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George Hondroyiannis
Evangelia Papapetrou
Pinelopi Tsalaporta

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BANK OF GREECE
Economic Analysis and Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

www.bankofgreece.gr

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EXPLORING THE ROLE OF TECHNOLOGICAL INNOVATION AND FERTILITY ON ENERGY INTENSITY: IS A FRESH NARRATIVE UNFOLDING?

George Hondroyiannis
Harokopio University and Bank of Greece

Evangelia Papapetrou
National and Kapodistrian University of Athens and Bank of Greece

Pinelopi Tsalaporta
National and Kapodistrian University of Athens and Bank of Greece

ABSTRACT

Amid the transition to sustainable energy systems, understanding the drivers of energy intensity is essential for informed policymaking. This paper investigates the influence of technological innovation and demographic dynamics on energy intensity across 27 OECD countries from 1990 to 2022, offering novel policy insights. Employing a multifaceted empirical strategy, we utilize dynamic common correlated effects (DCCE) estimators to address cross-sectional dependence and slope heterogeneity, both salient features of our dataset characterized by interdependent units. The empirical findings indicate that technological innovation significantly reduces energy intensity through improvements in efficiency and the adoption of cleaner technologies. Economic openness and GDP per capita are linked to lower energy intensity, underscoring the role of trade and wealth in driving energy efficiency. Conversely, higher fertility rates are linked to increased energy intensity, reflecting population growth and greater demand for energy-intensive services. Quantile regressions uncover heterogeneity across the distribution, with stronger effects of technological innovation and credit access at specific quantiles. We find that fertility positively influences energy intensity across most of the distribution, with the effect diminishing at the upper quantiles—highlighting that higher fertility is associated with increased energy consumption primarily at lower and middle levels of energy intensity. Promoting technological innovation and financial access, while accounting for demographic pressures, is essential for achieving sustainable energy transitions in developed economies.

Keywords: technological innovation; fertility; energy intensity; OECD panel; instrumental variables; quantile regression
JEL code: O30; Q55; J13; C33

Disclaimer: The views expressed are those of the authors and not those of their respective institutions.

Correspondence:
Evangelia Papapetrou
Bank of Greece
21 El. Venizelou Avenue, 102 50
tel: +30 210 320 2377
e-mail: epapapetrou@bankofgreece.gr

1. Introduction

Around the world, there is broad consensus on the critical importance of fostering technological innovation to address pressing energy challenges. Recent data indicate that global energy demand surged at an above-average rate in 2024, leading to an increased need for all energy sources, including oil, natural gas, coal, renewables, and nuclear power (IEA, 2025). This growing demand underscores the urgency of accelerating technological innovation to meet the needs of a rapidly changing energy landscape. Concurrently, population growth, urbanization, and rising living standards are contributing to higher energy consumption, while trends in energy intensity—energy use per unit of economic output—remain a challenge in many regions. Demographic shifts are intensifying pressure on energy demand, making the need for innovation in energy technologies even more critical to meet the evolving needs of a growing and changing global population (IEA, 2024).

The literature on the relationship between technological innovation and energy intensity has grown in recent years, yet it remains an area with considerable room for further exploration. Studies have primarily focused on specific countries or sectors, limiting the generalizability of findings. Studies on China highlight the critical impact of technological innovations such as artificial intelligence (AI), green finance, and industrial robotics in enhancing energy efficiency and reducing carbon emissions. AI has demonstrated varying effects across regions, with stronger impacts in economically developed areas (Li et al., 2025; Zhou et al., 2024). Green finance also plays a crucial role in optimizing energy structures, especially in resource-dependent regions (Lee et al., 2023). While much of the research centers on China, studies on the broader BRICS economies (Brazil, Russia, India, China, and South Africa) emphasize the positive relationship between environmental technologies and green growth, particularly through the promotion of renewable energy (Ulucak, 2020).

Related empirical analysis on the OECD countries is rather limited. Notable contributions include research on the role of AI in renewable energy systems and energy efficiency (Ahmad et al., 2021), as well as the impact of energy efficiency policies in OECD countries (Geller et al., 2006). Other studies, such as those by Paramati et al. (2022) and Yasmeen et al. (2023), highlight the importance of green technologies, financial development, and environmental policies in reducing energy consumption and carbon emissions. However, many studies neglect the influence of demographic factors like population growth or urbanization, which are increasingly important in shaping energy demand. While recent research, such as Lee et al. (2024), has begun to explore AI's role in energy transitions, there is still a gap in understanding the broader impacts of technological innovation, particularly in relation to the most up-to-date methodologies and demographic variables like fertility. Furthermore, while significant progress has been made in countries like those in the OECD, there remains considerable room for maneuver within these nations to further leverage technological innovation to drive energy efficiency and reduce carbon emissions. These gaps underscore the need for further research to comprehensively address how technological advances can meet the growing and changing energy needs of the global population.

To fill this gap, we contribute to the existing literature on technology and environmental sustainability by incorporating underexplored factors, such as fertility rates, into the analysis of energy intensity and technological innovation. Investigating fertility is critical, as demographic dynamics fundamentally influence resource consumption patterns, labor force structure, and long-term sustainability trajectories, thereby shaping both the demand for and the diffusion of technological solutions. Using the latest methodologies and focusing on 27 OECD countries from 1990 to 2022, while accounting for interdependencies across countries arising from unobserved common shocks and other forms of cross-sectional dependence, we aim to provide a more holistic understanding of how technological advancements and demographic trends intersect to shape future energy landscapes. Specifically, we present four main contributions to the extant literature.

First, the use of Dynamic Common Correlated Effects (DCCE) estimators represents an important methodological contribution to the study of energy intensity and technological innovation. DCCE estimators are particularly advantageous for panel data analysis, as they allow for modeling cross-sectional dependence, which is often present in large datasets like ours. In the context of global energy and technological trends, such dependence may arise from shared economic shocks, policy diffusion, or technological spillovers, highlighting the interdependence among countries. Moreover, slope heterogeneity is another key feature of such datasets, as countries differ significantly in their energy structures, demographic profiles, and levels of technological development. Ignoring these complexities can lead to biased or misleading results. By accounting for unobserved common factors that influence multiple units, DCCE estimators provide more accurate and robust estimates, especially in heterogeneous panels with varying energy and demographic dynamics. Applying DCCE to our analysis will help bridge gaps in the literature and offer more reliable insights into how technological innovation can meet the growing energy needs of diverse populations. To our knowledge, these methodological approaches have not been explored in the literature, offering a novel way to examine the association between technological innovation, fertility and energy intensity.

Second, we make a significant contribution by using information and communication technology (ICT) as a proxy for technological innovation. This approach provides a robust method for capturing the impact of technological advancements on energy intensity, as ICT encompasses the technologies that are revolutionizing nearly every sector. In today's digital age, ICT is at the heart of driving transformative change—from smart grids and energy management systems to the rise of AI—enabling more efficient energy use and better integration of renewable sources. By focusing on ICT, we can better understand how the diffusion of new technologies, such as digital infrastructure and advanced communication systems, influences energy demand and intensity. While ICT's benefits are well-recognized, its environmental impact remains debated, with significant variation among studies, and it has not been extensively studied in the context of our research. This gap in the literature presents an opportunity to further explore the complex relationship between ICT, demographics and energy intensity.

Third, we address a critical gap in the existing literature by analyzing the heterogeneous effects of technological innovation on energy intensity across the entire conditional distribution—not merely at the mean, but also at the distributional tails. While most prior studies concentrate on average effects, this approach overlooks important distributional dynamics that may vary substantially across countries. By employing simultaneous quantile regression for panel data, we uncover whether technological innovation exerts disproportionately stronger effects in reducing energy intensity among countries at the highest and lowest ends of the distribution. This distribution-sensitive analysis provides more nuanced policy implications, particularly for designing interventions tailored to the specific needs of countries with extreme energy intensity profiles. Our methodology captures unobserved heterogeneity through country-specific and temporal fixed effects, enabling robust inference across quantiles (Koenker 2005; Machado and Mata 2005; Koenker 2017).

Finally, fertility rates are often overlooked in energy analyses, particularly regarding energy intensity and technological innovation. While population growth and urbanization are commonly studied, fertility rates have not been widely incorporated into energy models. High fertility rates lead to larger, younger populations, increasing energy demand and affecting energy intensity. By integrating fertility into our analysis, we contribute novel insights into future energy demand, efficiency, and the role of technological innovation, addressing a key empirical gap and offering a more nuanced understanding of global energy dynamics under fiscal constraints such as high public debt. To this end, in estimating the relationship between energy intensity and its determinants, we account for potential endogeneity by employing an Instrumental Variables (IV) approach, using female employment as an instrument for fertility decisions that may be correlated with energy intensity. To assess potential regime-dependent effects on the relationship between fertility and energy intensity, we apply a threshold model using central government debt as the threshold variable; the results reinforce the robustness of the baseline specification, suggesting that a threshold structure is not warranted in this context.

The remainder of our paper is structured as follows. Section 2 presents the literature review. Section 3 contains the methodology and data. Section 4 reports the quantitative analysis and discussion and Section 5 concludes and proposes policy recommendations.

2. Literature review

In this section, we review the existing literature and outline the theoretical foundations underpinning the relationship between technological innovation and energy intensity. We begin by examining global and OECD-focused studies, followed by research specific to China, the BRICS, and Gulf Cooperation Council (GCC) countries, to identify key empirical findings, methodological approaches, and gaps that inform the present study.

i. OECD and world-wide

Academic research on the relationship between technological innovation and energy intensity is largely recent, indicating that there remains considerable room for further exploration in this area. While a growing body of literature has begun to address this connection, many studies focus on specific countries or narrow sectors, leaving various dimensions of the association underexplored. However, some notable studies have provided valuable contributions by providing, for instance, a qualitative discussion on the role of AI in the energy sector, focusing on its application in renewable energy systems and supply-demand management such as solar and hydrogen power generation, energy efficiency, predictive maintenance, and smart grid management (Ahmad et al., 2021). The authors underline the need for regulatory engagement to address issues such as customer safety and information security.

Geller et al. (2006) discuss trends in energy intensity and review the role of energy efficiency policies in reducing energy consumption across OECD countries over the past 30 years, focusing on Japan, the United States, and Western Europe. Using a decomposition technique to distinguish between efficiency improvements and structural changes in the economy, they show that energy intensity has significantly decreased, with key OECD nations using much less energy to fuel economic growth compared to 1973. The findings suggest that well-designed energy efficiency policies, which can target key sectors and leverage technology, are highly effective in achieving substantial energy savings. Similarly, Paramati et al. (2021) explore the impact of financial deepening, green technology, foreign direct investment (FDI), per capita income, and trade openness on carbon emissions across 25 OECD countries between 1991 and 2016. Utilizing the Augmented Mean Group (AMG) and Grouped-Mean Fully Modified Ordinary Least Squares (FMOLS) estimators, their results highlight that green technology, FDI inflows, and trade openness contribute to a reduction in carbon emissions, while financial deepening and per capita income have a positive association with increased emissions. Notably, demographic variables are not considered in this analysis, which mainly focuses on economic and technological factors. Another research by Paramati et al. (2022) explores the influence of environmental-related technologies on energy consumption and efficiency across OECD countries. Analyzing data from 1990 to 2014 using advanced panel techniques (the Fixed Effects estimation method, Dynamic Ordinary Least Square (DOLS), Fully Modified Least Squares

(FMOLS), and Autoregressive Distributed Lag (ARDL)), the study reveals that environmental technologies effectively decrease energy intensity. Moreover, their paper underscores the significant impact of financial development and income on energy demand. The focus of Wang et al. (2022) is directed towards the manufacturing sector. Their study explores the impact of industrial robots on manufacturing energy intensity across 38 countries and 17 manufacturing sectors, using the dynamic panel GMM estimation method. The research reveals that industrial robots significantly improve manufacturing energy intensity, driven by two main effects: the technology improvement effect and the technological complement effect between robots and labor. The study also identifies a heterogeneous relationship between industrial robots and energy intensity, noting that robots primarily influence non-renewable energy intensity, particularly in labor-intensive sectors rather than capital-intensive ones.

Turning to the most recent contributions on the field, Yasmeen et al. (2023) investigate the impact of green technology, environmental taxes, and natural resource management on energy efficiency and productivity in OECD countries, with a focus on the role of rule of law. Employing data from 2000 to 2020 for the energy intensity model, the study uses fixed effects and system GMM estimators to analyze the relationship between these variables over time, with green technology proxied by patents on environmental technology. They show that environmental tax and green technology lead to lower energy intensity, while population exerts the inverse impact on energy intensity. In the same vein, Lee et al. (2024) examine the role of AI in the energy transition, emphasizing how the digital economy supports this process. The research analyzes panel data from 64 countries worldwide between 2005 and 2019, utilizing the panel entropy weighting method. Empirical results demonstrate that AI has a positive impact on advancing the energy transition, with the digital economy further enhancing this effect. The study finds that AI's influence on the energy transition is stronger in high-income countries, such as those in Western Europe and the United States, as well as in resource-dependent nations like those in the Middle East and parts of Africa. The only demographic variable employed in the study is the level of urbanization, which is considered as a factor influencing the energy transition. On the fiscal front, Ebeke and Eklou (2023) utilize data from 18 European countries spanning the years 1997 to 2016 to examine the influence of automation on the effectiveness of fiscal policy in promoting job creation. The findings indicate that the pace of automation has, on average, reduced the sensitivity of employment to fiscal stimulus by approximately half. In particular, manufacturing employment shows a diminished response to fiscal stimulus in countries with higher automation rates, as robots increasingly substitute human labor in production processes. Furthermore, the study reveals that low-skill workers and female employees are particularly less responsive to fiscal policies in nations with extensive automation, underscoring the growing challenge of generating job creation in an era marked by rapid technological advancement.

Taking a slightly different perspective, Hondroyiannis et al. (2025) assess the impact of inflation on CO2 emissions, controlling for financial development, with a focus on 28 high-income countries from 1996 to 2021, and making use of various estimation methods, including regressions, quantile estimators, and impulse response functions. Empirical findings show a positive link between inflation and carbon emissions, while financial depth reduces emissions. The effects vary by country, with larger impacts in low-inflation countries. Energy inflation is identified as the main driver of CO2 emissions, suggesting the need for targeted monetary policies to address environmental concerns. Another insightful paper is by Wang et al. (2024) who examine how AI influences energy transition and carbon emissions, with a focus on the mediating role of trade openness. Using panel data from 69 countries between 1993 and 2019, the research employs the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) approach, mediation effect techniques, and panel threshold analysis to estimate these relationships. The findings reveal that AI promotes energy transition and reduces carbon emissions, with trade openness acting as a mediator. It identifies a threshold effect, where AI significantly reduces carbon emissions only when trade openness surpasses a certain level, and similarly, AI's positive impact on energy transition strengthens beyond another threshold of trade openness. The study also finds that trade thresholds for carbon emission reductions are lower in high-income countries and higher in regions with low AI levels.

Climate change remains a critical global challenge, and Sustainable Development Goals (SDG) emphasize the need for countries to reduce greenhouse gas emissions and address climate change by 2030. While recent research has explored the environmental impact of Information and Communications Technologies (ICTs), most studies have assumed that this impact is the same across all countries. To examine how ICT affects environmental degradation by considering differences in ICT quality among countries, Appiah-Otoo et al. (2023) investigate the relationship between ICT and environmental sustainability using data from 110 countries (2000-2018). Their findings indicate that ICT enhances environmental sustainability in countries with high ICT quality but leads to environmental degradation in nations with moderate or low ICT quality. The causality analysis reveals a bi-directional relationship between ICT and emissions in high and moderate ICT quality countries, while in low ICT quality countries, causality runs only from emissions to ICT. However, the study does not explore the potential benefits of quantile analysis, which could provide a more granular view of ICT's effects across varying levels of ICT quality.

ii. China, the BRICS and Gulf Cooperation Council countries

Several studies focus on China due to its significant role in global energy consumption and efforts to improve energy efficiency. As the world's largest energy consumer, China plays a critical role in both energy use and energy efficiency advancements. Li et al. (2025) examine the effect of AI on energy efficiency across 30 Chinese provinces from 2000 to 2021, using a two-way fixed effects model and a spatial Durbin specification to account for spatial dependencies. Their findings indicate that AI significantly enhances energy efficiency, with green technological innovation serving as a positive moderator. Notably, the impact of AI is more pronounced in economically advanced regions, while in energy-rich areas, it may exert adverse effects, underscoring spatial heterogeneity. In a similar vein, Lee et al. (2023) investigate the impact of green finance on energy efficiency in China, emphasizing the roles of green technological innovation and energy structure transformation. Utilizing a panel entropy weighting method and fixed effects estimation, they find that green finance significantly enhances energy efficiency, particularly by promoting green technologies and optimizing energy structures. The effects vary across regions, time periods, and industries, with the strongest impacts observed in resource-dependent areas and sectors with inefficient industrial structures.

Focusing on carbon emissions, Zhou et al. (2024) use provincial panel data from China (2010-2019) and a dual fixed effects model to control for time trends and regional differences, to find that industrial robots significantly reduce emissions intensity by enhancing energy efficiency and advancing pollution reduction technologies. The impact is more pronounced in China’s eastern and western regions, with varying mechanisms across these areas. Similarly, Qin et al. (2024) employ a Vector Autoregressive (VAR) model to investigate the interaction between AI and renewable energy indicators in China. The findings suggest that while AI encourages renewable energy development, its impact is sometimes weakened by the lower costs of non-renewable energy. Additionally, during the COVID-19 pandemic, a decline in renewable energy and stock markets hindered AI’s progress. The study also highlights the role of urbanization in influencing the AI-renewable energy relationship. Lee et al. (2025) take a human capital perspective, examining how AI impacts corporate energy consumption (CEC) in China and the moderating role of human capital (HC). Using data from 2013 to 2022, along with a Panel Smooth Transition Regression (PSTR) model, that allows for smooth transitions between regimes based on an endogenous threshold variable, their results reveal that AI increases CEC when HC is low, but this effect diminishes as HC improves. Additionally, increased HC helps AI reduce high-pollution energy consumption, particularly in state-owned and high-tech enterprises. Liu and Wan (2023) explore the connection between ICT and CO2 emissions, with a particular focus on the spillover effects in China's prefecture-level cities. Analyzing panel data from 285 cities over the period 2004-2018, the study reveals a positive relationship between ICT and CO2 emissions, highlighting significant spatial spillovers. Energy consumption is identified as a key mediator, with the ICT–emissions relationship varying by geography, population size, and urban density.

Ulucak (2020) investigates the impact of environmental technologies on green growth within BRICS economies. To address this, the study employs the Continuously Updated Fully Modified (CUP-FM) and Continuously Updated Bias-Corrected (CUP-BC) estimation methods. Empirical findings reveal a positive relationship between environmental technologies and green growth in the BRICS. The study also highlights that renewable energy contributes to green growth, while non-renewable energy consumption acts as a barrier. Turning to the Gulf Cooperation Council (GCC) countries, Islam and Rahaman (2023) explore the asymmetric impact of ICT on CO2 emissions, using panel data from 1995 to 2019 and applying the Westerlund cointegration test and nonlinear pooled mean group (PMG) estimation. The results support the Environmental Kuznets Curve (EKC) hypothesis, showing that while higher per capita GDP increases CO2 emissions, the squared GDP per capita has a reducing effect. Additionally, energy consumption, intensity, and trade contribute to higher emissions, while ICT and financial development help mitigate emissions.

Overall, although existing studies provide valuable insights into the relationship between energy intensity and technological innovation, there remains a significant gap in the literature, particularly concerning the use of recent estimation methods such as the Dynamic Common Correlated Effects estimators and the IV methodological approach. Quantile-based approaches have scarcely been explored in this context. Moreover, ICT-based proxies for AI, such as the balance of payments (BoP) data on ICT service exports as a percentage of total service exports, have yet to be fully utilized, thereby limiting a comprehensive understanding of AI's impact on energy intensity. Furthermore, fertility has not been included as a control variable, despite its potential to provide crucial context for understanding the broader dynamics at play, particularly with respect to demographic changes and their implications for energy demand and sustainability. These gaps underscore the need for further research to comprehensively examine how technological innovation, in conjunction with demographic factors, can contribute to addressing global energy challenges and advancing sustainable development.

3. Methodology and data

3.1 Econometric approach

To examine the impact of technological innovation and fertility on energy intensity, we make use of a panel dataset covering 27 OECD countries from 1990 to 2022, depending on data availability. As highlighted in the literature review, there is a scarcity of empirical studies examining this relationship within OECD countries. Focusing on OECD countries provides controlled and reliable results that can be generalized to other developed economies and offers insights for policy implementation and comparisons with emerging economies, particularly in relation to energy intensity and technological innovation, including AI. To address this issue, we leverage a unique longitudinal dataset and apply a combination of econometric techniques that are well-suited to the structure of our data. Building on the models in Paramati et al. (2022) and Li et al. (2025), the model is specified as follows:

$$energyint_{it} = a_1 + \beta_1 technology_{it} + \beta_2 fertility_{it} + \beta_3 open_{it} + \beta_4 credit_{it} + \beta_5 gdp_{it} + U_{it} \qquad (1)$$

$$energyint_{it} = a_1 + \beta_1 RD_{it} + \beta_2 fertility_{it} + \beta_3 open_{it} + \beta_4 credit_{it} + \beta_5 gdp_{it} + U_{it} \qquad (2)$$

where $energyint$ represents energy intensity of country i at time t and β_i denote coefficients to be estimated. $Technology$ is technological innovation, $fertility$ is the fertility rate, $open$ denotes the economic openness indicator, $credit$ is private sector credit, gdp is GDP per capita, and U_{it} is the error term. In equation (2), we utilize an alternative control variable, RD (Research and development expenditure), because R&D investments often influence innovation, productivity, and overall business performance, making it a critical factor to control for in the analysis. All variables are expressed in natural logarithms. The regressors are assumed to be uncorrelated with U_{it}. However, the disturbances themselves are allowed to be autocorrelated, heteroskedastic and cross-sectionally dependent.

To estimate equations (1) and (2), we apply both fixed effects (FE) and random effects (RE) models, as well as the Mean Group estimator that allows for individual-specific coefficients, meaning that each cross-sectional unit in the panel can have its own unique intercept and slope, which is especially useful when there is significant heterogeneity across groups by avoiding the assumption of identical relationships between variables, as is the case in our panel (Eberhardt 2012). We additionally apply the Dynamic Common Correlated Effects model that offers several advantages, particularly in situations where there is cross-sectional dependence across units by allowing for a common set of parameters across the panel while accounting for time-varying factors, which can lead to more accurate and robust estimates compared to other estimation methods (Ditzen 2019; Ditzen 2021). The superiority of the Mean Group and Dynamic Common Correlated Effects estimators lies in their ability to handle more complex panel data structures, such as slope heterogeneity and cross-sectional dependence, which traditional methods like fixed or random effects models may fail to capture. Slope heterogeneity and cross-sectional dependence are especially salient in our dataset, which comprises a diverse set of countries with varying levels of technological advancement, energy consumption patterns, and demographic trends—

conditions that inherently give rise to heterogeneity in slope coefficients and interdependence across cross-sectional units due to shared global shocks, regional integration, and policy spillovers. These advanced techniques provide more accurate and efficient estimates, improving the robustness and reliability of the results in heterogeneous panel data settings. Moreover, they have not been fully explored in the context addressed by our paper, making our analysis a novel contribution to the literature by applying these methods to this specific area.

To rigorously capture this distributional heterogeneity, we employ simultaneous quantile regression for panel data, which captures heterogeneous effects across different quantiles of the conditional energy intensity distribution and accounts for unobserved country-specific and temporal effects, thereby enhancing the robustness and granularity of inference (Koenker 2005; Machado and Mata 2005; Koenker 2017). The benchmark equation for quantile regression is:

$$Q_{\tau}\ (Y_i \mid X_i) = X_i\beta(\tau) + \varepsilon_i(\tau) \quad (3)$$

where $Q_{\tau}\ (Y_i \mid X_i)$ is the conditional τ-th quantile of the dependent variable Y_i, given the independent variables X_i. β_{τ} is the vector of coefficients to be estimated for the τ-th quantile and $\varepsilon_i(\tau)$ is the error term associated with the τ-th quantile. The equation represents how the τ-th quantile of the dependent variable is related to the independent variables X_i, with β_{τ} capturing the impact of predictors at the specific quantile τ.

This approach is particularly important because it allows estimation of the conditional quantiles of the dependent variable, providing a more detailed view of the relationship between variables, particularly in the presence of heteroscedasticity or non-normal error distributions. Unlike mean regression, which only provides insights into the average value of the dependent variable, quantile regression reveals how covariates impact different parts of the distribution, such as the lower or upper tails, offering a more comprehensive understanding of the effects across diverse subgroups or extreme outcomes. In our dataset, where energy intensity serves as the dependent variable and technological innovation is included as a control, quantile regression offers valuable insights by examining how technological advancements impact energy intensity across different quantiles. By analyzing these variations across countries and time periods, quantile regression sheds light on the diverse and often unequal effects of technological innovation and fertility on energy intensity, an aspect that has been largely overlooked in previous studies. Furthermore, by considering both technological innovation and fertility as independent variables, this approach provides important insights into how these factors influence environmental outcomes, with significant policy implications for sustainable development and energy transitions.

3.2 Data

This study utilizes a panel data set consisting of 27 OECD developed countries over the period from 1990 to 2022, based on data availability. The sample includes Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Estonia, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom, and the United States. The primary data source is the World Bank World Development Indicators (WDI) database, unless otherwise specified. The WDI database adheres to internationally accepted standards and norms across countries and time periods, ensuring the consistency and reliability of the statistical information. All variables in the analysis are entered in their logarithmic form (l) to account for scale differences and allow for a more robust interpretation of the estimated relationships.

The dependent variable in this study is the energy intensity level of primary energy (energyint), which is the ratio of energy supply to gross domestic product (GDP) measured at purchasing power parity. Energy intensity indicates how much energy is required to produce one unit of economic output. A lower ratio suggests greater energy efficiency, while a higher ratio indicates higher energy consumption per unit of output, often linked to industrial or energy-intensive economies. Energy intensity is chosen as the main dependent variable because it reflects how efficiently an economy uses energy to produce goods and services. Lower energy intensity is generally associated with technological advancements, energy-efficient systems, or a shift towards service-based economies. An alternative dependent variable is total greenhouse gas emissions per capita (carbon), which includes annual emissions from the six greenhouse gases covered by the Kyoto Protocol across the energy, industry, waste, and agriculture sectors. These emissions are standardized to carbon dioxide equivalent values and divided by the population. Carbon emissions are key to understanding a country's environmental impact and its contribution to global climate change. They are also crucial in the context of the Paris Agreement, which aims to limit global warming by reducing greenhouse gas emissions and promoting sustainable development.

Independent variables include: ICT service exports (technology), which serve as a strong proxy for technological innovation and AI. ICT service exports encompass computer and communications services (such as telecommunications, postal, and courier services) and information services (including computer data and news-related transactions). Key examples of ICT service exports are software development and IT services, telecommunications services, business process outsourcing (BPO), IT consulting and system integration, web and mobile app development, cybersecurity services, digital marketing services, e-commerce and online platforms, as well as cloud hosting and data storage. These services are essential in facilitating global access to specialized technology and expertise, reflecting a country's engagement with advanced technologies, including AI, and its integration into the global digital economy. Another proxy for AI is Research and Development expenditure (RD), expressed as a percentage of GDP. This includes both capital and current spending across business enterprises, government, higher education, and private non-profits. Research and Development covers basic research, applied research, and experimental development. High Research and Development investment indicates a country's focus on technological advancements, including AI, and reflects its capacity for innovation and integration of AI into the economy. Total Fertility Rate (fertility) is included as a control variable in the analysis, representing the number of children a woman would bear if she lived through her childbearing years. Higher fertility rates typically lead to a growing, younger population, which can increase energy demand and raise energy intensity. Conversely, lower fertility rates may reduce population growth, potentially lowering energy intensity. Economic openness, measured by the ratio of total trade (exports plus imports) to GDP (open), serves as another control variable. The relationship between openness and energy intensity is multifaceted, as both trade expansion and technology transfer influence energy use. Higher economic openness can facilitate access to energy-efficient technologies, potentially reducing energy intensity. To account for financial sector activity, we use domestic credit to the private sector by banks (credit). This measure represents the financial resources provided to the private sector, including loans and credit. Increased access to credit can facilitate investment in energy-efficient technologies and infrastructure, helping to reduce energy intensity. By enabling businesses to adopt more sustainable practices, domestic credit can promote efficiency and lower energy consumption per unit of output. To capture income effects, we include GDP per capita (gdp) in the analysis. Higher GDP per capita often reflects greater economic wealth, which can provide the resources necessary for investments in energy-efficient technologies and infrastructure. As a result, wealthier economies may be better equipped to reduce energy intensity, even with higher levels of energy consumption, through technological advancements and more sustainable practices.

The summary statistics are presented in Table 1, offering an overview of the key descriptive measures for the variables used in the analysis, including their mean, standard deviation, minimum, and maximum values. Appendix A displays the graph of energy intensity by country, illustrating the variations across different nations. Appendix B provides a detailed list of variables and their corresponding sources.

TABLE 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
energyint	479	4.15	1.91	1.09	15.65
carbon	479	12.00	5.12	5.55	28.75
technology	479	10.02	10.00	0.50	60.42
RD	479	2.03	1.03	0.24	5.71
fertility	479	1.64	0.38	0.81	3.11
empfem	479	49.49	6.95	29.51	70.72
open	479	100.14	64.15	19.56	393.14
credit	479	92.67	37.96	0.19	254.55
gdp	479	52,293.84	21,341.02	23,264.59	140,435.80

4. Quantitative analysis and discussion

4.1. Preliminary tests

Before performing the regression analysis, we conduct a series of preliminary tests. To assess the impact of technological innovation and fertility on energy intensity while controlling for other variables, we utilize Pesaran's CD test (Pesaran, 2015). Unlike some other tests for cross-sectional dependence, the CD test is robust to heteroscedasticity and autocorrelation in the residuals and involves straightforward calculations of pairwise correlations of residuals. As shown in Table 2, the null hypothesis of weak cross-sectional dependence is rejected, confirming the presence of cross-sectional dependence. We proceed with the slope homogeneity test by Pesaran and Yamagata (2008) that allows for testing the assumption of slope homogeneity in the presence of cross-sectional dependence. This is particularly important because in panel data analysis, the assumption that the coefficients are the same across all cross-sectional units (homogeneity) may not always hold, especially when there are unobserved common factors or cross-sectional dependence as is the case in our panel. The null hypothesis of slope homogeneity is rejected in the Delta and the Delta-adjusted versions of the dispersion test. Given the evidence of both cross-sectional dependence and slope heterogeneity, we move forward with the Fisher-type panel unit root tests (Choi, 2001). The Fisher-type panel unit root tests are advantageous for panel data because they can handle unbalanced panels, are robust to cross-sectional dependence, increase test power by pooling information across cross-sectional units, and allow for heterogeneity across units, making them ideal for panel datasets. The results in Table 3 indicate that the null hypothesis of non-stationarity is rejected, suggesting that the series are stationary.

TABLE 2. Tests for cross-sectional dependence and slope homogeneity

		value	p-value
Cross-sectional dependence*	Pesaran test	CD = 23.427	0.000
Slope homogeneity**	Delta test	Delta = 12.415 Delta-adjusted (Δadj) = 15.956	0.000 0.000

Notes: * The null hypothesis is that errors are weakly cross-sectional dependent.
** The null hypothesis is that slope coefficients are homogeneous.

TABLE 3. Panel unit root tests

	variable	value	p-value
Fisher-type panel unit root test	lenergyint	8.5158	0.0000
	lcarbon	12.6863	0.0000
	ltechnology	15.3917	0.0000
	lfertility	13.0913	0.0000
	lempfem	12.3627	0.0000
	lopen	10.0511	0.0000
	lcredit	6.7112	0.0000
	lgdp	7.3425	0.0000

Note: The null hypothesis is that the series are non-stationary.

4.2 Benchmark regression

Based on the findings from the preliminary tests, Table 4 presents benchmark results at the mean level utilizing a range of different estimators to further enhance the robustness of the analysis. Columns 1-2 and 5-6 report results from panel OLS with fixed and random effects, columns 3 and 7 use the Mean Group estimator, and columns 4 and 8 present results from the Dynamic Common Correlated Effects estimator.

From the perspective of technological innovation (ltechnology), proxied by ICT, the coefficient is negative and significant at the highest significance levels across all specifications, a finding that aligns with the existing literature (Li et al., 2025). Under the Dynamic Common Correlated Effects estimator (column 4), the coefficient is -0.098 and is statistically significant at the 5% level. This suggests that as ICT usage (ltechnology) increases, energy consumption per unit of economic output decreases, leading to a reduction in energy intensity (lenergyint). This can occur through various mechanisms, such as enhanced energy efficiency in industries via automation and optimization, the development of smart grids for improved energy management, and the shift toward less energy-intensive service-based economies. Additionally, ICT promotes energy-saving practices, including remote work, virtualization, and the integration of renewable energy sources, while the use of energy-efficient devices further contributes to reducing energy demand.

Similar outcomes can be observed using the alternative proxy for technological innovation and AI, namely R&D expenditure (lRD). The results presented in columns 5,6 and 7 suggest that as investment in research and development increases, energy consumption per unit of economic output decreases. Higher R&D spending often drives the development and adoption of more energy-efficient technologies, innovations, and sustainable practices across various sectors. R&D fosters more efficient resource use, thereby reducing energy intensity and contributing to more sustainable economic growth. These findings are consistent with the results reported by Paramati et al. (2022) and Yasmeen et al. (2023).

A consistently positive and significant association between fertility rates (lfertility) and energy intensity (lenergyint) suggests that as fertility rates increase, energy consumption per unit of economic output also rises. Higher fertility rates often lead to population growth, which can drive up the demand for energy-intensive services such as transportation, housing, and healthcare. As the population expands, energy consumption typically rises to meet both residential and industrial needs, contributing to increased energy intensity. Additionally, larger populations may place greater pressure on existing infrastructure and resources, further escalating energy demand. This relationship underscores the challenge of managing energy use as population growth accelerates. Related issues are discussed in Lee et al. (2024).

Regarding other control variables, results indicate a negative and statistically significant association between economic openness (lopen) and energy intensity (lenergyint), though this effect is only significant under the OLS estimators, not the Mean Group or Dynamic Common Correlated Effects estimators. Consistent with Yasmeen et al. (2023), increased trade openness is associated with lower energy consumption per unit of economic output. Empirical evidence indicates that trade openness can stimulate the diffusion of best practices in energy efficiency while simultaneously reducing energy intensity through the adoption of cleaner technologies. Additionally, trade fosters industry specialization, with countries focusing on less energy-intensive sectors, further reducing energy consumption.

Similarly, GDP per capita (lgdp) is negatively associated with energy intensity (lenergyint) across all columns. In line with Li et al. (2025), as a country's GDP per capita increases, energy consumption per unit of economic output decreases. This can be attributed to the adoption of energy-efficient technologies and practices as economies grow wealthier. Higher income levels often lead to increased investments in clean energy, improved infrastructure, and more efficient production processes. Additionally, wealthier countries may shift toward less energy-demanding service industries, further reducing energy consumption per unit of GDP. This suggests the potential for economic growth to be decoupled from energy use as income rises.

In conclusion, our preferred model, the Dynamic Common Correlated Effects estimator (column 4), which accounts for both slope heterogeneity and cross-sectional dependence, reveals several important findings. Technological innovation has a significant negative impact on energy intensity, while fertility rates exhibit a significant positive effect at high levels of statistical significance. Additionally, GDP plays a crucial role in reducing energy intensity. The relationship between private sector credit (lcredit) and energy intensity (lenergyint) is ambiguous at the mean, but we have yet to explore the quantiles, where the pattern may differ.

TABLE 4. Energy Intensity and Technological Innovation

	Panel OLS (Fixed effects)	*Panel OLS (Random effects)*	*Mean Group*	*Dynamic Common Correlated Effects*	*Panel OLS (Fixed effects)*	*Panel OLS (Random effects)*	*Mean Group*	*Dynamic Common Correlated Effects*
Columns	1	2	3	4	5	6	7	8
VARIABLE	lenergyint	lenergyint	lenergyint	lenergyint	lenergyint	lenergyint	lenergyint	lenergyint
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
ltechnology	-0.040***	-0.045***	-0.123***	-0.098**	-	-	-	-
	(-3.215)	(-3.625)	(-3.539)	(-2.338)				
lRD	-	-	-	-	-0.134***	-0.130***	-0.246**	-0.228
					(-5.632)	(-5.523)	(-2.272)	(-1.548)
lfertility	0.186***	0.187***	0.288***	0.296**	0.164***	0.170***	0.268**	0.302**
	(3.350)	(3.357)	(2.895)	(2.510)	(2.997)	(3.100)	(2.338)	(2.255)
lopen	-0.315***	-0.302***	-0.055	-0.003	-0.247***	-0.247***	0.064	0.091
	(-8.885)	(-8.691)	(-0.847)	(-0.047)	(-6.637)	(-6.835)	(0.943)	(1.257)
lcredit	-0.007	-0.005	-0.086	-0.039	0.001	0.001	-0.059	-0.019
	(-0.549)	(-0.436)	(-1.556)	(-0.613)	(0.095)	(0.113)	(-0.858)	(-0.265)
lgdp	-0.814***	-0.787***	-0.633***	-0.407**	-0.853***	-0.834***	-0.785***	-0.515*
	(-15.863)	(-15.552)	(-4.776)	(-2.513)	(-19.860)	(-19.444)	(-3.998)	(-1.961)
constant	11.560***	11.240***	8.884***	8.303***	11.654***	11.464***	9.899***	10.714***
	(21.560)	(21.016)	(6.340)	(4.989)	(25.292)	(24.572)	(4.613)	(4.556)
observations	479	479	479	479	479	479	479	479
countries	27	27	27	27	27	27	27	27

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.3 Quantile regression analysis

We employ quantile regression to examine how key explanatory variables influence the conditional distribution of energy intensity across different quantiles (Q10, Q25, Q50, Q75, and Q90), as reported in Table 5. This approach is particularly suited to uncovering heterogeneous effects that may be obscured in traditional mean regression frameworks, which estimate only average relationships. By modeling the entire conditional distribution, quantile regression provides a more granular view of how technological innovation, fertility, and credit affect energy intensity at different points of the distribution—ranging from the least to the most energy-intensive contexts. To enhance inference across quantiles and account for within-panel heterogeneity, we adopt a simultaneous quantile regression framework for panel data, which allows for efficient estimation while controlling for unobserved country-specific and temporal effects (Koenker, 2005; Machado and Mata, 2005; Koenker, 2017).

The quantile regression analysis reveals several important distributional differences that are masked in mean regression. Technological innovation (ltechnology) is negatively associated with energy intensity (lenergyint) across all quantiles except for Q90, indicating that its impact on energy intensity is more pronounced at lower and middle levels, but weaker at the upper tail of the distribution. Similarly, fertility (lfertility) shows a positive association with energy intensity (lenergyint) at all quantiles except for Q90, suggesting that higher fertility rates tend to lead to higher energy consumption per unit of economic output at lower and middle levels of energy intensity, but this relationship weakens in the upper quantiles of the distribution. GDP (lgdp), on the other hand, is primarily significant at the higher levels of energy intensity, particularly at Q75, underscoring its role in reducing energy intensity in wealthier or more industrialized contexts.

Interestingly, credit (lcredit) exhibits a significant negative association with energy intensity (lenergyint) at the 1% level in the middle of the distribution (Q25, Q50, and Q75), suggesting that increased access to credit can help reduce energy intensity in countries with moderate energy consumption. This finding implies that enhanced financial access may incentivize investment in energy-efficient technologies and infrastructure, especially in economies where energy consumption is neither too high nor too low. Moreover, it could signal that the financial sector plays a crucial role in promoting sustainable practices by providing the necessary capital for businesses and households to adopt cleaner, more efficient energy solutions within this segment of the conditional energy intensity distribution. These results highlight significant distributional heterogeneity that may be overlooked when focusing solely on the mean, underscoring the added value of quantile regression in offering a more nuanced and precise understanding of such relationships. Although their focus differs, related concerns are discussed in Lee et al. (2023).

TABLE 5. Energy Intensity and Technological Innovation (Quantile Regression)

	Quantiles				
Columns	1	2	3	4	5
VARIABLE	lenergyint Q10	lenergyint Q25	lenergyint Q50	lenergyint Q75	lenergyint Q90
ltechnology	-0.200***	-0.172***	-0.217***	-0.202***	-0.071
	(-4.943)	(-5.442)	(-5.725)	(-5.784)	(-0.905)
lfertility	0.497***	0.546***	0.533***	0.336*	0.027
	(3.699)	(4.998)	(5.078)	(1.723)	(0.117)
lopen	-0.048	-0.028	-0.021	0.002	-0.101
	(-1.031)	(-0.832)	(-0.428)	(0.051)	(-1.230)
lcredit	-0.037	-0.089***	-0.225***	-0.168***	-0.050
	(-0.674)	(-3.240)	(-2.742)	(-3.250)	(-1.062)
lgdp	-0.133*	-0.081	-0.126*	-0.220***	-0.294*
	(-1.851)	(-1.569)	(-1.948)	(-3.777)	(-1.703)
constant	2.979***	2.613***	3.944***	4.840***	5.662***
	(4.264)	(4.901)	(5.135)	(9.686)	(2.772)
observations	479	479	479	479	479

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.4 Robustness

To assess the robustness of our findings, we replace the dependent variable with carbon emissions (lcarbon) in Table 6. The results largely mirror those from Table 4, with technological innovation (ltechnology and lRD), fertility (lfertility), and openness (lopen) maintaining similar effects on carbon emissions as they did on energy intensity. This consistency further supports the robustness of our findings across different environmental outcomes. However, GDP (lgdp) does not exhibit the same relationship with carbon emissions as it did with energy intensity. This divergence suggests that while economic growth may help reduce energy intensity through the adoption of energy-efficient technologies and practices, its direct impact on carbon emissions might be more complex and influenced by other factors, such as the energy mix or industrial structure.

A noteworthy finding is the significant negative relationship between credit (lcredit) and carbon emissions (lcarbon) observed across most empirical specifications. This suggests that increased access to credit can lead to more sustainable environmental practices. Credit enables firms and households to invest in cleaner technologies, energy-efficient infrastructure, and renewable energy projects, which, in turn, help reduce carbon emissions. The ability to secure financing may lower the barriers for adopting greener practices, such as upgrading to energy-efficient systems or implementing carbon-reducing technologies. Financial access also promotes innovation in environmental sustainability, encouraging the development of cleaner products and processes. This finding aligns in spirit with the results of Hondroyiannis et al. (2024).

In conclusion, although the factors influencing energy intensity and carbon emissions exhibit a high degree of similarity, the role of credit emerges as a particularly salient factor in fostering environmentally sustainable practices. The robust negative relationship between credit and carbon emissions underscores the potential of financial access as a crucial policy instrument for advancing sustainability goals. This suggests that improving access to credit could facilitate the widespread adoption of cleaner technologies, thereby acting as a key enabler of the transition towards a low-carbon economy. Moreover, the ability to secure financing enhances both firm-level and household-level investments in energy-efficient infrastructure and renewable energy initiatives, which are integral to mitigating carbon emissions. This finding aligns with recent literature on the intersection of finance and environmental sustainability (Lee et al., 2023), further highlighting the importance of financial innovation in promoting green technologies and supporting a sustainable economic transformation.

TABLE 6. Carbon Emissions and Technological Innovation

	Panel OLS (Fixed effects)	*Panel OLS (Random effects)*	*Mean Group*	*Dynamic Common Correlated Effects*	*Panel OLS (Fixed effects)*	*Panel OLS (Random effects)*	*Mean Group*	*Dynamic Common Correlated Effects*
Columns	1	2	3	4	5	6	7	8
VARIABLE	lcarbon	lcarbon	lcarbon	lcarbon	lcarbon	lcarbon	lcarbon	lcarbon
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
ltechnology	-0.068***	-0.075***	-0.205***	-0.172***	-	-	-	-
	(-4.192)	(-4.716)	(-4.039)	(-3.248)				
lRD	-	-	-	-	-0.215***	-0.208***	-0.340***	-0.281**
					(-7.005)	(-7.016)	(-3.367)	(-2.300)
lfertility	0.246***	0.248***	0.405***	0.420***	0.211***	0.224***	0.382**	0.392**
	(3.404)	(3.454)	(3.011)	(3.101)	(3.011)	(3.212)	(2.348)	(2.202)
lopen	-0.380***	-0.342***	-0.100	-0.018	-0.272***	-0.270***	0.056	0.092
	(-8.241)	(-7.818)	(-1.300)	(-0.214)	(-5.678)	(-6.032)	(0.688)	(1.111)
lcredit	-0.027*	-0.026	-0.246***	-0.182**	-0.015	-0.015	-0.202*	-0.167
	(-1.698)	(-1.625)	(-2.866)	(-2.038)	(-0.971)	(-0.975)	(-1.859)	(-1.582)
lgdp	0.040	0.078	0.000	0.091	-0.031	0.003	-0.113	0.196
	(0.593)	(1.223)	(0.001)	(0.442)	(-0.570)	(0.052)	(-0.578)	(0.750)
constant	3.801***	3.248***	4.081**	3.251	4.042***	3.664***	4.282*	5.093**
	(5.456)	(4.801)	(2.294)	(1.595)	(6.818)	(6.230)	(1.930)	(2.269)
observations	479	479	479	479	479	479	479	479
countries	27	27	27	27	27	27	27	27

Note: t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.5 Further insights into the effects of fertility on energy intensity and carbon emissions

To address potential endogeneity in the relationship between energy intensity, carbon emissions, and their key determinants—specifically those outlined in equations (1) and (2)—we employ an Instrumental Variables (IV) estimation approach, as proposed by Baum et al. (2003). This methodology enables efficient estimation in the presence of endogenous regressors while explicitly accommodating heteroskedasticity and serial correlation. Baum et al. (2003) rigorously demonstrated that this approach yields robust standard errors and valid inference regarding instrument relevance and exogeneity, thereby enhancing the credibility of the estimates. Additionally, endogeneity concerns are further acknowledged and addressed via the Lewbel (2012) heteroscedasticity-based estimator, as applied by Barkat et al. (2023), which enables robust identification when traditional instruments are unavailable.

To mitigate biases arising from reverse causality and omitted variable confounding, we use female employment as an instrument for fertility decisions, which may be endogenously linked to energy intensity.[1] This application constitutes a novel contribution to the extant literature by facilitating a more precise and reliable assessment of the interplay between technological innovation, fertility, and energy intensity. The estimation results are presented in Table 7.

Technological innovation (ltechnology) is negatively associated with both energy intensity and carbon emissions, with the relationship being statistically significant at conventional levels. Fertility rates (lfertility) exhibit a consistent positive correlation with both energy intensity and carbon emissions, indicating a potentially amplifying effect of demographic growth on environmental outcomes. Openness to trade (lopen) reveals complex trade-offs between international integration and environmental sustainability that are specific to this particular empirical context. Access to credit (lcredit) is negatively correlated with carbon emissions, consistent with the findings presented in Table 6. Finally, GDP (lgdp) is negatively associated with energy intensity, yet positively correlated with carbon emissions, highlighting the nuanced and multifaceted relationship between economic growth and environmental dynamics. These results underscore the critical roles of technological innovation, demographic factors, financial access, and economic growth in shaping the energy and carbon trajectories.

Finally, to examine potential threshold effects and discontinuities in the relationship between the dependent and independent variables, we implement a Threshold Effect Analysis following the methodology proposed by Lee et al. (2025). Specifically, we evaluate whether the association between energy intensity and its determinants, including fertility, varies across regimes defined by government debt levels. The level of government debt may signal differing fiscal capacities or policy priorities, which could, in turn, influence how demographic factors like fertility affect

[1] The female employment-to-population ratio (empfem) indicates how efficiently an economy provides jobs for women who want to work. A high ratio means that a large proportion of the female population is employed. We use female employment as an instrumental variable to examine its effect on fertility, addressing potential endogeneity. Female employment is assumed to influence fertility through factors like the opportunity cost of childbearing and access to family planning, while being uncorrelated with unobserved factors that might affect fertility decisions (For an extended discussion on the relationship among employment and fertility see, among others, Alderotti et al. 2021 and Papapetrou, 2004).

energy demand.[2] This inquiry is pertinent as demographic dynamics and fiscal capacity jointly shape energy demand trajectories, particularly in contexts where high fertility amplifies the need for energy-intensive public services (such as healthcare, education, and housing) while elevated debt burdens may constrain the state's ability to invest in energy-efficient infrastructure and public service provision. In this specification, fertility is modeled as the regime-switching variable, while government debt serves as the threshold (or regime-determining) variable. The results are reported in Table 8.

The estimated threshold value is 3.2956, with a 95% confidence interval ranging from 2.8794 to 3.3008. However, the threshold effect test yields an F-statistic of 11.84 and a p-value of 0.5767, based on 300 bootstrap replications. Since the p-value exceeds conventional significance levels, the null hypothesis of no threshold effect cannot be rejected. Furthermore, the observed F-statistic falls below the critical values at the 10, 5, and 1 percent levels, reinforcing the lack of statistical significance. These results provide no compelling evidence of a regime-dependent relationship between fertility and energy intensity conditional on government debt. Consequently, allowing the effect of fertility to vary across debt regimes does not materially improve the model's explanatory power. Overall, the absence of a significant threshold effect suggests that the fertility–energy intensity relationship remains stable across debt levels, thereby reinforcing the robustness of our empirical results.

[2] In the threshold analysis, central government debt (as a percentage of GDP) is employed as the threshold variable to examine regime-dependent effects. Debt refers to the total stock of direct government fixed-term contractual obligations to external and domestic creditors, including currency and deposits, securities other than shares, and loans. It is measured as the gross amount of government liabilities, net of equity and financial derivatives held by the government (Source: World Bank).

TABLE 7. Energy Intensity, Carbon Emissions and Fertility

Instrumental Variables (IV)				
Columns	1	2	3	4
VARIABLE	lenergyint Mean	lenergyint Mean	lcarbon Mean	lcarbon Mean
ltechnology	-0.636***	-	-0.353***	-
	(-7.187)		(-6.324)	
lRD	-	-0.057	-	-0.042
		(-0.885)		(-0.935)
lfertility	3.357***	2.050***	1.623***	0.919***
	(6.273)	(4.966)	(4.807)	(3.211)
lopen	0.332***	-0.022	0.132***	-0.067**
	(4.207)	(-0.454)	(2.662)	(-2.013)
lcredit	0.048	0.052	-0.089**	-0.086**
	(0.833)	(0.970)	(-2.476)	(-2.302)
lgdp	-0.420***	-0.421***	0.472***	0.473***
	(-4.519)	(-4.937)	(8.043)	(7.997)
constant	3.872***	4.833***	-2.948***	-2.434***
	(4.471)	(5.926)	(-5.394)	(-4.304)
observations	479	479	479	479
countries	27	27	27	27

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 8. Threshold effect test

Threshold estimator (level = 95):

model	Threshold	Lower	Upper
Th-1	3.2956	2.8794	3.3008

Threshold effect test (bootstrap = 300):

Threshold	RSS (Residual Sum of Squares)	MSE (Mean Squared Error)	Fstat (F-statistic)	Prob (p-value)	Crit10	Crit5	Crit1
Single	33.012	0.0371	11.84	0.5767	23.3153	27.0627	32.9433

Notes: * The null hypothesis is that there is no threshold effect.
**The critical values for the test at different significance levels are: Crit10 (for a 10% significance level), Crit5 (for a 5% significance level) and Crit1 (for a 1% significance level).

5. Conclusions and policy implications

As the global transition toward sustainable energy systems accelerates, understanding the key drivers of energy intensity and carbon emissions becomes increasingly imperative. This study contributes novel insights into the interplay of technological innovation, demographic dynamics, and economic factors shaping energy outcomes across OECD countries—an area that remains insufficiently explored in existing research. To this end, we analyze the impact of technological innovation and fertility on energy intensity using a unique panel dataset encompassing 27 OECD countries from 1990 to 2022, employing a diverse suite of advanced estimation techniques. We apply Dynamic Common Correlated Effects (DCCE) estimators, a robust method seldom utilized in the energy intensity literature, which effectively accounts for cross-sectional dependence and slope heterogeneity, enhancing the robustness of our empirical results. This approach enables a more nuanced and comprehensive understanding of the determinants of energy intensity in OECD countries, advancing the literature with both theoretical and empirical rigor.

The results demonstrate that technological advancements play a pivotal role in significantly reducing energy intensity, highlighting the transformative potential of innovation—particularly through ICT and R&D—in mitigating energy consumption. Economic openness and higher GDP per capita further contribute to lower energy intensity, emphasizing the importance of trade and economic growth in facilitating the adoption of energy-efficient technologies. Conversely, higher fertility rates are associated with increased energy intensity, driven by population growth and heightened demand for energy-intensive services.

The quantile regression analysis unveils significant heterogeneities along the conditional distribution of energy intensity. Technological innovation exerts stronger negative effects on energy intensity at lower and middle quantiles, with its influence diminishing toward the upper tail; conversely, fertility is positively associated with energy intensity following a similar pattern, with stronger effects at lower and middle quantiles that weaken toward the upper tail. Additionally, credit shows a significant negative impact at the middle quantiles, underscoring the critical role of financial access in enabling energy-efficient investments within these segments.

Robustness checks using carbon emissions as the dependent variable confirm the consistency of the results. Technological innovation, fertility, and openness exhibit similar effects, while the significant negative impact of credit underscores its critical role in enabling cleaner technologies that drive emissions reduction. Collectively, these findings reinforce the stability and explanatory power of the baseline model in advancing sustainable development objectives.

This study underscores the transformative potential of technological innovation, particularly through ICT and R&D, in enhancing energy efficiency. However, it also reveals that demographic factors, such as fertility rates, pose significant challenges for sustainable energy transitions. To address these challenges, future policy efforts should prioritize fostering technological innovation by increasing investments in R&D and ICT infrastructure. Additionally, policies aimed at improving access to credit are crucial for enabling energy-efficient investments, particularly in the middle quantiles of the distribution. Given the enduring impact of demographic trends, it is essential that targeted strategies be devised to address the energy demand implications of fertility dynamics. Ultimately, a comprehensive policy framework that effectively integrates technological advancement, financial accessibility, and demographic considerations will be paramount in advancing sustainable energy systems and achieving long-term energy efficiency objectives.

While this study offers valuable insights into the relationship between technological innovation, energy intensity, and fertility, several limitations can be considered, primarily related to data availability. Future research could benefit from extending the analysis to include additional control variables and countries, contingent upon improved data availability. Such an extension would provide deeper insights into the evolving role of technological innovation in energy dynamics. These limitations also present important avenues for further exploration.

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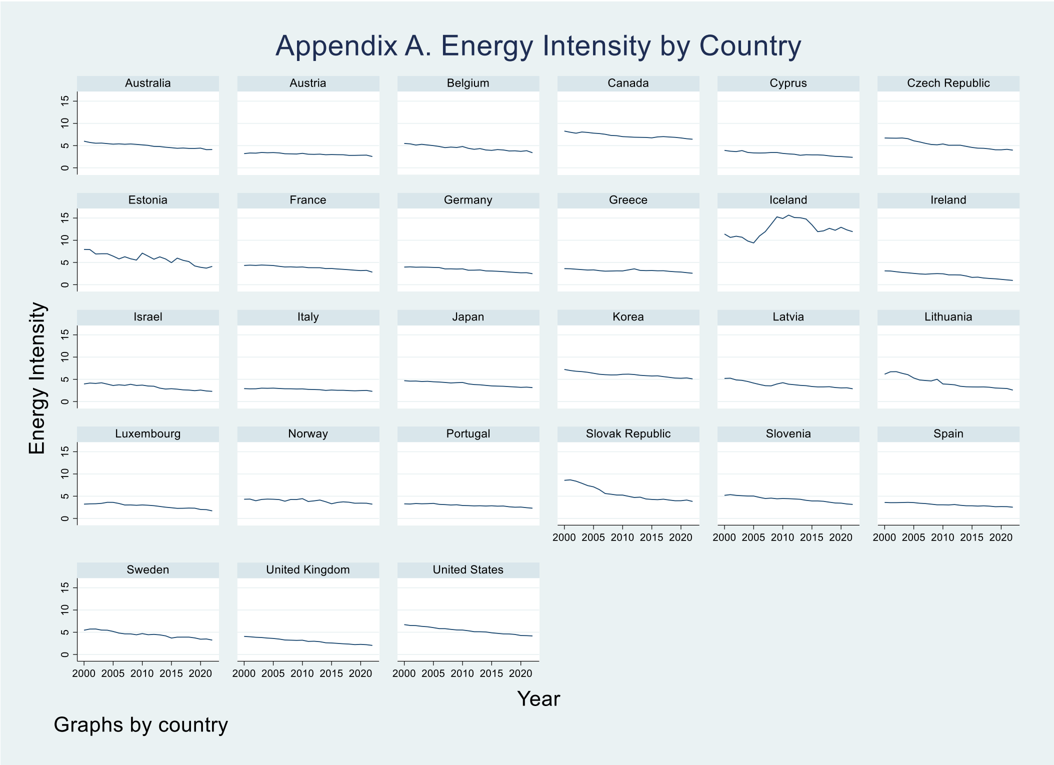
TABLES

APPENDICES



Appendix B

Overview of variables and data sources

Abbreviation	Name of variable	Description	Source
energyint	Energy intensity level of primary energy	Energy intensity level of primary energy is the ratio between energy supply and gross domestic product measured at purchasing power parity. Energy intensity is an indication of how much energy is used to produce one unit of economic output. Lower ratio indicates that less energy is used to produce one unit of output.	World Bank
carbon	Total greenhouse gas emissions per capita	Total annual emissions of the six greenhouse gases (GHG) covered by the Kyoto Protocol (carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphurhexafluoride (SF_6)) from the energy, industry, waste, and agriculture sectors, standardized to carbon dioxide equivalent values divided by the economy's population. This measure excludes GHG fluxes caused by Land Use Change Land Use and Forestry (LULUCF), as these fluxes have larger uncertainties.	World Bank
technology	ICT service exports (% of service exports, BoP)	Information and communication technology service exports include computer and communications services (telecommunications and postal and courier services) and information services (computer data and news-related service transactions).	World Bank/IMF
RD	Research and development expenditure (% of GDP)	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP. They include both capital and current expenditures in the four main sectors: Business enterprise, Government, Higher education and Private non-profit. R&D covers basic research, applied research, and experimental development.	World Bank
fertility	Fertility rate, total (births per woman)	Total fertility rate represents the number of children that would be born to a woman if she were to live to the end of her childbearing years and bear children in accordance with age-specific fertility rates of the specified year.	World Bank
empfem	Employment to population ratio, female (%) (modeled ILO estimate)	Employment to population ratio is the proportion of a country's population that is employed. Employment is defined as persons of working age who, during a short reference period, were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period (i.e. who worked in a job for at least one hour) or not at work due to temporary absence from a job, or to working-time arrangements.	World Bank
open	Economic openness	Openness is calculated as the ratio of imports plus exports to GDP. Imports of goods and services represent the value of all goods and other market services received from the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments. Exports of goods and services represent the value of all goods and other market services provided to the rest of the world.	World Bank
credit	Domestic credit to private sector by banks (% of GDP)	Domestic credit to private sector by banks refers to financial resources provided to the private sector by other depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises.	World Bank

gdp	GDP per capita, PPP	GDP per capita based on purchasing power parity (PPP). PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the country plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2021 international dollars (constant 2021 international $).	World Bank

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