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REGULATIONS, INNOVATION AND ENERGY CONSUMPTION: EVIDENCE FROM EU HOUSEHOLD

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ABSTRACT

This research intended to help us establish the relationship between energy efficiency (EE) and economic development by studying environmentally focused technology advancements. With data from 20 EU countries (ranging from 2008 to 2022), the analysis examines energy consumption by household sectors, focusing on the two main sources of energy, electricity and gas. Two additional indicators added in the analysis to examine their role on EE. We employed cointegration analysis through first generation Dynamic Panel ARDL models (Autoregressive Distributed Lag) to determine the long run and short-run fluctuations of relationship between variables in panel data framework. Three error correction-based test; Pooled mean group (PMG), Mean group (MG) and Dynamic fixed effect (DFE) were employed on four different models for estimating dynamic heterogeneous panel data. While PMG gives contrasting outcomes, MG and DFE come out with conflicting findings, none of which strongly supports a causal link between EE and development. Tests for cross-sectional dependence (Pesaran, 2004; Friedman, 1973) clearly show the need for using second-generation methods of cointegration. Following the use of CCE estimators, there is still not enough proof, which means that a clear connection between EE and economic growth not observed in many countries.

Keywords: *Economic development; Energy efficiency; Dynamic Panel ARDL models; cross-sectional dependence; Panel data; Europe.*

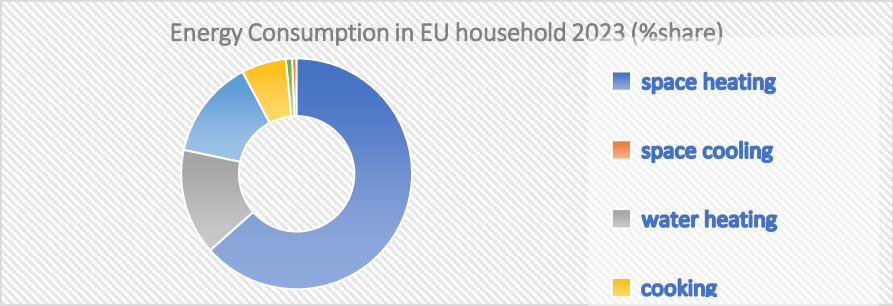
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1. INTRODUCTION

There is an appreciable shift in Europe's energy demand, which is becoming more efficient and shifting towards renewable energy sources instead of fossil energy. The region's total energy consumption has decreased gradually over the past few years, mainly because of strongly implemented policies meant to streamline carbon emission and efficiency measurement. The IEA 2023 report on Europe's energy mix points out that, total primary energy consumption has declined by an average of 2% annually over the last decade via the effectiveness of energy and structural reforms in the region's economy. Renewable and non-renewable energy sources form part of Europe's energy mix. Even as other cleaner options become popular, natural gas, oil and coal are still in high demand, but their influence in the total energy sector is decreasing. In comparison with 2008, the share of natural gas in primary energy has declined over the years, being 25% down to the current rate of 20 cent. Even so, it remains an important aspect of Europe's energy mix. Meanwhile, coal seems to be playing a smaller and smaller role. It has reduced its share roughly to a mere one-half from a significantly higher level because of the strict emissions rules. However, renewable energy sources have had a phenomenal improvement in the recent past. In 2023, the proportion of renewables such as wind, biomass and solar in the European energy mix was about 35%. The highest share among renewables comes from wind power, offering nearly 15% of the area's electricity. Although solar currently plays a smaller role, it is progressing, due to the Green Energy Policy by the European Union. The European Environment Agency (EEA) report estimates that renewable energy capacity has increased fifty percent in the last five years, due to firm commitments to investments in infrastructure and innovations. Such advancements align very much with the intentions of the European Green Deal, to bring Europe to climate neutrality by 2050, with a primary emphasis on moving to renewable sources of energy rather than non-renewable resources.

Europe has a relatively good record in terms of efficiency improvement in energy consumption even though the outcomes vary significantly depending on the sector or the country. Several governments around the region have implemented various policies intending to enhance Energy efficiency. Energy and reduced-energy goals in all sectors were kept with the Energy Efficiency Directive and the European Green Deal of the EU. In the residential sector, the principal existing programs that have contributed significantly to the increase in efficiency include building renovations and strict energy codes. For instance, Germany reduces household energy consumption by 10 % within the framework of the Energiewende Program by using energy-efficient appliances and improved insulation for the period 2000 to 2020 (Federal Ministry for Economic Affairs and Climate Action, 2021). Similarly, France's Plan de Bâtiment Durable revealed that residential energy has reduced by 15% per square meter in the last two decades (Ministry for the Ecological Transition, 2022).

Fig.1: The Household energy consumption in Europe (2023)

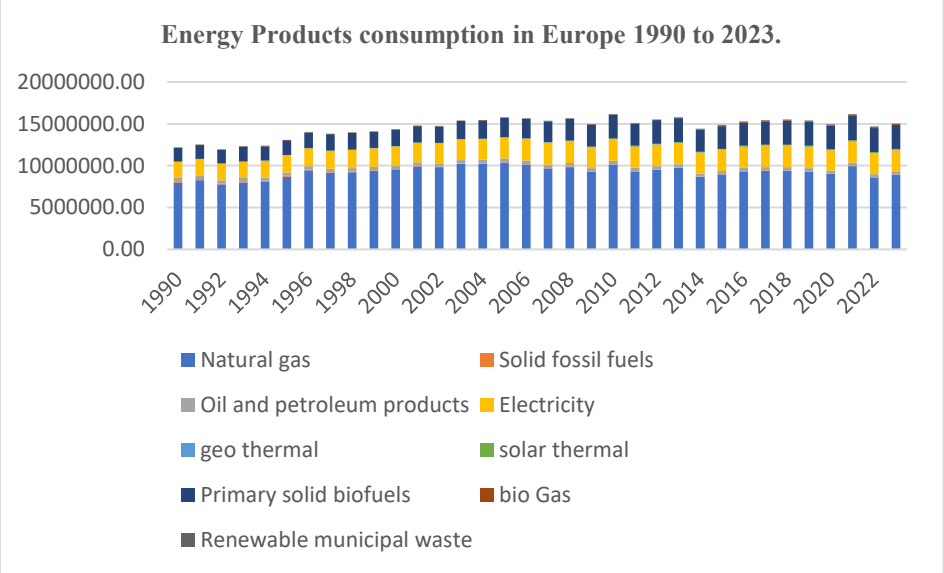


Source: Eurostat

In the industrial and commercial sectors, where policies such as the Industrial Emissions Directive in the EU have encouraged efficiency through improved technology and processes. The energy intensity in industries in Sweden in the period 2000-2020 reduced by 35%, while in the Netherlands; the Energy Efficiency Action Plan has contributed to a 20 % reduction in industrial energy use since 2005.

However, there are still inequalities between the low-income and the high-income EU countries. Some countries such as Romania and Bulgaria still have a high-energy intensity because they do not have proper infrastructure and regulation systems. The energy intensity of energy use in Romanian households stands at 0.22 MJ per 1 unit of GDP, even exceeding the EU average of 0.15 MJ. In contrast, Bulgarian households directly consume 25% more energy per capita than the norm in the EU. Closing this gap will require a real effort to fund the investment in infrastructure along with selective improvement in energy efficiency policy.

Fig. 2: Regional energy product consumption trends (1990–2023)



Source: Eurostat

European energy demand affected by price changes and the levels of income in different sectors, making for a quite complex association among the economy and energy consumption. An increase in energy prices usually leads to low consumption due to the implementation of efficiency measures by consumers and producers. For instance, the IEA has observed that increased fuel prices lead to more energy conservation among consumers and producers due to the adaptation of energy-saving practices. On the other hand, low prices increase the consumption level by improving the affordability of the consumer.

Sectoral income levels also have a substantial function. The manufacturing and chemical industries, which contribute to high output, demand much energy to maintain production. "The industrial development is accompanied by a proportional rise in energy demand, indicating a solid relationship between economic activity and energy consumption because sectors with higher output use additional resources to run their activities"(European Commission, 2021). Therefore, energy price and sectoral income, associated with output level, are key determinants of energy demand and control economic and industrial energy usage.

National energy taxing, environmental spending and investment in environmental technologies are central to sustainability policies and energy efficiency. "Energy taxes,

such as carbon taxes and fuel levies, effectively discourage excessive fossil fuel consumption by increasing costs, thus promoting energy-efficient alternatives and reducing greenhouse gas emissions" (World Bank, 2021). Similarly, carbon taxes promote the decrease in carbon emissions and use of renewable energy sources. These results imply that well-structured environmental taxes can reduce CO2 emissions (He, 2024).

At the same time, environmental protection expenditure is a significant factor in supporting the infrastructure and promoting energy efficiency programs. It includes funding for pollution control, conservation, and renewable energy funding which supports a green economy (OECD, 2022). Investing in environmental technologies including the developments in clean energy and efficient waste management systems advances the progress through innovation and efficient energy performance in various sectors (IEA, 2023). According to Xia et al. (2024), two measures taken by governments around the world include "carbon tax" and "carbon subsidy" efforts. The carbon subsidy scheme entails governments transferring funds to businesses in order to change to sustainable technology or reduce their emissions. It is known as the carrot policy (Chen et al., 2019; Zolfagharinia et al., 2023). On the other hand, carbon tax is an instrument that requires the state to charge an emissions tax specific to greenhouse gases, thus reducing the risk of companies implementing harmful technologies, and is labeled as the stick approach. Sun et al. (2022), Fan et al. (2023), Drake et al. (2016). Moreover, the state can employ the carrot and stick approach at the same time, giving out financial privileges and imposing fines on sustainability.

These collective actions of national policies not only minimize energy consumption but also work for the better future of energy and clearly show how they are indispensable for long-term environmental objectives.

2. REVIEW OF LITERATURE

Energy efficiency (EE) has continued to take a center stage in realizing sustainable economic growth and fulfilling climate policy objectives. Nevertheless, the nature of defining and measuring EE is complicated. The earlier publications by Farrell (1957) formed the basis of measuring productive efficiency whereas subsequent developments consist of deterministic frontier models (Afriat, 1972; Richmond, 1974; Schmidt, 1976) and stochastic frontier analysis (Aigner et al., 1977). Along with newer models (Cornwell et al., 1990; Battese & Coelli, 1992), time-varying efficiency entered consciousness, whereas traditional EE indices (Nilsson, 1993; Liddle, 2010) continue to be commonplace, although criticized as having little capability of capturing the full efficiency dynamics (Patterson, 1996; Hu & Wang, 2006).

The proposal relies on Environmental Kuznets Curve hypothesis (EKC) according to which environmental effects are likely to increase at the initial phases of economic progress but will decrease beyond a specific income level (Grossman and Krueger, 1995; Dinda, 2004). Applying it to EE implies that lower- and middle-income economies can be characterized by increasing energy intensity at first, whereas higher-income nations can gain efficiency by structural change and innovation (Shahbaz et al., 2017). Other connected frameworks like rebound effect (Saunders, 2021) and the Porter Hypothesis (Porter & van der Linde, 1995) define expectations on the correlation between energy efficiency (EE) and economic growth.

In line with the Environmental Kuznets Curve (EKC) hypothesis, Grossman & Krueger (1995), Dinda (2004), Shahbaz et al. (2017), Alvarez-Herranz et al. (2017), Pata (2021), and Apergis & Payne (2010) show that the growth of an economy leads to an upward shift in energy consumption and intensity, but at a later stage of development, strength changes and innovation lead to higher efficiency. Nonetheless, rebound effect, partially counterbalances the gains with the increase in consumption because of cost reductions in efficiency as demonstrated in Sorrell (2009), Saunders (2021), Dimitropoulos (2007), and Brnnlund et al. (2007). Conversely, it is the Porter Hypothesis that states that to some

extent, a well-developed policy can trigger the innovation of EE and counter any rebound effect; where the EU-countries are concerned, Popp (2019), Costantini & Mazzanti (2012), Lanoie et al. (2008), and Marin & Vona (2019) support such a claim.

Based on these theoretical assumptions, various academic studies have carried out empirical research to explore the association between EE and development in different contexts. The approach used in empirical studies on EE and economic development plays a key role in determining if findings are valid and strong. The Pooled Mean Group, Mean Group and Dynamic Fixed Effects estimators are some of the major econometric methods of handling panel data. Each of these methods has some advantages and some drawbacks regarding heterogeneity, cross-sectional dependency, time varying trends across countries or regions. Moreover, realizing that panel data often have cross-sectional dependence led researchers to apply second-generation cointegration methods that assure more reliable and consistent findings. Pooled Mean Group estimator, proposed by Pesaran, Shin and Smith (1999), applied a lot in macroeconomic and environmental economics research. The PMG model assumes that the slope coefficients are similar in the long term for each unit in the panel, but may differ and have different error variances in the short term. The model is effective under circumstances where one has a theoretical explanation indicating that, relationships are stable over time across nations but the readjustment process may remain dramatically different due to the diverse structures or systems. As an example, Lee and Chang (2007) applied the PMG estimator to analyze the relationship between energy consumption and economic growth and concluded that industrialized countries exhibit a long-run relationship in this field. Similarly, Narayan and Narayan (2005) used PMG to examine the Environmental Kuznets Curve (EKC) hypothesis within developing countries and they discovered that carbon emissions had a smooth association with the income levels in the long run. Mean Group estimator, proposed by Pesaran and Smith (1995), has the regressions run separately on each group, and pools the estimates of the parameters. This approach is able to deal with different county-specific long run and short run trends since homogeneity of slope is not require by this method. It is most appropriate in studies where the panel units vary considerably with each other. In 2006, Dinda and Coondoo examined income and CO2 emissions in various nations with the MG estimator, finding that different economies result in various environmental results. The key distinction between the Dynamic Fixed Effects estimator and PMG or MG is that the Dynamic Fixed Effects assumes that each unit is the same across short and long run and this is more restrictive. Although this may help estimates be more accurate if the assumption applies, it may produce results that are biased and inconsistent when there are major differences between countries. According to Eberhardt and Teal (2010), DFE should use with care in heterogeneous panels, because it might disregard important features unique to individual countries.

In recent years, the topic of cross-sectional dependence (CD) in macro- panel data has become the center of attention. CD occurs because of shocks, policy influences or unexpected global forces that affect all countries differently. If cross-sectional dependence ignored, the analyses may not give correct and valid outcomes. Pesaran (2004) introduced a CD test that is valid across a broad range of dynamic heterogeneous panel models. Friedman (1973) also introduced early methods to check cross-sectional dependence, underscoring how important it is in panel data statistics.

Second-generation cointegration models developed because first-generation methods like Pedroni and Kao tests assume that all cross-sectional units are uncorrelated. They try to include cross-sectional dependence using either a multifactor error structure or correlated common effects. Pesaran (2006) introduced the Common Correlated Effects Mean Group (CCEMG) and Common Correlated Effects Pooled (CCEP) estimators and these are now among the leading second-generation techniques. They use standard panel regressions with cross-sectional averages of the variables, which helps capture how common and unobserved factors affect the results. Chudik and Pesaran (2015) added additional

elements to the framework, introducing the CS-ARDL model that offers even better estimation for data with weakly exogenous variables and dynamic panels. In environmental and energy economics, such techniques are increasingly being used to investigate how energy use, emissions, economic growth and technological progress are related in the long run. For example, Kapetanios et al. (2011) showed that CCE estimates are more reliable and consistent for panels with multifactor error structures that are not stationary, surpassing the performance of traditional methods. Eberhardt and Presbitero (2015) suggest that both variation in slopes and the correlation between cross-sections should considered in panel models. The authors show that this can result in incorrect suggestions for policymakers, especially when it involves public debt and energy. Considering that economic and environmental policies often guided by international trends and exchanges, it makes these methodological issues increasingly key. Some recent studies applying second-generation panel methods have looked for more detailed and accurate relations among energy efficiency and economic development. As an example, Salahuddin and Gow (2016) have used the CCEMG estimator to test the impact of renewable energy and economic growth on carbon emissions in the United Arab Emirates, Saudi Arabia, Kuwait, Oman, Qatar, and Bahrain who are members of the Gulf Cooperation Council (GCC). CD inclusion was found to be a significant difference in coming up with reliable long-term projections. Similarly, Destek and Aslan (2017) applied second-generation panel cointegration tests to examine the relationship between energy and growth in new EU member states indicating that it requires tailor-made policy responses.

Generally, existing studies indicate that despite the fact that the respective estimators including PMG, MG and DFE are useful, careful application of these methods should made when data are cross-sectionally dependent and have heterogeneous slopes. Second-generation methods in cointegration better capture the complicated connections between variables in large macroeconomic data sets. Since global environmental and energy issues are evolving, future studies should depend more on these advanced technologies to direct evidence-based policy decisions. Although theoretically, there are chances that the relationship between EE and GDP may be non-linear, varying in accordance with income levels and the sector of activity, and prone to be sensitive to both institutional and policy conditions. The insights can be especially applicable to the European context, with varying levels of income, industry structure, and environmental policy in countries (Zafar et al., 2021; Arcelus et al., 2018).

3. MODEL SETTING AND EMPIRICAL METHODOLOGY

3.1. Model Setting, Sample Countries and Data

In order to determine how Economic development (ED) influences Energy Efficiency (EE), we have estimated four models. We used two forms of energy; Electricity and Gas and divided them in household and non-household sectors. We also include two Environment related variables to find out their impact on EE.

We consider 20 European Union member states. The EE-economic development linkage for our sample EU regional states is tested. The data on Household GDP (HGDP) acquired from United Nations Conference on Trade and Development UNCTAD stat. While the data on Household electricity Consumption (HEC), Household Gas Consumption (HGC), Household electricity Prices, (HEP), Household Gas Prices (HGP), Household Energy Taxes (HET) collected from Statistics agency of the European Union (EURO stat). Expenditure on Environmental protection (EEP) series sourced from International monetary fund (IMF) while Environment related technology (ERT) data comes from Organization for Economic Co-operation and Development (OECD Stat).

3.2. Empirical Methodology

3.2.1. Estimating the general-most version of EE-economic development linkage the method of identifying Cointegrating relationships

The introduction of the concept of cointegration around 1980 became a main development in time-series econometrics by Granger (1981). Cointegration analysis helps researchers to work with non-stationary data without worrying about generating deceptive or flawed outcomes. Under this approach, the long/term equilibriums among variables can be analyzed using actual time-series data. For the purpose of theoretical representation of EE-Economic Development proposition, 1st consider the following Time series long-run estimable regression equation:

$$ee_{kt} = \alpha + \beta_0 ert_t + \beta_1 ep_t + \varepsilon_t \quad (1\text{-}a)$$

$$ee_{kt} = \alpha + \beta_0 ert_t + \beta_1 ep_t + \beta_2 gdp_t + \beta_3 eep_t + \beta_4 et_t + \varepsilon_t \quad (1\text{-}b)$$

$$k = non - renewable\ and\ renewable$$

Where subscript *t* denotes year. Amongst the set of deterministic regressors, α is the individual (country-specific) intercept term. β_1 and β_2 are the individual slope coefficients. *ee* is some indicator of energy efficiency, *ert* represents environment related technology, *gdp* represents GDP, e*p* is energy price measure, *eep* is national expenditures on environmental protection, and *et* is energy-relatead taxes. In addition to taking into account the direct impact of economic growth on EE levels, we also are accounting for the its indirect effects, since, *eep, and et* are evidently treated in earlier papers as indirect channels through which the effects of economic development may reflect on the state of resource consumption and usage.

This model specification in the research based on the past empirical work on the relationship between energy efficiency (EE) and innovation, economic growth and environment policy, specifically the frameworks proposed by Shahbaz et al. (2017) and Alvarez-Herranz et al. (2017). Important theoretical expectations are reflected through equation (1-a) and (1-b). This consideration of environment-related technology (ERT) is an implication of the Porter Hypothesis (Porter & van der Linde, 1995) that it is possible to improve EE through innovation. Energy prices (EP) are a form of market incentives and related to rebound effects, which are likely to occur (Sorrell, 2009) whereas GDP will be included to test the EKC hypothesis that there will be no linear relationship between growth and EE (Grossman & Krueger, 1995). Environmental protection expenditure (EEP) and energy taxes (ET) further amount to regulatory and policy-induced influences on EE results. Such a model structure allows investigating both market-based and policy-induced factors of EE in EU countries, in line with the existing literature on this subject.

In addition to validating our theoretical model specified in equation (1-a) through single equation and multivariate time-series cointegration methods, we also aim at validating our findings through panel data cointegration tests. Because panel data analysis can use data from more than one countries and different periods, it has a better statistical power than single-country time-series analysis. Since the number of years of data that are normally available is quite limited, the time-series studies can produce weak values of t and F, implying that both short-run and long run estimates are not very trustworthy. The limitation is mostly evident in studies, which utilize yearly data where the economic records are mostly of less than fifty years. The panel data estimation methods therefore have an advantage in this regard since the data series can be pooled as panels of various countries. This mitigates the problem of small numbers of observations for researchers. Using panel data sets on EE-Economic Development proposition, the estimable version of equation (1-a) is:

$$ee_{it} = \alpha + \beta_0 ert_{it} + \beta_{1i} ep_{it} + \varepsilon_t \quad (2\text{-}a)$$

$$ee_{it} = \alpha_i + \delta_i t + \beta_0 ert_{it} + \beta_{1i} ep_{it} + \beta_{2i} gdp_{it} + \beta_{3i} eep_{it} + \beta_{4i} et_{it} + \varepsilon_{it} \quad (2\text{-}b)$$

Here, the country is represented by the subscript i and t represents the year. The letter α_i is the country-specific intercept; δ_i takes the time trend's coefficient and β_{1i} and β_{2i} are the slope coefficients for each country.

3.2.2. Testing for Cross-Sectional Dependence

The evidence of the relationship between energy efficiency and economic development presented in the traditional cointegration models gives biased results due to not considering the aspect of cross-sectional dependence that should be crucial to the analyses in the field of regions. When this dependency overlooked, it might result in incorrect findings, since it conditions the fundamental features of panel data estimation (Andrews, 2005; Pesaran, 2015; Demetrescu and Homm, 2016). In the second step of our estimation process, we thus identify the actual position of cross-sectional dependence in our sample countries using the CSD tests suggested by Pesaran (2004). The estimable formulation of Pesaran (2004) test is:

$$\boldsymbol{CD_{Pesaran\ (2004)}} = \sqrt{\frac{2}{i(i-1)}} \sum_{k=1}^{i=1} \sum_{j=k+1}^{i} \boldsymbol{T_{k,j}}\, \widehat{\boldsymbol{\rho}}_{\boldsymbol{k,j}} \sim \boldsymbol{N(0,1)} \qquad \textbf{(3)}$$

According to the above stated formulation, CD has zero mean and constant variance. To identify whether CD is present, CD claimed to be absent (null hypothesis) and first tested against a claim of significant CD (alternative hypothesis). In addition, we also use the Friedman (1937) CD test to further verify the results we obtained from the Pesaran (2004) CD test.

3.2.3. Testing for EE-economic development linkage using Second Generation Cointegration Models

When we have substantial cross-sectional dependence (CD) in our panel we have to reexamine the relationship between energy efficiency (EE) and economic development through the second-generation cointegration methodologies. Such advanced econometric models are specifically suggest to cover the problem of CD that is commonly a problem in panel-based datasets, particularly featuring countries within the same geographical region. The second-generation cointegration methods provide robust and reliable estimates than their first-generation counterparts by allowing the assumption of cross-sectional independence among the panel units to be relaxed; this is especially the case when CD is sufficiently non-trivial.

In our analysis, we apply four estimators, which are under the second generation of cointegration tests. Even though these estimators formulated differently, they have a similar purpose, i.e. they aim to include unobserved common factors, which are general in panel data.

(i) Common Correlated Effects (CCE) Estimator:

The CCE estimator, introduced by Pesaran (2006), is particularly appropriate to use when there are large panels, and the individual units are susceptible to unobserved common shocks. The estimable version of the model presented as:

$$\boldsymbol{y_{it} = \alpha_i + \beta_i' x_{it} + \delta_i' f_t + \varepsilon_{it}} \qquad \textbf{(4)}$$

Where y_{it} represents dependent variable and x_{it} is a vector of explanatory variables. f_t Represents unobservable common factors and ε_{it} denotes white noise error term. f_t Cannot be measured directly, and the model uses proxies based on the cross-sectional averages of y_{it} and x_{it} in order to capture these effects.

(ii) Dynamic Common Correlated Effects (DCCE) Estimator:

The DCCE estimator is an extension of the CCE estimator, which adds dynamics into the model. It should especially use when the data have both time-series dynamics and cross-sectional dependence. The model has lagged-dependent variables as regressors:

$$\boldsymbol{y_{it} = \alpha_i + \varphi y_{it-1} + \beta_i' x_{it} + \delta_i' f_t + \varepsilon_{it}} \qquad \textbf{(5)}$$

Here, y_{it-1} is the lagged dependent variable, which is a measure of time persistence. The DCCE estimator allows controlling the unobserved common influences using both contemporaneous and lagged cross-sectional averages of the variables.

(iii) Common Correlated Effects Pooled (CCEP) Estimator

A pooled form of CCE method is the CCEP estimator. It is easy to estimate since it implies regression of the dependent variable on the averages of the explanatory variables over the cross-sections. With this method, it is assume that the average can well represent the prevalent unobserved factors:

$$\boldsymbol{y_{it} = \beta_i' x_{it} + \delta_i' f_t + \varepsilon_{it}} \qquad \textbf{(6)}$$

Where y_{it} represents dependent variable and x_{it} is a vector of explanatory variables. f_t Represents unobservable common factors and ε_{it} denotes white noise error term. f_t Cannot be measured directly, and the model uses proxies based on the cross-sectional averages of y_{it} and x_{it} in order to capture these effects.

(iv) Cross-Sectional Error Correction Model (CS-ECM)

The CS-ECM expands the error correction model to support a cross-sectional dependence, state both short, and long relations in estimating relations. The standard ECM model employs the historical variation in $\Delta \boldsymbol{y_{it}}$ and the variation in the long-run equilibrium relationship. This model is provide as:

$$\boldsymbol{\Delta y_{it} = \alpha_i + \varphi_i(y_{it-1} + \beta_i' x_{it-1}) + \gamma \Delta x_{it} + \eta_{it}} \qquad \textbf{(7)}$$

In this formulation, the lagged value of the dependent variable modeled by y_{it-1} and used as explanatory variables in this model. Δ refers to first-difference operator and γ donates Short-run dynamics. φ_iIs speed of adjustment coefficient representing the rate at which the system moves back towards equilibrium, $y_{it-1} + \beta_i' x_{it-1}$ represents Long-run disequilibrium

4. Results and Discussion

4.1. Estimating the general-most version of EE-economic development linkage – the method of identifying Cointegrating relationships

As all variables were stationary at the first-difference level, we carried on the cointegration analysis based on first-generation Dynamic panel ARDL (Autoregressive Distributed Lag) models. These models found useful in indicating not only long-run equilibrium relationships but also short-run dynamics in a panel data analysis. To split these dynamics, we used three estimators based on error correction, which are Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE). These estimators used in two different models aimed at measuring dynamic heterogeneous panel relationships.

Such an analysis is more effective using the PMG estimator proposed by Pesaran, Shin, and Smith (1999). It considers one common long-run relationship between variables across the panel and allows short-run coefficients, error variances and adjustment speeds to vary cross-sectionally

We are starting with our first model, Household Electricity Consumption. TABLE 1 shows the long-run estimation results based on the PMG estimator, which gives empirical evidence on the long-term relationship between energy efficiency and economic development.

Table 1: Long run Results for EE-economic development linkage using Pooled Mean Group (PMG) Cointegration Estimator for household Electricity

Long-Run coefficient		Standard Errors	Z-Statistics
hep	-3.153*	0.321	-9.79
hgdp	2.300*	0.293	7.85
het	-0.695*	-0.153	4.53
eep	-0.098**	0.043	-2.27
ert	0.332*	0.076	4.36

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

Table 1 shows that Household Electricity Prices (HEP) is statistically significant and have a coefficient of 3.153 which is consistent with theory. It means that a one-unit rise in HEP brings a 3.153-unit drop in HEC and similarly, a same-sized decrease in HEP causes increase in HEP. These results also indicate that HGDP, HET and ERT display long-run coefficients of 2.300, 0.695 and 0.332, respectively and these are statistically significant and have the right sign. The results based on the PMG estimator give good evidence of a long-run association between energy efficiency and economic development among the sample countries in the EU region.

PMG estimators take into account both short- and long-term trends but this study chiefly examines long-term factors, as many believe the EE-economic development link evolves over time. Furthermore, previous studies (Sadorsky, 2010; Stern, 2004; Wang & He, 2022; Apergis & Payne, 2010; Pao & Tsai, 2011) have pointed out that these relationships last for a long period.

Alternatively, outcomes from using MG method differ greatly, possibly showing that the same EE-economic development relationship does not exist among different countries. Because the MG approach gives different estimates for every nation, it highlights the diverse nature of this link across countries. Table 2 (in annexure) shows detailed results from the MG estimator.

Household Electricity Prices (HEP) data reveal that only Italy, the Netherlands and Türkiye demonstrate a significant long-run bond with an expected negative connection. This reveals that one unit change in HEP reduces HEC by -0.597, -0.779 and -2.903. Household GDP (HGDP) shows only Czechia, Slovenia and Slovakia having a statistically significant and positive long-run effect, with coefficients of 1.595, 2.623 and 0.384, respectively.

From the Household Energy Taxes (HET) results, Czechia and Slovenia are the only nations with a clear negative relationship, as seen in their coefficients of -0.460 and -1.237. According to the results for EEP, Czechia, Germany and Italy show remarkable negative coefficients at -0.080, -0.119 and -0.335, respectively. While Environment-Related Technology (ERT) shows, Austria and Slovenia both exhibit positive and significant long-run effects, with coefficients of 0.587 and 0.327.

Next, we used the Dynamic Fixed Effects (DFE) approach that permits equal long-run coefficients and the equal speed of short-term changes and adjustments in countries. The estimates in Table 3 shows long run results and used to test how energy efficiency and economic development relate for household electricity.

Table 3: Investigating EE-economic development linkage Using Dynamic fixed effects (DFE) Cointegration Estimator for household Electricity

Long-run cointegration vector			
Long-Run coefficient		**Standard Errors**	**Z-Statistics Conclusion**
hgp	-16.9*	2.34	-7.22
hgdp	0.299	.212	1.41
het	-0.410*	0.112	-3.65
eep	0.049	0.041	1.17
ert	0.161**	0.074	2.18

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

The value of the long run coefficients of HEP, HET and ERT are insignificant and 0.102, 0.003 and 0.067 respectively. While HGDP and EEP are significant at 5% and 1% respectively with only HGDP having intuitively correct Signs. Therefore, DFE indicates mixed results. Now we applied same estimators for our second model of Household Gas. Table 4 shows the PMG results.

Table 4: Long Run Estimates for EE-economic development linkage Using Pooled Mean Group (PMG) Cointegration Estimator for household Gas

Long-Run Cointegration Results			
Long-Run Coefficient		**Standard error**	**Z-Statistics Conclusion**
hep	0.102	0.484	0.21
het	0.003	0.104	0.03
hgdp	0.300*	0.125	2.40
eep	0.073**	0.032	2.26
ert	0.067	0.057	1.16

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

There is very strong and negative association between Household Gas Consumption (HGC) and Household Gas Prices (HGP) over time, as the coefficient is -16.9 and statistically significant. Therefore, a rise of one unit in HGP results in a fall of 16.9 units in HGC, as predicted by economic theory. At the 1% and 5% levels, Household Energy Taxes (HET) and Environment-Related Technology (ERT) play significant roles, with their long-run coefficients being -0.410 for HET and 0.161 for ERT as expected. On the other hand, both Household GDP (HGDP) and Environmental Protection Expenditure (EEP) are statistically insignificant. Overall, the PMG estimator provides inconclusive results on the energy efficiency and economic developed in Europe over time. However, the MG estimator returns contradictory results that do not favour the belief that energy efficiency and economic growth are closely related. The long run outcomes of MG as shown in Table 5 provided in annexure.

Only a small number of the 20 countries exhibited a reliable and theoretical connection between major factors and Household Gas Consumption (HGC) over time. According to the results, both Romania (-130.414) and Slovakia (-16.235) shared a significant negative relationship, demonstrating a substantial fall in household gas consumption when gas prices go up. When it comes to Household GDP (HGDP), the only countries that emerged with notable effects were Hungary and Romania. They suggest that greater income results in more gas used by households. Likewise, when it comes to household energy taxes

(HET), Italy and Romania had negative coefficients of –2.489 and –0.232, which means that higher taxes cause people to consume less. There was a strong adverse impact on environmental protection expenditures in both Italy (–1.653) and Hungary (–0.684), showing that increased environmental investment helps reduce the use of energy. With regard to environment-related technology (ERT), Italy and Romania both had positive effects of 1.135 and 0.124, which may suggest that higher gas consumption resulted from better access to technology, or a rebound effect.

Table 6: Investigating EE-economic development linkage Using Dynamic fixed effects (DFE) Cointegration Estimator for household Gas

Long-Run Cointegration Results			
Long-Run Coefficient		**Standard error**	**Z-Statistics**
hgp	3.69	3.75	-0.98
hgdp	0.059	0.619	0.10
het	-0.176	0.251	-0.70
eep	-0.080	0.097	-0.82
ert	0.301**	0.141	2.13

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

The long run coefficient values of HEP, HET, HGDP and EEP are insignificant. While ERT are significant at 5 percent with having intuitively correct Sign. Therefore, the result of DFE indicates mixed results in the long run.

We can conclude from our results that of PMG estimator gives mixed results and MG and DFE are conflicting and strongly negating the valid existence of EE-economic development linkage in our all four models. These outcomes are in line with Gillingham et al. (2008), World Bank (2018), Bhat (2020) and, Bayar and Gavriletea (2020)**.**

The reason behind these results may be that these first-generation panel data models**,** including PMG, MG and DFE, were design without addressing potential correlations across cross-sectional units. However, in real-world applications, such dependencies are common, especially in datasets involving countries. Therefore, we applied Cross-sectional dependence tests because if cross-sectional dependence is present, PMG and MG estimators might lead to biased/Invalid results, and second-generation techniques may be more appropriate.

4.2. Results of Cross Sectional Dependence

The researchers should check on the problem of cross-sectional dependence prior to estimating panel data models. The presence or absence of this issue contributes greatly to the choice of which estimation approaches to use. If variables found to be cross-sectionally dependent, then suitable methods applied to handle the problem in the following analysis. We perform two cross-sectional dependence test on our two models: the Pesaran test (2004) and the Friedman test (1973). They evaluate the mean pairwise correlation present in OLS residuals when using panel regressions on each observation. When the null hypothesis is, true (no cross-sectional dependence) the test statistics distributed normally. The results of the CD test of our first model that examines Household Electricity shown in the table below. Pesaran CD test and the Friedman CD test reject the null hypothesis that no cross-sectional dependence exists. The results clearly indicate a robust cross-sectional relationship among European countries, which holds up to the significance level of 1 percent.

Table 7: Tests for Cross Sectional Dependence for Household Electricity

Tests	T-Statistics	p-Value	Conclusion
Pesaran (2004)	13.453*	0.000	Significant
Friedman (1937)	72.017*	0.000	Significant

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

This outcome is significant as both models rely on the assumption that observations are cross-sectionally independent. Model residuals correlated across cross-sectional units in presence of cross-sectional dependence (CSD) when common factors affecting all countries within the sample are unadjusted (Pesaran et al., 1999). This causes a desperate violation of a fundamental assumption of classical error structures, that of independently distributed residuals.

Since our dataset is highly cross-sectionally dependent, re-evaluation of the relationship between energy efficiency and economic development becomes a necessity using the second-generation panel cointegration estimators. As already mentioned, the main advantage of these sophisticated estimators is to be able to capture the effect of cross-sectional dependence. In line with this, we re-estimate our models with four estimators, which fall under the second-generation cointegration framework namely Common Correlated Effects (CCE) estimator, Dynamic Common Correlated Effects (DCCE) estimator, Common Correlated Effects Pooled (CCEP) estimator, and Cross-Sectional Error Correction Model (CS-ECM). Results for all four tests on our first model of Household electricity shown in table 8 (in annexure).

According to the results, Common Correlated Effects (CCE) estimator can yield unclear or mixed results. Household Electricity Prices (HEP), Household GDP (HGDP) and Expenditure on Environmental Protection (EEP) are significant at the 10%, 1% and 5% levels based on the results. As predicted, GDP and EEP display the correct signs, with their long-run coefficients being 1.654 for GDP, 0.705 for EEP and -0.348 for HEP.

Based on the result of Dynamic Common Correlated Effects (DCCE) estimator, HEP, GDP and EEP are significant at the 10%, 1%, and 5% level respectively with the correct signs as per the theory. The long-run coefficients found by regression are -1.231 for HEP, 2.683 for HGDP and -0.461 for EEP. Alternatively, the findings from Common Correlated Effects Pooled (CCEP) estimator and Cross-Sectional Error Correction Model (CS-ECM) strongly reveal a weak connection between EE and economic development.

Table 9: Tests for Cross Sectional Dependence for Household Gas

Tests	T-Statistics	p-Value	Conclusion
Pesaran (2004)	17.594*	0.000	Significant
Friedman (1937)	99.260*	0.000	Significant

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

Now moving towards our second model of Household Gas, results for CCE estimators given in Table 10 (in annexure).

The outcomes of the estimators CCE, DCCE and CS-ECM in the CCE family failed to find the association between economic development and energy efficiency (EE) due to the regard of cross-sectional dependence. Conversely, CCEP estimator results indicate that no variable is statistically significant, but only GDP is significant at the 1 percent level.

Our outcomes for four CCE estimators are also somehow conflicting and strongly negating the valid existence of EE-economic development linkage. It implies that even after controlling the cross sectional dependence, our findings still deny valid presence of EE-economic development linkage. Our outcomes are in line with Gillingham et al. (2008), World Bank (2018), Bhat (2020), Bayar, and Gavriletea (2020).

This research fails to establish a clear or unified association between energy efficiency (EE) and economic development among EU countries, which is consistent with the findings in earlier studies, which emphasized the relationship in energy efficiency-and-development nexus is a complex issue. The efficiency returns could nullified by the rebound effect (Jevons Paradox) and the macro-level improvements might trigger growth and energy demand (Brookes, 1990; Saunders, 2021; Sorrell, 2009). The results are also dependent on the levels of income and sectoral composition. Energy intensity tends to be lower in high-income economies, whereas in middle-income economies, especially the industrial sector, the connection between energy efficiency and GDP can be bidirectional. (Arcelus et al., 2018; Zafar et al., 2021). Policy design and institutional quality is also relevant, because good governance and effective regulations can increase effectiveness reducing rebound effects (Costantini & Mazzanti, 2012; Porter & van der Linde, 1995; Popp, 2019). Outcomes also determined contextually by development stage, subsidies and infrastructure (Narayan et al., 2010; Filippini & Hunt, 2011) which in the case of emerging economies is particularly effected. Moreover, there are regional trends in the European region that contribute to EE outcomes variations caused by their differences in development, governance, energy mix and cultural norms. Nordic and Western countries tend to be more responsive to policy action because they have better institutions and pro-environment cultures; Eastern and Southern Europe have structural limitations. Such differences highlight a greater necessity to reflect the national and regional conditions in the EU energy efficiency policy-making.

5. CONCLUSION

The central purpose of the study is to find out the relationship between energy efficiency (EE) and economic growth and more specifically how environment-related technological innovations are significant contributors. To determine the influence of Economic development on Energy Efficiency, we have estimated two models. We used two forms of energy; Electricity and Gas for household sectors. We also include two Environment related variables to find out their impact on EE. We consider 20 European Union member states for our analysis from 2008-2022. We chose Household GDP (HGDP), Household Electricity Consumption (HEC), Household Gas Consumption (HGC), Household Electricity Prices (HEP), Household Gas Prices (HGP), Household Energy Taxes (HET), Expenditure on Environmental protection (EEP) and Environment related technology (ERT) to study how they influence energy efficiency and economic development linkage. Data on our variables acquired from United Nations Conference on Trade and Development (UNCTAD), Statistics agency of the European Union (EURO stat) International monetary fund (IMF) and Organization for Economic Co-operation and Development (OECD Stat).

We employed cointegration analysis using Dynamic Panel ARDL models. Three EC-based test; Pooled mean group (PMG), Mean group (MG) and Dynamic fixed effect (DFE) were employed on two different models for estimating dynamic heterogeneous panel data. We can conclude from our results that of PMG estimator gives mixed results and MG and DFE are conflicting and strongly negating the valid existence of EE-economic development linkage in our all four models. We apply two cross-sectional dependence (CD) tests: the Pesaran (2004) test and the Friedman (1973) test on our two models. In the instance of valid CD existing in our panel, there is need for re-estimating our EE-economic development linkage using second-generation cointegration models. Our results for four

CCE estimators are also somehow conflicting and strongly negating the valid existence of EE-economic development linkage. This means that after controlling the cross sectional dependence, our outcomes still negate the presence of EE-economic development linkage. The in concise evidence of the relationship between household electricity consumption (HEC) and the major economic and policy factors: household GDP, electricity prices, energy taxes, environmental protection expenditure, and environment-related technologies supports the complexity of enhancing the household energy efficiency in the EU member states. Conventional policy levers, including price-based mechanisms, or general technological investments, do not seem effective in their own right to bring significant efficiency improvement to the residential sector. Rather, structural and behavioral aspects are likely to modify the effectiveness of such measures in terms of the housing stock quality, consumption patterns, energy infrastructure, and socio-cultural attitudes. Detailed strategies using a regulatory framework with a comprehensive, context-sensitive mix of financial incentives, social, and behavioral change are therefore the broader strategies to seek by the policymakers. Moreover, the extensive heterogeneity among countries shows that a variety of policy approaches developed to consider national social-economic and institutional situations, cultural dynamics, and differences is much needed, as opposed to a standard EU-level policy. These regional differences ought to reflect and clearly addressed in the future EU energy policy as part of their effort to make the policy as effective as possible and to ensure a sustainable decoupling of the usage of energy and the development of the economy.

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Annexure

Table 2: Long Run Results for EE-economic development linkage Using Mean Group (MG) for household Electricity

Czechia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	1.876*	0.174	10.76
het	-0.460*	0.054	-8.51
hgdp	1.595*	0.157	10.14
eep	-0.080*	0.027	-2.91
ert	-0.030	0.026	-1.15
Germany			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	0.818*	0.374	2.18
het	1.28**	0.173	7.40
hgdp	-2.63**	0.408	-6.45
eep	-0.119*	0.052	-2.30
ert	-0.0016	0.0772	-0.02
Estonia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-708.17	51638.24	-0.01
het	-53.63	3859.17	-0.01
hgdp	138.07	10015.87	0.01

eep	-56.47	4130.61	-0.01
ert	0.737	52.06	0.01
Italy			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-0.597*	0.135	-4.39
het	0.962*	0.115	8.32
hgdp	-1.36*	0.129	-10.59
eep	-0.335*	0.064	-5.21
ert	-0.348*	0.032	-10.76
Netherland			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-0.779*	0.057	-13.59
het	0.42*	0.040	10.45
hgdp	-2.734*	0.135	-20.13
eep	0.009***	0.005	1.69
ert	-0.386*	0.031	-12.41
Portugal			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-8.21	12.152	-0.68
het	-4.68	9.822	-0.48
hgdp	-3.98	9.110	-0.44
eep	0.032	0.322	0.10
ert	2.450	4.604	0.53
Slovakia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	0.959	0.769	1.25
het	0.371*	0.152	2.44.
hgdp	0.384***	0.230	1.67
eep	0.215*	0.040	5.32
ert	-0.004	0.075	0.06
Slovenia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-16.51	15.7	-1.05
het	-1.23**	0.65	-1.89
hgdp	2.623*	0.69	3.79
eep	0.300	0.36	0.83
ert	0.327*	0.13	2.42
Turkiye			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hep	-2.903*	0.858	-3.38
het	0.396*	0.109	3.61
hgdp	0.067	0.107	0.64
eep	0.411*	0.062	6.57
ert	0.021	0.016	-1.36

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

Table 5: Long Run Results for EE-economic development linkage Using Mean Group (MG) for household Gas

Belgium			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	-1.051	4.227	-0.25
het	-0.455	0.5248	-0.87
hgdp	-0.789	1.327	-0.59
eep	0.247	0.293	0.84
ert	1.197	1.952	0.61
Germany			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	4.805	3.313	1.45
het	3.094*	0.668	4.63
hgdp	-4.164*	1.115	-3.73
eep	0.320	0.377	0.85
ert	0.404	0.888	0.45
Estonia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	2.801	6.063	0.46
het	-0.016	0.684	-0.02
hgdp	0.0742	0.687	0.11
eep	0.541	0.598	0.91
ert	0.0318	0.096	0.33
Italy			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	0.053	1.487	0.04
het	-2.489*	0.915	-2.72
hgdp	1.560	1.005	1.55
eep	-1.653*	0.446	-3.70
ert	1.135*	0.377	3.00
Hungary			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	3.88	4.441	0.87
het	.372**	0.195	1.90
hgdp	1.616**	0.749	2.16
eep	-.684*	0.265	-2.58
ert	-1.035*	0.297	-3.48
Portugal			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	-10.252	16.670	-0.61
het	-0.370	2.028	-0.18
hgdp	-2.05	4.29	-0.48
eep	0.309	0.310	1.00
ert	0.713	1.17	0.61
Romania			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	-130.414*	5.159	-25.27
het	-0.232 *	0.0700	-3.33
hgdp	0.512*	0.086	5.90
eep	0.504*	0.037	13.55
ert	0.124*	0.010	11.78

Slovakia			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	-16.235*	6.27	-2.59
het	-0.637	0.398	-1.60
hgdp	0.431	0.493	0.88
eep	0.005	0.097	0.05
ert	0.392	0.341	1.15
Turkiye			
Variable	**Long-Run coefficient**	**Standard Errors**	**Z-Statistics**
hgp	144.365	365.337	0.40
het	-10.919	28.816	-0.38
hgdp	14.197	34.015	0.42
eep	-0.580	4.627	-0.13
ert	-1.011	2.607	-0.39

*Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

Table 8: Results for CCE estimators for Household Electricity

	CCE	**Dynamic CCE**	**CCE Pooled**	**CS-ECM**
hep	1.654***	-1.231***	-0.209	-0.786
	(0.946)	(2.671)	(2.163)	(1.534)
gdp	0.705*	2.683*	0.640	0.566
	(0.241)	(1.989)	(1.971)	(1.508)
het	0.070	0.056	-0.007	-0.137
	(0.150)	(0.363)	(0.209)	(0.460)
eep	-0.348**	-0.461**	0.006	-0.023
	(0.157)	(0.373)	(0.294)	(0.373)
ert	-0.233	-0.808	0.062	0.109
	(0.175)	(0.501)	(0.308)	(0.883)
c	-6.392*	-16.11*	-1.478	
	(2.650)	(16.047)	(8.33)	

Country-Specific Results of CCE

	Germany	**Ireland**	**Spain**	**Austria**	**Italy**	**Netherland**	**Portugal**	**Slovakia**
hep	-0.0498	-2.864*	2.850*	7.986	1.785**	-0.525	5.503**	3.318*
	(1.042)	(0.0509)	(0.538)	(11.016)	(0.768)	(0.560)	(2.842)	(0.294)
gdp	1.780*	-1.364*	1.226*	1.186	-0.024	0.382	1.020	-0.510*
	(0.732)	(0.025)	(0.145)	(4.543)	(0.505)	(0.622)	(0.679)	(0.069)
het	0.197	0.227*	-0.565*	0.153	1.695*	0.389	0.447	-0.272*
	(0.248)	(0.004)	(0.119)	(0.608)	(0.552)	(0.533)	(0.349)	(0.037)
eep	-0.601*	0.368*	-0.042	-0.921	-1.799*	0.053	0.584**	0.098*
	(0 .171)	(0.009)	(0.025)	(1.630)	(0.657)	(0.072)	(0.311)	(0.027)
ert	-0.314	-0.585*	-0.147	-3.090	-0.075	0.126	0.254***	-0.052**
	(0.230)	(0.006)	(0.089)	(4.996)	(0.462)	(0.151)	(0.144)	(0.025)
c	-24.893*	4.641*	-6.700*	0.373	-15.665***	-9.869	-11.326	-0.151
	(8.322)	(0.175)	(1.684)	(37.032)	(8.421)	(6.601)	(8.860)	(0.493)

Country-Specific Results of the Dynamic CCE

	Czechia	**Estonia**	**France**	**Spain**	**Italy**	**Austria**	**Hungary**	**Romania**	**Slovenia**	**Slovakia**
hep	-2.154*	-5.078*	-30.354	2.766*	-26.18	19.931**	4.001	5.660*	-1.598***	3.376*
	(0.693)	(2.135)	(24.823)	(1.048)	20.885	(8.783)	(3.103)	(1.609)	(0.853)	(0.792)
gdp	1.294*	0.380	39.651	1.198*	-3.681	6.487***	1.049	0.383*	0.565*	-0.549
	(0.341)	(0.261)	(26.702)	(0.318)	2.350	(3.739)	(0.639)	(0.050)	(0.176)	(0.469)
het	0.238	0.092	-5.788	-0.56*	3.181	0.727	-0.782	-	0.339*	-0.278*
	(0.197)	(0.1907)	(5.035)	(0.178)	2.314	(0.459)	(0.625)	0.152*	(0.138)	(0.087)
								(0.061)		
eep	-0.019	0.329	-6.77***	-0.045	-1.461	-1.890***	-	0.179*	-0.038	0.094
	(0.046)	(0.348)	(3.890)	(0.044)	0.959	(1.092)	0.330**	(0.045)	(0.030)	(0.060)
							(0.151)			
ert	0.215**	0.252*	-7.472	-0.129	-0.740	-6.950**	0.160	0.245*	-0.028	-0.051
	(0.116)	(0.070)	(5.483)	(0.198)	0.545	(3.54)	(0.120)	(0.048)	(0.018)	(0.040)
c	-8.478 *	5.832**	-307.57	-6.212	45.81*	-43.033**	-21.383	9.843*	-1.815	-0.080
	(3.371)	(2.960)	(198.54)	(4.863)	19.465	(30.548)	(13.693)	(2.301)	(0.725)	(1.090)

NOTE
(i) Country specific results are given for the selected states. Estimates for full sample can be provided on request.
(ii) Standard errors given in parenthesis.
*(iii) Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*

Table 10: Results for CCE estimators for Household Gas

	CCE	**Dynamic CCE**	**CCE Pooled**	**CS-ECM**
hgp	2.936	-2.277	0 .406	3.988
	(2.898)	(4.127)	(1.671)	(9.336)
gdp	0.459	0.556	0.862*	1.061
	(0.735)	(0.521)	(0.111)	(0.721)
het	-0.171	0.372	-0.103	-0.215
	(0.433)	(0.253)	(0.196)	(0.745)
eep	0.224	-0.343	-0.017	-0.088
	(0.401)	(0.344)	(0.136)	(0.274)
ert	-00.127	0.133	0.010	-0.022
	(0.438)	(0.340)	(0.063)	(0.674)
c	-5.147	-1.936	-1.186	
	(5.831)	(5.727)	(1.511)	

Country-Specific Results of CCE

	Czechia	**Spain**	**Luxemburg**	**Hungry**	**Netherland**	**Romania**	**Slovakia**	**Sweden**
hgp	-9.863	12.688	8.799	9.886	17.758	-0.427	-4.422	16.072***
	(25.080)	(11.604)	(78.319)	(10.956)	(15.635)	(9.311)	(8.550)	(9.374)
gdp	0.182	1.841	-0.682	3.306***	-1.474	1.627**	0.399	6.538
	(5.522)	(3.109)	(6.699)	(1.773)	(7.214)	(0.718)	(0.937)	(5.183)
het	-0.755	-0.868	0.302	-1.355***	1.748	-1.153**	0.536	3.083
	(1.188)	(2.275)	(0.981)	(0.786)	(3.794)	(0.549)	(0.596)	(3.077)
eep	-0.325	-0.252	2.502	-0.218	0.807	0.062	0.308	1.622
	(0.731)	(0.543)	(2.586)	(0.682)	(0.692)	(0.471)	(0.407)	(2.374)

ert	0.171	-0.780	-0.353	-0.300	0.936	0.434	0.288	4.877
	(1.332)	(2.065)	(1.954)	(0.427)	(2.103)	(0.379)	(0.577)	(5.754)
c	1.533	2.504	-4.639	-1.568	-6.340	-2.754	2.309	-70.45***
	(30.520)	(26.952)	(46.322)	(8.210)	(66.369)	(7.982)	(9.692)	(40.361)
Country-Specific Results of the Dynamic CCE								
	France	**Italy**	**Hungry**	**Poland**	**Portugal**	**Romania**	**Slovenia**	**Slovakia**
hgp	11.894	13.628**	13.434*	-7.830	2.159	-12.317**	7.091	-4.447
	(8.802)	(7.023)	(3.804)	(7.013)	(7.011)	(5.701)	(7.692)	(3.750)
gdp	-1.550	0.969**	2.708*	0.400	1.390	1.376*	-0.636	0.638
	(3.961)	(0.525)	(0.617)	(0.402)	(1.679)	(0.329)	(1.670)	(0.418)
het	0.660	0.404	-0.396	0.112	0.614	-0.320	0.976	0.183
	(0.674)	(1.174)	(0.35)	(0.679)	(1.741)	(0.367)	(0.989)	(0.285)
eep	-0.214	-3.539**	0.250	0.455	-0.238	0.132	0.231	-0.061
	(1.150)	(1.715)	(0.258)	(0.433)	(1.793)	(0.210)	(0.291)	(0.215)
ert	0.604	1.055	-0.231	-0.372	-0.101	0.183	0.109	0.203
	(1.389)	(0.888)	(0.145)	(0.656)	(0.301)	(0.187)	(0.245)	(0.254)
c	12.997	9.089	2.079	-3.295	-16.895	1.613	0.154	5.087
	(15.64)	(7.823)	(2.916)	(10.353)	(37.177)	(3.824)	(6.542)	(4.347)

NOTE

(i) Country specific results are given for the selected states. Estimates for full sample can be provided on request.

(ii) Standard errors given in parenthesis.

*(iii) Note: Asterisks *, ** and *** indicate statistical significance of the estimated coefficients at the 1, 5, and 10 percent level, respectively.*