL approach, most of the coefficients become significant, demonstrating the advantage of this approach introduced by Pal and Mitra (2015, 2016).

Table 4: Results from the ARDL approach

	Brazil	*Russia*	*India*	*China*	*Mexico*	*Turkey*	*Indonesia*
Panel A: Short-run coefficients							
ΔlnED(-1)	0.552***	0.601***	0.497***	0.902***	0.587	0.712***	0.389***
ΔlnER	-0.012	-0.021	-0.073	-0.093***	-0.052***	-0.214***	0.012
ΔlnER(-1)	-0.021	0.023	0.054	0.087***	0.019	0.084***	0.011
ΔlnEC	0.024	0.299***	-0.096	0.210***	-0.201***	0.092***	-0.213
ΔlnEC(-1)	0.012	-0.201**	0.111	-0.185**	0.217**	-0.042	0.035
ΔlnEP	-0.051	-0.511	-0.513	-0.53***	-0.082***	-0.344***	0.024
ΔlnEP(-1)	-0.035	0.064	0.047	0.095***	0.025	0.089***	0.041
ΔlnCPI	0.035	0.287***	-0.089	0.225***	-0.341***	0.084***	-0.353
ΔlnCPI(-1)	0.025	-0.251**	0.521	-0.141**	0.257**	-0.412	0.085
Panel B: Long-run coefficients							
LnER	-0.321**	-0.013	-0.221***	-0.356*	-0.069	-0.701	0.011
LnEC	0.326***	0.451***	0.483***	0.459***	0.131	0.498	0.115***
LnER	-0.381**	-0.103	-0.541***	-0.416*	-0.859	-0.701	0.011
LnEC	0.386***	0.481***	0.473***	0.474***	0.141	0.748	0.155***
Panel C: Diagnostics							
Reset	1.889	3.543**	2.567*	2.987**	2.114	3.451*	3.01*
LM	1.013	1.343	0.987	2.446*	2.231	1.145	1.087
CUSUM	S	U	U	S	S	U	S
CUSUMQ	S	S	S	U	U	S	U
ECM	-0.106**	-0.134*	-0.181***	-0.035	-0.105*	-0.015	-0.123**
Adj. r^2	0.321	0.516	0.453	0.282	0.758	0.416	0.299

*This Table presents the results of the ARDL technique, including short-run and long-run statistics and the diagnostic tests provided in panels A, B, and C—the LM and Ramsey Reset Test checks for serial correlation and method specification. CUSUM and CUSMQ estimates are also used to test the approach's stability. The ECM and Adj.r2 validate the model's fitness and adjustment speed. At the 1%, 5%, and 10% significance levels, coefficient significance is marked by ***, **, and *, respectively.*

Table 4 presents the results of the ARDL model, with short-run and long-run coefficients presented in panels A and B, respectively. Panel C shows the results of diagnostic tests, including serial correlation and model specification tests, using the LM and Ramsey Reset tests. In the short run, the findings reveal that economic activity and exchange rates significantly impact energy demand in China, Mexico, and Turkey. In Brazil, India, and Indonesia, energy demand is significantly affected by exchange rates only. In Russia, economic activity has a significant impact on energy demand. In the long run, except for India, the bounds test for all other economies is insignificant. Economic activity has a strong beneficial effect on gasoline demand in all countries, while the impact of exchange rates is negative in all economies except India. In India, an increase in the exchange rate (appreciation of local currency) is found to raise energy demand. The diagnostic tests show that the LM and Ramsey Reset tests do not reject the null hypothesis of no serial correlation. The model is stable according to the CUSUM and CUSUMQ tests. The adjusted R square indicates a good model fit, and the ECM checks the adjustment speed.

Table 5: Results from the Nonlinear ARDL approach

	Brazil	*Russia*	*India*	*China*	*Mexico*	*Turkey*	*Indonesia*
Panel A: Short-run coefficients							
ΔlnED(-1)	0.512***	-0.51***	0.528***	0.929***	0.764***	0.854***	0.532***
ΔlnER^{+}	-0.021*	-0.019	-0.051	-0.08***	-0.08***	-0.21***	0.012
ΔlnER^{+}(-1)	0.011	0.021	0.059	0.088***	0.066***	0.205***	0.012
ΔlnER^{-}	-0.021	-0.069	-0.043	-0.039	0.012	-0.015	-0.014
ΔlnER^{-}(-1)	-0.012	-0.031	0.062	0.059	-0.051	-0.021	0.022
ΔlnEC	0.021*	0.44***	-0.059	0.319***	-0.22***	0.085***	-0.311
ΔlnEC(-1)	-0.020	-0.231**	0.081	-0.286**	0.523***	-0.029	0.013
ΔlnEP	0.011	0.021	0.079	0.084***	0.076***	0.215***	0.022
ΔlnEP(-1)	-0.057	0.044	0.067	0.094***	0.045	0.079***	0.051
ΔlnCPI	0.037	0.24***	-0.049	0.241***	-0.04***	0.054***	-0.453
ΔlnCPI(-1)	0.024	-0.271**	0.528	-0.251**	0.241**	-0.512	0.095
Panel B: Long-run coefficients							
LnER^{+}	-0.31***	0.021	0.059	-0.712***	-0.201	0.321	0.051
LnER^{-}	-0.199	0.201	-0.887***	1.112	0.049	-2.854	0.218
LnEC	0.294***	0.554**	0.322***	0.765***	0.198	-0.222	0.301***
LnEP	0.047	0.34***	-0.059	0.251***	-0.05***	0.014***	-0.443
LnCPI	0.054	-0.371**	0.527	-0.351**	0.244**	-0.812	0.094
Panel C: Diagnostics							
Reset	1.71	1.99**	1.432	2.001	1.182	5.001	1.899*
LM	1.123	2.008	2.123	1.897	0.995	0.798	0.498
CUSUM	S	S	S	S	S	S	U
CUSUMQ	U	U	U	U	S	S	S
ECM	-0.031**	-0.033*	-0.097***	-0.019**	-0.039**	-0.009***	-0.055***
Adj. r^2	0.124	0.765	0.423	0.756	0.645	0.632	0.321
Wald$_{SR}$	1.234	1.643	1.748	4.124***	6.553***	3.234***	1.786
Wald$_{LR}$	1.912	1.223	6.432***	4.532**	1.984	1.245	1.876

*Note: In panels A, B, and C, this Table provides the findings of the NARDL technique, encompassing short-run, long-run, and diagnostic statistics. Ramsey Reset and LM tests examine the model specification and serial correlations. CUSUM and CUSMQ tests are used to ensure the stability of the approach, while ECM and Adj.r2 are used to assess the speed of adjustment and model fitness. WaldLR and WaldSR test the null symmetry hypothesis in the long and short run. The significance levels of ***, **, and * denote the significance of the coefficients at 1%, 5%, and 10%, respectively.*

The estimations of the nonlinear ARDL technique are shown in Table 5. Panels A, B, and C depict the short-run coefficients, long-run coefficients, and diagnostic test statistics, respectively. The exchange rate is fragmented into positive (ER^+) and negative (ER^-) series to determine if the exchange rate has a symmetric or asymmetric influence on energy demand in E7 economies. In Brazil, India, Indonesia, and Russia, the short-run coefficients for negative and positive variations in the exchange rate are typically small, showing a symmetric impact of the exchange rate on energy demand. Few of the previous studies support these findings (Chang, 2020; Chang and Rajput, 2018; Peng et al., 2022; Noman et al., 2023), whereas other studies contradict our findings (Gohar et al., 2022b, 2022c, 2022d; Wang et al., 2022). In other countries like China, Mexico, and Turkey, the exchange rate has an unbalanced impact on energy demand. The decline in the exchange rate has no significant impact on energy demand in these economies, whereas the increase in the exchange rate significantly impacts energy demand. According to the data, energy demand remains unaltered when the local currency appreciates.

The findings indicate that policy decisions should be altered during local currency depreciation as exchange rates influence energy demand. In the long run, the bounds test results indicate that the exchange rate's impact on energy demand is insignificant for all economies except India. Long-run findings suggest that a drop in the currency rate has a major impact on energy demand. In contrast, a rise in the exchange rate has an insignificant effect, supporting asymmetric impact in India's context.

The diagnostic estimations in panel C of Table 5 show that the $Wald_{LR}$ and $Wald_{SR}$ estimations have been appropriately applied to reveal long-run and short-run asymmetry. The null hypothesis of long-run and short-run asymmetry is that there is a symmetric impact. The short-run findings in China, Mexico, and Turkey's context reject the null hypothesis and support the asymmetric impact in these economies, as stated earlier. However, the asymmetric impact is supported by the Wald estimation in India's context only.

The multiple threshold nonlinear ARDL approach results are presented in Tables 6 and 7. To save the space we present these Tables in the Appendix A. Table 6 displays the results for the quintile group, whereas Table 7 displays the results for the decile group. Both tables present short-run, long-run, and diagnostic test results in panels A, B, and C, respectively. The exchange rate is disintegrated into five fractional additions, with the lowest and highest returns denoted as $ER\eta_1$ to $ER\eta_5$, respectively, in Table 6. The short-run coefficients show a symmetric impact on energy demand in Brazil, India, Indonesia, and Russia. However, the coefficients reveal an asymmetric impact in China, Mexico, and Turkey. The exchange rate has an insignificant impact on energy demand at lower quintiles but significantly impacts it at upper quintiles ($ER\eta_4$ to $ER\eta_5$). Panel C shows the Wald test short-run findings ($Wald_{SR}$) that support the asymmetric impact in China, Mexico, and Turkey.

The nonlinear ARDL approach suggests an asymmetric impact only for India, while the multiple threshold nonlinear ARDL approach shows that all economies except Turkey exhibit asymmetric impact. The impact varies depending on the exchange rate series, with Brazil showing an impact at $ER\eta_1, ER\eta_2, and\ ER\eta_5$, Russia showing an impact at $ER\eta_3\ and\ ER\eta_4$, and India showing an impact at $ER\eta_4$. In China, there is a negative impact on energy demand at the upper quintile and a significant positive impact at the lower quintile. The Wald test long-run (WaldLR) results in panel C support asymmetric impact in all economies except Turkey.

To ensure the robustness of our findings, we applied the multiple threshold nonlinear ARDL approach with a series of deciles. We presented the results in Table 7. The short-run findings in Table No: 07 support the results obtained from Table 6. Moreover, the long-run findings of the multiple threshold nonlinear ARDL approach with a series of deciles revealed asymmetric impacts for all economies except Turkey. Previous studies also obtain similar findings (Chang et al., 2022a, 2022b; Maydybura et al., 2022). It highlights the approach's robustness when dividing the exchange rate series into deciles. Overall, our results suggest that a multiple threshold nonlinear ARDL approach with a series of quintiles and deciles is more effective in identifying significant asymmetric impacts of exchange rate variations on energy demand, which are often neglected by the usual nonlinear ARDL approach (Chang et al., 2018; Chang et al., 2020a, 2020b). These findings have important policy implications, indicating that formulating policies based on fluctuating exchange rates may result in adverse outcomes. Our studies also support the existing literature, such as Ali et al. (2022); Uche et al. (2022a). Similarly, studies like Chang et al. (2019a; 2019b), Hashmi and Chang (2023), and Uche et al. (2022b) also obtained consistent findings.

Finally, the results of our study, presented in Table 8, given in Appendix A, based on the Granger causality test, demonstrate that the coefficients are significant across all quantiles. Therefore, our findings suggest that the exchange rate significantly influences energy consumption at all levels, and economic activity also significantly impacts energy consumption at all quantiles. However, energy consumption can only impact exchange rates and economic activity at one or two lower quantiles. These results suggest that the exchange rate and economic activity are the primary drivers of energy demand rather than the other way around.

5. Conclusion

The study aims to investigate the impact of exchange rates on energy demand and explore the nonlinear link between them. The available studies lack a particular focus on the currency rate as a factor of energy demand and neglect to account for the asymmetric dynamics of financial and macroeconomic factors. Thus, this research aims to bridge this gap by dividing the series of exchange rates into quintiles and deciles to determine whether the influence of modest and substantial shifts in exchange rates on energy demand differs significantly. The study employs the multiple threshold nonlinear ARDL approach introduced by Pal and Mitra (2015, 2016) and compares its results with those of conventional ARDL and traditional nonlinear ARDL approaches. This study also employs Granger causality in the quantile test for the robustness purposes.

The results from the conventional ARDL and nonlinear ARDL approaches did not yield significant findings. The bounds test for these approaches only revealed a long-run relationship between the variables for some economies, except for India. Additionally, the estimations from the nonlinear ARDL approach only supported nonlinear impacts in the short run in China, Mexico, and Turkey. However, the multiple threshold nonlinear ARDL approach showed that the short-run nonlinear impact was only present in these three economies. Conversely, the multiple threshold nonlinear ARDL approach with a series of deciles showed significant variation in the long-run impact for all economies.

Additionally, the research finds that the impact of the currency values on energy demand is asymmetric in China, Mexico, and Turkey's context, where an increase in the exchange rate leads to a significant impact on energy demand. In contrast, a decrease in the exchange rate has an insignificant effect. Therefore, policymakers should consider implementing policies to mitigate the negative impacts of currency depreciation on energy demand in these economies. Moreover, the findings of this study suggest that the conventional nonlinear ARDL approach may neglect the variations in the impact of minor to major variations in the exchange rate on energy demand, which is evident when employing the multiple threshold nonlinear ARDL approach. Finally, our results based on the Granger causality in quantile test suggest that the effect varies over various quantiles. Overall, this study's results can help policymakers formulate better policies that consider the impact of exchange rate fluctuations on energy demand in emerging economies.

Our study draws several policy recommendations. First, our study's findings help policymakers in emerging countries better understand the impact of exchange rate changes on their energy imports and exports and develop appropriate trade policies. Second, emerging countries' energy demand is expected to increase significantly in the coming decades. The study's findings can inform policymakers about how changes in exchange rates affect energy demand, which can have important implications for energy security. More specifically, our findings suggest when appropriate policies need to be devised when there are large variations in the exchange rate and when there are small variations in the exchange rates. The findings can also have implications for economic growth in emerging countries. Third, energy is an essential input for economic activity, and fluctuations in energy demand can affect economic growth. Policymakers can use our study's results to understand better the relationship between exchange rates, energy demand, and economic growth and design policies to mitigate the negative effects. Fourth, exchange rate fluctuations can affect foreign investment in emerging countries. Investors may be deterred from investing in a country if exchange rate volatility increased the risks associated with investment. Therefore our study's findings could help policymakers in emerging countries to better understand the relationship between exchange rates and energy demand and develop policies to attract foreign investment.

Data Availability Declaration: The data that assist this study's results are accessible from the corresponding author upon acceptable request.

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