Analysing the Impact of Carbon Emissions and Non-Renewable Energy Use on Infant and Under-5 Mortality Rates in Europe: New Evidence Using Panel Quantile Regression

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Abstract
This study critically examines the health-environment discourse and uses infant and under-5 mortality rates, carbon emissions, and non-renewable energy to investigate the inherent associations. We argue that the concentration of greenhouse gas emissions is considered to increase and can undermine the access to basic resources necessary for leading a healthy life, such as access to food, water, health, and the environment. Environmental health is closely linked to human health. The world is witnessing a substantial increase in greenhouse gas emissions, which pose a significant threat to both environment and human health. Hence, this study contributes to the discourse with unbalanced panel data on 46 European countries from 2005 to 2015 to investigate the impact of carbon emissions and non-renewable energy on infant and under-5 mortality rates. Consistent findings from static and dynamic analyses reveal that (1) carbon emission is positively associated with mortality rate; (2) non-renewable energy shows a significant negative relationship; (3) persistency in mortality rates exists; (4) positive (negative) association of emissions (non-renewable energy) dwindles (increases) in absolute value at higher distributions of mortality rates; and (5) Euro Union countries show lower mortality rates relative to non-Euro Union members. Policy recommendations are discussed.

Keywords Carbon emissions · Mortality rate · Non-renewable energy · Socio-economic factors · Europe

JEL Classification I00 · I10 · I15 · I18 · I19

1 Introduction
Environmental health is closely linked to human health. The world is witnessing an increase in greenhouse gas emissions (GHG) which pose a significant threat to the environment and human health [1]. Among the class of GHG emissions, carbon emissions linked to intense consumption of non-renewable energy resources are one of the significant drivers behind global warming and environmental degradation with a negative impact on human health [2–4]. Also, the direct effect of climate change can be seen in the rising sea level and the increase in heat waves [5]. The indirect impact of climate change on health can be realised through changes in nutrition and the development of infectious diseases [86]. The World Health Organization [6] projected that in 2030–2050, about 250,000 deaths annually can be attributed to climate change. This seems to be a probability given the pattern of GHG emissions during the last decades. On the other hand, energy is necessary for economic growth,
productivity, and human development. The need to replace fossil fuels with renewable resources is more urgent than ever, which will not help economies achieve sustainability in terms of environment and micro-perspective since a healthy population is crucial to economic productivity and sustainable development [7]. As the world population increases, the quest for energy increases. However, suppose these energy requirements are met by continuously burning fossil fuels. In that case, it will affect the world population, suffering injuries and deaths due to fossil fuel combustion. Furthermore, the empirical literature documents that non-renewable energy consumption is associated with adverse human capital impact [2, 8–11], which ought to be further investigated and serves as the motivation for this study.

The focus on Europe is not far-fetched as the effect of emissions-related pollution on health has become a leading concern in the region. Global warming is considered a new health threat for Europe [12] and some studies document the environmental impact of environmental pollution and climate change on health, adolescence, and premature mortalities in Europe. The United States Environmental Protection Agency [13] reports that European Union countries are one of the top carbon emitters after the USA and China. The climate change effect has mostly been felt in the region through heat waves. It is estimated that 100,000 deaths yearly in European cities are linked to ambient air pollution, shortening life expectancy by an average of a year [1]. The 2005 Report on Health Effects of Transport-Related Air Pollution from the World Health gives a detailed assessment of air pollution and the potential risks to human health.

Epidemiological and toxicological evidence from Krzyzanowski et al. [14] shows the adverse effects of emission-related pollution on pregnancies. Other birth outcomes are a rise in postneonatal infant mortality and a decline in male fertility. Also, reduced emission-related air pollution may directly lessen acute asthma attacks in infants and under-5 children. Long-term reduction in emission-related air pollution is associated with bronchial, respiratory, and cardiovascular disease falls. Such decreases in emission-related air pollution appear to provide a gain in life expectancy. Few studies [15–18] analyse the effects on the health of specific interventions and even fewer focus on emission-related air pollution. Scheers et al. [68] showed that an increase in aerodynamic diameter ≤ 10 μm (PM10) causes increased mortality in adults and infants in Western Europe. Though not directly related to infant and under-5 mortality, Khomenko et al. [19] deployed a quantitative impact health assessment to reveal that ambient air pollution is a major environmental cause of European morbidity and mortality. Although European countries have invested considerably to increase the quality of their environment by building renewable and clean energy technologies, the impact of emissions and pollution on human health in these countries is still significant, which poses a burden on their health budgets [20, 21].

The noticeable gap in these studies is the non-consideration of the impact of carbon emissions and non-renewable energy vis-à-vis other socio-economic factors that may affect infant and under-5 mortalities in Europe. Therefore, we extend these studies by comprehensively examining infant and under-5 mortalities in Europe. In addition, we probe the discourse on the effects of atmospheric pollution using carbon dioxide emissions [22–24] which is a component of greenhouse gas (GHG) and non-renewable energy consumption. Given these, we contribute to the health-environment literature by investigating the intrinsic nexus of carbon emissions, energy usage, and a set of socio-economic variables on infant and under-5 mortality rates. The objectives of the study are threefold: (1) show whether carbon emissions and non-renewable energy are independently associated with infant and under-5 mortality rates; (2) if the association is significantly different across the dis-aggregated groups; and (3) if mortality rate is persistent.

To achieve the research objectives stated above, we use data on 46 European countries disaggregated into Euro and non-Euro Union countries from 2005 to 2015. In line with the literature [2, 25–28], we deploy a blend of panel spatial correlation consistent least squares dummy variable (PSCC-LSDV), system generalised method of moments (GMM), and quantile regression techniques to ascertain the robustness of our results and to explore if there are significant differences between the two groups. To the best of our knowledge, this is the first study to adopt this approach. Our results hold when we control for time-varying common shocks and regional fixed effects. For the most part, our results are consistent. We find that carbon emissions display mortality-increasing properties, non-renewable energy reduces mortality rates, persistency in mortality rates exists, and Euro Union countries show lower mortality rates than non-Euro Union members. We expect the outcomes of this study to be generalisable to other regions with similar characteristics to Europe. The rest of the study is structured as follows: Sect. 2 discusses the empirical literature; Sect. 3 outlines the data and model; Sect. 4 interprets the results, and Sect. 5 concludes with policy recommendations.

2 Literature Review

The impact of carbon emissions and environmental degradation on health indicators have been examined extensively in the empirical literature [11, 29–32]. These studies can be grouped into three strands. The first deals with the relationship between life expectancy and the environment, the second documents the

1 https://www.euro.who.int/en/data-and-evidence/evidence-informed-policy-making/publications/hen-summaries-of-network-members-reports/what-are-the-effects-on-health-of-transport-related-air-pollution

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association between mortality and the environment, and the third strand argue on the relationship between the environment and health expenditures.

From the first strand, it has been argued that environmental degradation can lead to lower life expectancy. For instance, Ali and Audi [29] deployed the ARDL technique and found that environmental degradation and life expectancy have a significant negative relationship in Pakistan. Using a similar approach, Hossain et al. [30] showed for Bangladesh that life expectancy and environmental degradation have a negative association. Employing a neural network approach, Kolasa-Więcek and Suszanowicz [31] investigated the correlation between life expectancy and air pollution in Europe. The most frequent correlation in their analysis was observed for fine particles, indicating that fine particles have a more significant influence compared to other pollutants on European residents. Correspondingly, Geels et al. [20] showed a positive relationship between changes in climate, air pollution, and premature deaths such that reductions in emissions cause a significant decrease in mortality.

The second strand of literature deals with the relationship between the environment and mortality. Mehrara and Nasibparast [32] examined the factors determining child mortality in developing countries using the Bayesian model averaging approach. The results revealed that per capita GDP and literacy rate negatively affect child mortality. Erdoğan et al. [33] used infant mortality and life expectancy as health indicators to analyse how they are affected by carbon emissions in Turkey. The study found that a rise in carbon emissions increases infant mortality rate and simultaneously decreases life expectancy. Using comparative analysis, Orru et al. [86] showed that an increase in climate change causes an increase in the concentration of ground-level ozone, which is associated with respiratory morbidity and mortality. This is like the findings of Atkinson et al. [75], who conclude that acute health effects such as respiratory and cardiovascular disease are the resultant outcomes of increasing ground-level ozone [34–36], and chest tightness and asthma [37, 38]. Similarly, an increase in ambient ozone levels is associated with an increase in hospital admissions for respiratory diseases and chronic obstructive pulmonary disease [39–41]. Likewise, Owusu and Sarkodie [42] examined the association between ambient particulate matter and ozone, mortality, and welfare costs for 195 countries and found strong evidence for the impact of air pollution on premature deaths, mortality, and daily adjusted life years. Most of the studies use carbon emissions as a proxy for environmental degradation. However, Jian et al. [82] constructed an environmental quality index and assessed its effects on the mortality rate in the USA. This index was created out of 5 variables such as land, water, built, air, and socio-demographics. Findings revealed that if the environmental quality is poor, mortalities increase. In another study, Patel [88] found that infant mortality increased monotonically due to poor air quality among non-Hispanic whites and blacks. A detailed examination of the dynamic interdependence among health, carbon emissions, and economic growth was carried out by Katrakilidis et al. [43] for Greece. Employing the Kuznets-type models, their causality result identified causal effects from income to infant mortality and carbon emissions.

The third strand of literature deals with environmental quality and health expenditures. Ahmad et al. [44] considered carbon emissions from coal, natural gas, and petrol as measures of environmental degradation and explored how the increase in these emissions can affect the health quality of China. They found the long-run negative impact of these emissions on health status. On the other hand, Farooq et al. [45] found that carbon emissions increase health issues in 30 Chinese provinces in a different framework. The study also found that population is an effective determinant of health issues. Recently, Zeeshan et al. [46] attempted to analyse the asymmetric relationship between carbon emissions, pollution, and household health expenditures in China. Using nonlinear autoregressive distributed lag (NARDL), they found positive impacts on health spending due to positive shocks of carbon emissions and environmental pollution in the long- and short-run. Still, they found that adverse shocks negatively affect health spending. On 15 Economic Community of West African States, Alimi et al. [47] analysed how national healthcare expenditure, and private and public healthcare expenditure can be affected by environmental quality. Employing panel data techniques, the study found that environmental pollution, proxied by carbon emissions, positively affects the overall health expenditure and public healthcare expenditure. Considering this, Badulescu et al. [48] used European countries to demonstrate how environmental pollution, non-communicable diseases, and economic growth can determine health expenditures. Economic growth was found to be a critical determinant for health expenditures in both the short and long run. However, the result was mixed for the effect of carbon emissions on health expenditures.

A cross-country analysis of 51 countries based on income groups was carried out by Chaabouni et al. [49], who examined the causal relationship between carbon emissions, health expenditures, and economic growth. The result showed that health expenditures and economic growth, carbon and economic growth are bi-directionally related. Shahzad et al. [50] showed that renewable energy consumption negatively and significantly affected health expenditures in Pakistan, similar to the findings of Ullah et al. [90]. Empirical studies have also been carried out using Organization for Economic Cooperation and Development (OECD) countries to determine the relationship between health status and other indicators, including environmental quality. Mujtaba and Shahzad [1] analysed the relationship between economic growth, environmental pollution, and public health in OECD countries. Their result revealed that carbon emission and renewable energy Granger-cause healthcare
spending in OECD economies. Lastly, Wang et al. [51] also investigated the OECD countries to examine the long-run association between GDP, carbon, and healthcare expenditure. The results revealed that healthcare and GDP are bi-directionally related for Germany and the USA. Results for New Zealand and Norway showed a two-way relationship between healthcare spending and CO₂ emissions, while for Canada, Germany, and USA, bidirectional causality was found between GDP growth and carbon emissions. A comprehensive, cross-country analysis of the impact of carbon emissions, non-renewable energy, and other socio-economic factors that influence European infants and the under-5 mortality rate is missing in the literature. We differ by engaging more robust analyses using aggregated and disaggregated samples and static and dynamic estimation techniques to interrogate these inter-woven relationships.

## 3 Data and Empirical Approach

### 3.1 Data

This study fills a gap in the literature by interrogating the health-environment dynamics in Europe. It uses an unbalanced panel data of 46 European countries from 2005 to 2015, two dependent variables—infant (MINF) and under-5 (MU5) mortality rates; two key explanatory variables—carbon emissions (CO₂PC) and nonrenewable energy (ENUPC); and six control variables—per capita GDP (PC); female secondary school enrollment (SECF), health expenditure per capita (HEXPC), urbanization (URB), access to basic sanitation (BSAN), and inflation rate (INFL). All variables are sourced from World Bank [52] World Development Indicators. On a priori expectations, carbon emissions, non-renewable energy, inflation, and urban population are expected to increase mortality rates. Hence, positive coefficients are expected. Whereas, per capita income, female secondary school enrolment, health expenditures, and basic sanitation are expected to reduce mortality rates. Table 1 details the variables’ description and expected signs.

### 3.2 Models and Specifications

To address the first and second objectives, the mortality rate (infant and under-5) is expressed as a function of carbon emissions, non-renewable energy, and a set of control variables. Adapting, Barua et al. [2], Adeleye et al. [53, 54], the equation is stated as:

$$
\ln M_{it} = \eta_0 + \eta_1 \ln CO2PC_{it} + \eta_2 \ln ENUPC_{it} \\
+ \eta_3 \ln PC_{it} + \eta_4 \ln HEXPC_{it} \\
+ \eta_5 \ln SECF_{it} + \eta_6 \ln INFL_{it} + \eta_7 \ln BSAN_{it} \\
+ \eta_8 \ln URB_{it} + d_i + e_{it},
$$

(1)

where \(M\) represents infant mortality/under-5 mortality rate; \(\ln\) denotes natural logarithm; \(\eta(i = 0, 1, 2, \ldots, 8)\) are parameters to be estimated; \(d\) is the time dummy to control for yearly variations of the dependent variable; and \(e\) is the error term. To control for outliers and establish an elasticity relationship, all variables with the exception of \(INFL\) are transformed into their natural logarithms to capture elasticities, account for skewness

| Code | Variables | Expectations |
|------|-----------|--------------|
| MINF | Mortality rate, infant (per 1000 live births) | N/A |
| MU5  | Mortality rate, under-5 (per 1000 live births) | N/A |
| CO₂PC| CO₂ emissions (metric tons per capita) | + |
| ENUPC| Non-renewable energy consumption per capita | - |
| PC   | GDP per capita (constant 2010 US$) | - |
| HEXPC| Current health expenditure per capita (current US$) | - |
| SECF | School enrolment, secondary, female ( % gross) | - |
| INFL | Inflation, consumer prices (annual %) | + |
| BSAN | People using at least basic sanitation services ( % of the population) | - |
| URB  | Urban population ( % of the total population) | + |

Source: Authors’ Compilations

MINF infant mortality rates, MU5 under-5 mortality rate, CO₂PC carbon emissions per capita, ENUPC non-renewable energy per capita, PC GDP per capita (constant 2010), HEXPC health expenditure per capita, SECF female secondary school enrolment, INFL inflation rate, BSAN access to basic sanitation, URB urban population, N/A not applicable.

### Table 1 Variable description and expectations

3 European Union (26): Austria (Since 1995), Belgium (Since 1998), Bulgaria (Since 2007), Croatia (Since 2013), Cyprus (Since 2004), Czech Republic (Since 2004), Denmark (Since 1973), Estonia (Since 2004), Finland (Since 1995), France (Since 1958), Germany (Since 1958), Greece (Since 1981), Hungary (Since 2004), Ireland (Since 1973), Italy (Since 1958), Latvia (Since 2004), Lithuania (Since 2004), Luxembourg (Since 1958), Netherlands (Since 1958), Poland (Since 2004), Portugal (Since 1986), Slovak Republic (Since 2004), Slovenia (Since 2004), Spain (Since 1986), Sweden (Since 1995), United Kingdom (Since 1973; Exited 2020).

Non-European Union (20): Albania, Andorra, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Georgia, Greenland, Iceland, Kosovo, Moldova, Montenegro, North Macedonia, Norway, Romania, Russian Federation, Serbia, Switzerland, Turkey, Ukraine.
and nonlinear relationship between the outcome and explanatory variables. The variables are as defined in Table 1.

To address the third objective, Eq. (1) is augmented to include the lagged values of mortality rates and the equation is expressed as:

$$\ln M_i = \eta_0 + \gamma_1 \ln M_{i-1} + \gamma_2 \ln CO2PC_i + \gamma_3 \ln ENUPC_i + \gamma_4 \ln PC_i + \gamma_5 \ln HEXPC_i + \gamma_6 \ln SECF_i + \gamma_7 \ln INF_i + \gamma_8 \ln BSAN_i + \gamma_9 \ln URB_i + d_i + v_i,$$

where $\gamma_i (i = 0, 1, 2, ..., 9)$ are parameters to be estimated; $d$ is a time dummy which controls for yearly variations of the dependent variable; and $v$ is the error term. Lastly, to check if the outcomes of Eq. (1) differ by union classification, the sample is divided into two distinct groups $^3$: (i) Euro Union members $^4$ and (ii) non-Euro Union members.

### 3.3 Estimation Techniques

This study follows Shobande [11] and employs both static and dynamic models to investigate the health-environment dynamics. These techniques have been used in various panel data studies [2, 55]. For the static model, panel spatial correlation consistent least squares dummy variables techniques (PSCC-LSDV) while the two-step system GMM is used to analyse the dynamic model. The PSCC estimator uses the Driscoll and Kraay [56] robust standard errors technique and corrects the standard errors of the coefficient estimates for possible dependence [57, 80]. The underlying algorithm routines the OLS/WLS$^5$ and fixed effects (within) regression and computes spatial correlation consistent standard errors for linear panel models. Among its several advantages, such as correcting for heteroscedasticity and autocorrelation, which endears its usage to researchers, the PSCC method uses at least a one-period lag of the regressors in the underlying algorithm to control for reverse causality and endogeneity. The LSDV component of the technique, also known as the fixed effects, accounts for heterogeneities across the panel observations using dummy variables.

If the dependent and independent variables may not be strictly exogenous, the two-step system generalised methods of moments (Sys-GMM) are used to analyse the dynamic model. Sys-GMM also controls for endogeneity, heteroscedasticity, and omitted variables [58, 59]. Endogeneity broadly refers to situations in which an explanatory variable is correlated with the error term. Li [60] noted that the endogeneity problem creates problems for true relationships among variables. Instrument variables are also used to control problems like endogeneity as suggested by Anderson and Hsiao [61]. Studies like Noman et al. [84] study financial stability variable as endogenous. Ebire et al. [62] also used the GMM model to control endogeneity problems in a study of capital flows and financial stability. Moudud-Ul-Huq et al. [81] used two-step GMM by modelling the financial stability of banks. Arellano and Bond [58] first induced the GMM that used instrument variables and Hansen [63] used lagged variable of dependent variables in GMM to obtain robust estimations. Finally, suppose the dependent variables exhibit non-normal distributions such that the impact of the covariates changes along their conditional distribution. In that case, deploying a suitable technique that models this scenario becomes relevant. The most appropriate method is the quantile regressions proposed by Koenker and Basset [83], Koenker and Hallock [64], and Koenker [65]. This technique is also more robust in the presence of outliers or weaker linear correlation between variables [66, 67].

### 4 Results and Discussions

#### 4.1 Summary Statistics

The results presented in Table 2 are the detailed summary of the model variables, which includes the entire sample statistics and the statistics for countries in the European Union (EU) and those outside the union. The mean values of infant mortality rate and under-5 mortality rate of children per 1000 live births within the total sample consideration are 6.52 and 7.645, respectively. This shows that for every recorded 1000th birth, there are about 7 infants and approximately 8 under-5 children’s mortalities. The European countries’ healthcare focus on child life, according to the sample statistic above, reveals that only about 4 infants and 5.127 children below age 5 die at birth compared to 1000 children born within the same sample period. For the non-EU nations, almost twice the number of infant (9.795) and under-5 (11.283) deaths per 1000 live births are observed. Also, the average values of carbon emissions, non-renewable energy per individual, income, health expenditure by government, enrolment and inflation rates, sanitation, the urban populace, and natural resources rent are reported as seen in Table 2 for the total sample, EU, and non-EU zones respectively.

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$^3$ Dynamic analysis is performed only on the full sample due to insufficient data on under-5 mortality rate for the non-European Union sample.

$^4$ The EU is a political and economic union made up of 27 member states. Its citizens share a currency, a single market, and common history and culture.

$^5$ Weighted least squares.
4.2 Pairwise Correlation Analysis

Table 3 displays the pairwise correlations evidenced in the data and the associations are statistically significant at the 1%, 5%, and 10% levels, respectively. All the variables, except inflation rate (INFL) show a statistically significant correlation with infant mortality and under-5 mortality rates. Due to the high collinearity coefficient of 0.946 between PC and HEXPC, both variables are excluded in subsequent analyses to test the robustness of our results.

4.3 Results from Static Models

4.3.1 PSCC‑LSDV Results

Controlling for yearly variation of the dependent variable, results from the PSCC-LSDV technique are presented in Table 4. Columns 1 and 2 for the entire sample show that carbon emission is positively associated with infant and under-5 mortality rates by 0.054 and 0.039%, on average, *ceteris paribus*. These outcomes suggest that poor environmental quality leading to health problems may increase the death of infants and children. These findings support Scheers et al. [68], Khomenko et al. [19], and Barua et al. [2]. Other studies that show a positive relationship between environmental degradation, emissions, and health outcomes are Fotourehchi [69], Ahmad et al. [70], Adedotun et al. [71], Erdogan et al. [33], Azam and Awan [72], and Adeleye et al. [73] to mention a few. However, contrary to Anser et al. [8] and Asghar et al. [9], non-renewable energy is negatively associated with mortality rates. However, this finding aligns with Shobande [11], who argues that enhancing human welfare through energy consumption reduces child mortality while environmental deterioration exacerbates child mortality, respectively. Also, the control variables, except urbanization, are negatively associated with the mortality rate. We provide some insights into these outcomes. According to Euro-Peristat [74], reveal that the main causes of death during the first month of pregnancy are congenital anomalies, prematurity, and other conditions that may arise during pregnancy. Environmental degradation stemming from rising emissions may contribute to poor living conditions and other socio-economic factors affecting mothers’ and newborns’ health. Also, quality healthcare can significantly reduce the number of infant deaths, particularly by addressing life-threatening issues during the neonatal period (i.e. the first month of life).

For robustness checks, PC and HEXPC are excluded from the analyses due to high collinearity and variance inflation factors (VIF) bloating. The results shown in columns 7 and 8 are not significantly different from those of columns 1 and 2, thereby sustaining our earlier findings. We, therefore, conclude that
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Carbon emissions and non-renewable energy indicate asymmetric effects. Furthermore, using non-Euro Union members as the base dummy, the intercept coefficients of Euro Union countries are consistently negative, implying that European Union countries have lower mortality rates than non-Euro Union members. Lastly, the models’ goodness-of-fit shows that the \( R^2 \) ranges around 0.87 and indicates that the regressors explain about 87% variation in mortality rates. Also, the F-statistics show that all the regressors are jointly significant in explaining mortality rates.

### 4.3.2 PSCC-LSDV Results, Sub-Samples

The sample is divided into Euro and non-Euro Union to probe the discourse further. Interpretation is limited to the variables of interest (carbon emissions and non-renewable energy). A cursory observation of the results shown in columns 3 to 6 reveals some significant differences. Though negative, the impact of carbon emissions on both sub-samples is statistically insignificant for the main models. This outcome may not be unconnected to Europe’s stance in promoting environmentally friendly initiatives. On the other hand, non-renewable energy reveals a significant negative association with mortality rate across both samples. Like the full sample, we submit that the enhancement of human welfare through energy consumption may result in the reduction of child mortality [2, 11]. For robustness checks, \( PC \) and \( HEXPC \) are excluded from the analyses due to high collinearity and variance inflation factors (VIF) bloating. Except for carbon emission, which indicates a statistically significant negative association for Euro Union countries, the remaining results shown in columns 9 to 12 are not significantly different from those of columns 3 to 6, thereby sustaining our earlier findings.

### 4.4 Results from GMM Dynamic Models

Controlling for possible endogeneity of the variables, omitted variables, and heteroscedasticity, the results from the two-step system GMM are displayed in Table 5. Findings reveal the persistence of infant and under-5 mortalities in the region, given the statistical significance of the lagged dependent variable at the 1% level. For others, the signs and statistical significance of non-renewable energy align with those from the PSCC-LSDV models. At the same time, the coefficient of carbon emissions is primarily positive and statistically significant in one of four models. Overall, this study submits that (1) the mortality rate is persistent; (2) carbon emission is positive but weakly associated with mortality rate; and (3) non-renewable energy reveals a significant negative association, for the most part.

### 4.5 Results from Simultaneous Quantile Analysis, Full Sample

For brevity, interpretations focus only on the effect of carbon emissions and non-renewable energy across different quantiles of infant and under-5 mortality rates. Tables 6 and 7 show that carbon emission is positively associated with infant and under-5 mortalities, though with higher statistical significance on infant mortality rate. Supporting earlier results from the PSCC-LSDV and system GMM techniques, Table 6 reveals that a percentage change in emissions is associated with an increasing infant mortality rate from between 0.483% at the 0.05 quantile to 0.424% at the 0.95 quantiles.

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**Table 3** Correlation analysis

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|-----------|---|---|---|---|---|---|---|---|---|----|----|
| (1) lnMINF | 1.000 | | | | | | | | | | |
| (2) lnMU5 | 0.998*** | 1.000 | | | | | | | | | |
| (3) lnCO2PC | -0.625*** -0.615*** | 1.000 | | | | | | | | | |
| (4) lnENUPC | -0.741*** -0.729*** | 0.788*** 1.000 | | | | | | | | | |
| (5) lnPC | -0.801*** -0.803*** | 0.664*** 0.768*** | 1.000 | | | | | | | | |
| (6) lnHEXPC | -0.815*** -0.824*** | 0.568*** 0.709*** | 0.976*** | 1.000 | | | | | | | |
| (7) lnSECF | -0.573*** -0.570*** | 0.337*** 0.468*** | 0.543*** | 0.550*** | 1.000 | | | | | | |
| (8) lnINFL | 0.312*** 0.328*** | -0.089* -0.099* | -0.385*** | -0.438*** | -0.199*** | 1.000 | | | | | |
| (9) lnBSAN | -0.725*** -0.735*** | 0.459*** 0.467*** | 0.603*** | 0.648*** | 0.382*** -0.260*** | 1.000 | | | | | |
| (10) lnURB | -0.564*** -0.561*** | 0.555*** 0.708*** | 0.691*** | 0.641*** | 0.593*** | -0.081* 0.518*** | 1.000 | | | | |

Source: Authors’ Computations

ln natural logarithm, MINF infant mortality rates, MU5 under-5 mortality rate, CO2PC carbon emissions per capita, ENUPC nonrenewable energy per capita, PC GDP per capita (constant 2010), HEXPC health expenditure per capita, SECF female secondary school enrolment, INFL inflation rate, BSAN access to basic sanitation, URB urban population, TNRR total natural resource rent

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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6 The coefficients of the constant term represent those of non-Euro Union countries.
Table 4: PSCC-LSDV results, full sample

| Variables          | Main model Full sample [1] | Main model Euro [2] | Main model Non-Euro [3] | Robustness model Full sample [7] | Robustness model Euro [8] | Robustness model Non-Euro [9] |
|--------------------|----------------------------|---------------------|-------------------------|----------------------------------|--------------------------|------------------------------|
|                    | lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 | lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 | | lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 | lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 lnMINF lnMU5 |
| lnCO2PC            | 0.0537*** 0.0395** 0.0063 0.0010 0.0172 0.0248 | (3.57) (2.55) (0.50) (0.08) (0.43) (0.64) | | 0.0454** 0.0369* 0.0057*** 0.0090*** 0.0171 0.0083 | (2.25) (1.86) (−0.39) (−0.44) (0.42) (0.21) |
| lnENUPC            | −0.4534*** −0.4092*** −0.1391*** −0.1072*** −0.5129*** −0.4790*** | (−35.23) (−37.45) (−3.45) (−2.77) (22.90) (28.16) | | −0.5982*** −0.5572*** −0.2713*** −0.2503*** −0.6575*** −0.6203*** | (−39.12) (−37.72) (−2.86) (−28.10) |
| lnPC               | −0.1200** −0.0876* −0.4396*** −0.4139*** 0.0917 0.1111 | (−2.33) (−1.85) (−7.37) (−7.06) (0.92) (1.29) | | | |
| lnHEXPC            | −0.0890* −0.1202** 0.1911*** 0.1591* −0.3074*** −0.3224*** | (−1.70) (−2.52) (3.17) (2.67) (−3.10) (−3.82) | | | |
| lnSECF             | −0.3538*** −0.3089*** −0.1129 −0.0838 −0.10762*** −0.9577*** | (−6.00) (−5.33) (−0.89) (−0.64) (−5.55) (−6.21) | | −0.5544*** −0.5343*** −0.1692* −0.1593* −1.6537*** −1.5748*** | (−23.61) (−21.95) (−1.98) (−1.84) (−10.35) (−9.72) |
| lnINFL             | −0.0073* −0.0055* 0.0219*** 0.0223*** 0.0122*** −0.0102*** | (−2.22) (−0.81) (4.53) (4.62) (−3.64) (−3.38) | | 0.0054 0.0077 0.0351*** 0.0371*** 0.0042 0.0064 | (0.82) (1.18) (7.12) (7.04) (0.68) (1.05) |
| lnBSAN             | −2.7914*** −2.7070*** −3.3026*** −3.1619*** −2.3545*** −2.4200*** | (−20.66) (−21.19) (−16.70) (−17.46) (−5.72) (−6.55) | | −3.5549*** −3.5137*** −3.6875*** −3.6005*** −3.5806*** −3.6288*** | (−16.12) (−15.96) (−19.37) (−19.46) (−11.66) (−11.92) |
| lnURB              | 0.6940*** 0.6716*** 0.2555*** 0.2525*** 1.2054*** 1.2141*** | (29.07) (36.12) (4.02) (4.03) (13.63) (17.38) | | 0.5387*** 0.5268*** 0.1264*** 0.1212*** 1.1035*** 1.1260*** | (17.71) (18.69) (2.14) (2.14) (10.80) (12.18) |
| Euro Union         | −0.2474*** −0.2234*** | (−10.18) (−10.29) | | −0.2673*** −0.2382*** | (−7.53) (−7.03) |
| Constant           | 18.7124*** 17.9451*** 20.1826*** 19.3359*** 17.8823*** 17.4141*** | (21.07) (20.86) (15.18) (14.96) (8.46) (9.03) | | 23.1050*** 22.7125*** 20.8727*** 20.4688*** 26.3112*** 25.9491*** | (22.85) (22.15) (24.38) (23.93) (14.40) (13.95) |
| VIF                | 5.92 5.92 5.49 5.49 8.63 8.63 | (5.92) (5.92) | | 2.02 2.02 2.04 2.04 2.43 2.43 | (2.14) (2.14) |
| Time dummies       | Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes |
| No. of Obs.        | 390 390 271 271 119 119 407 407 271 271 136 136 | (390) (390) (271) (271) (119) (119) | | 407 407 271 271 136 136 | (407) (407) (271) (271) |
| R-squared          | 0.872 0.878 0.815 0.825 0.939 0.946 | (0.872) (0.878) | | 0.843 0.841 0.764 0.768 0.882 0.881 | (0.843) (0.841) |
| F statistic        | 41.309.923 65.552.458 45.195.883 107.264.922 780.975 1046.176 | | | 25.200.988 20.038.360 119.275 991.080 | (41.309.923) (65.552.458) |

Source: Authors’ Computations

*ln* natural logarithm, *MINF* infant mortality rates, *MU5* under-5 mortality rate, *CO2PC* carbon emissions per capita, *ENUPC* nonrenewable energy per capita, *PC* GDP per capita (constant 2010), *HEXPC* health expenditure per capita, *SECF* female secondary school enrolment, *INFL* inflation rate, *BSAN* access to basic sanitation, *URB* urban population, *VIF* variance inflation factor

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively
This finding supports earlier literature on the devastating effect of emissions on human health [10, 42]. We observe that the positive association declines at the higher distribution of infant mortality rate. The plausible explanation is that modern technology and the adoption of renewable energy by more prosperous European countries can dampen the hazardous effects of carbon emissions. Also, non-renewable energy indicates a significant negative association with infant mortality at the 0.30 to 0.95 quantiles. Cursory observation shows that at the higher distribution of infant mortality rate, the negative association increases in

### Table 5 2-step system GMM results, full sample

| Variables | Main models | Robustness | Models |
|-----------|-------------|------------|--------|
| lnMINF/lnMU5 | 0.933*** (0.016) | 0.867*** (0.011) | 0.917*** (0.016) |
| lnCO2PC | 0.016 (0.014) | 0.057* (0.030) | 0.051 (0.038) |
| lnENUPC | −0.056*** (0.017) | −0.090*** (0.037) | −0.051* (0.027) |
| lnPC | −0.035* (0.015) | −0.022 (0.016) | |
| lnHEXPC | 0.046*** (0.012) | 0.038*** (0.009) | |
| lnSECF | −0.209*** (0.041) | −0.211*** (0.038) | −0.292*** (0.072) |
| INFL | −0.002*** (0.001) | −0.001*** (0.000) | −0.003*** (0.001) |
| lnBSAN | −0.203 (0.133) | −0.182 (0.202) | −0.495*** (0.128) |
| lnURB | 0.096* (0.049) | 0.045 (0.064) | −0.092 (0.086) |
| Constant | 1.983*** (0.568) | 3.860*** (0.794) | 0.553 (0.573) |
| Time dummies | Yes | Yes | Yes |
| Observations | 355 | 371 | 371 |
| AR(2)/Hansen | 0.734/0.132 | 0.588/0.092 | 0.369/0.109 |
| Instruments/groups | 30/39 | 30/39 | 30/41 |
| Wald statistics | 1.010e+06 | 2.001e+06 | 457,583 |

Source: Authors’ Computations

\(\ln\) natural logarithm, MINF infant mortality rates, MUS under-5 mortality rate, CO2PC carbon emissions per capita, ENUPC non-renewable energy per capita, PC GDP per capita (constant 2010), HEXPC health expenditure per capita, SECF female secondary school enrolment, INFL inflation rate, BSAN access to basic sanitation, URB urban population

*** and * denote statistical significance at the 1% and 10% levels, respectively

This finding supports earlier literature on the devastating effect of emissions on human health [10, 42]. We observe that the positive association declines at the higher distribution of infant mortality rate. The plausible explanation is that modern technology and the adoption of renewable energy by more prosperous European countries can dampen the hazardous effects of carbon emissions. Also, non-renewable energy indicates a significant negative association with infant mortality at the 0.30 to 0.95 quantiles. Cursory observation shows that at the higher distribution of infant mortality rate, the negative association increases in

### Table 6 Distributional effects of carbon emissions and non-renewable energy consumption on infant mortality rate

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| lnCO2PC | 0.483*** (0.168) | 0.478*** (0.144) | 0.471*** (0.117) | 0.460*** (0.084) | 0.453*** (0.077) | 0.447*** (0.065) | 0.442*** (0.058) | 0.433*** (0.047) | 0.424** (0.037) | 0.420* (0.026) |
| lnENUPC | −0.217 (−0.024) | −0.241 (−0.027) | −0.275 (−0.031) | −0.322** (−0.038) | −0.356*** (−0.046) | −0.394*** (−0.053) | −0.425*** (−0.063) | −0.445*** (−0.070) | −0.465*** (−0.082) | −0.479*** (−0.093) |
| lnPC | −0.580** (−0.289) | −0.521** (−0.247) | −0.444** (−0.188) | −0.386** (−0.081) | −0.322** (−0.066) | −0.261*** (−0.056) | −0.215*** (−0.044) | −0.166 (−0.032) | −0.113 (−0.018) | −0.073 (−0.011) |
| lnHEXPC | −0.166* (−0.011) | −0.190** (−0.016) | −0.217*** (−0.021) | −0.238*** (−0.026) | −0.261*** (−0.029) | −0.291*** (−0.034) | −0.319*** (−0.040) | −0.338*** (−0.046) | −0.353*** (−0.052) | −0.380*** (−0.059) |
| lnSECF | −0.355 (−0.209) | −0.307 (−0.152) | −0.244 (−0.107) | −0.197 (−0.065) | −0.146 (−0.033) | −0.095 (−0.024) | −0.046 (−0.011) | 0.013 (0.003) | 0.064 (0.016) | 0.117 (0.026) |
| INFL | 0.002 (0.004) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) | 0.003 (0.003) |
| lnBSAN | −1.353 (−1.230) | −1.420 (−1.259) | −1.500 (−1.298) | −1.571*** (−1.326) | −1.646*** (−1.433) | −1.749*** (−1.572) | −1.822*** (−1.663) | −1.900*** (−1.786) | −1.980*** (−1.935) | −2.060*** (−2.089) |
| lnURB | −2.419** (−1.019) | −2.495*** (−0.877) | −2.592*** (−0.709) | −2.665*** (−0.600) | −2.745*** (−0.510) | −2.848*** (−0.467) | −2.944*** (−0.420) | −3.011*** (−0.392) | −3.063*** (−0.356) | −3.155*** (−0.320) |

Source: Authors’ Computations

\(\ln\) natural logarithm, MINF infant mortality rates, MUS under-5 mortality rate, CO2PC carbon emissions per capita, ENUPC non-renewable energy per capita, PC GDP per capita (constant 2010), HEXPC health expenditure per capita, SECF female secondary school enrolment, INFL inflation rate, BSAN access to basic sanitation, URB urban population

*** and * denote statistical significance at the 1% and 10% levels, respectively
absolute terms. Again, the most plausible explanation could be that the departure from using non-renewable energy to adopting cleaner and environmentally friendly energy sources may attenuate the devastating effect of non-renewable energy on infant mortality rates.

From Table 7, corresponding results show that emission is positively associated with under-5 mortalities, but the effect of 0.424% and 0.421% is significant only at the 0.70 and 0.80 quantiles. Like the patterns observed in Table 6, the positive association of carbon emissions on under-5 mortality reduces across the quantiles, though primarily statistically not significant. For non-renewable energy, a significant negative association is evident at the 0.70 and 0.80 quantiles, with the effect ranging between −0.404% and 0.424%. Again, the reducing effect increases (in absolute terms) across the quantiles, though the effect is mostly statistically insignificant. Due to the high collinearity between PC and HEXPC, we estimated the quantile models backing these two variables. These results serve as additional robustness checks and are displayed in Tables 8 and 9. These outcomes are not significantly different from Tables 6 and 7.

### Table 7 Distributional effects of carbon emissions and nonrenewable energy consumption on under-5 mortality rate

| Variables | (1)    | (2)    | (3)    | (4)    | (5)    | (6)    | (7)    | (8)    | (9)    | (10)   | (11)   |
|-----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| InCO2PC   | 0.454  | 0.450  | 0.447  | 0.442  | 0.438  | 0.433  | 0.427  | 0.424***| 0.421***| 0.415  | 0.411  |
|           | (1.725)| (1.554)| (1.333)| (1.077)| (0.871)| (0.592)| (0.293)| (0.146)| (0.139)| (0.439)| (0.657)|
| InENUPC   | −0.201 | −0.222 | −0.250 | −0.282 | −0.307 | −0.343 | −0.381 | −0.404* | −0.424**| −0.467 | −0.495 |
|           | (2.595)| (2.337)| (2.005)| (1.620)| (1.310)| (0.891)| (0.441)| (0.220)| (0.209)| (0.660)| (0.988)|
| InPC      | −0.577 | −0.532 | −0.474 | −0.407 | −0.353 | −0.279 | −0.198 | −0.151 | −0.109 | −0.018 | 0.040  |
|           | (2.946)| (2.654)| (2.277)| (1.839)| (1.488)| (1.011)| (0.501)| (0.250)| (0.238)| (0.750)| (1.123)|
| InHEXPC   | −0.175 | −0.191 | −0.211 | −0.235 | −0.254 | −0.280 | −0.309*| −0.326***| −0.341***| −0.373 | −0.394 |
|           | (0.963)| (0.868)| (0.744)| (0.601)| (0.486)| (0.331)| (0.164)| (0.082)| (0.078)| (0.245)| (0.367)|
| InSECF    | −0.313 | −0.280 | −0.238 | −0.188 | −0.149 | −0.095 | −0.035 | −0.000 | 0.031  | 0.097  | 0.140  |
|           | (2.353)| (2.120)| (1.819)| (1.469)| (1.188)| (0.808)| (0.400)| (0.200)| (0.190)| (0.599)| (0.897)|
| INFL      | 0.002  | 0.003  | 0.003  | 0.004  | 0.004  | 0.005  | 0.005  | 0.005  | 0.006  | 0.006  |
|           | (0.045)| (0.041)| (0.035)| (0.028)| (0.023)| (0.016)| (0.008)| (0.004)| (0.004)| (0.012)| (0.017)|
| InBSAN    | −1.363 | −1.413 | −1.478 | −1.554 | −1.614 | −1.697 | −1.789 | −1.842*| −1.889*| −1.991 | −2.057 |
|           | (12.888)| (11.608)| (9.960)| (8.043)| (6.508)| (4.423)| (2.191)| (1.094)| (1.038)| (3.277)| (4.908)|
| InURB     | −2.640 | −2.692 | −2.759 | −2.837 | −2.899 | −2.985 | −3.079*| −3.134***| −3.182***| −3.288 | −3.355 |
|           | (10.005)| (9.011)| (7.731)| (6.244)| (5.052)| (3.433)| (1.701)| (0.849)| (0.806)| (2.544)| (3.810)|
| Observations | 390  | 390  | 390  | 390  | 390  | 390  | 390  | 390  | 390  | 390  |

Standard errors in ()

* p < 0.1; ** p < 0.05; *** p < 0.01

### 5 Conclusion and Policy Recommendations

This study aligns with the 2030 United Nations Sustainable Development Goals 3 and 11, which aim to promote healthy lives and wellbeing and make cities and human settlements sustainable, resilient, and safe. It exclusively contributes to the health-environment discourse by using infant and under-5 mortality rates, carbon emissions, non-renewable energy, and a set of socio-economic variables to investigate these intrinsic relationships. The study uses an unbalanced sample of 46 European countries from 2005 to 2015. For the full sample, consistent findings from the PSCC-LSDV, system GMM and quantile regressions reveal that carbon emission is positively associated with infant and under-5 mortality rates while non-renewable energy exhibit a significant negative association. Noticeably, the positive association with emissions reduces while the negative association with non-renewable energy increases at the higher distribution of infant and under-5 mortality rates. For the sub-samples, we find that emission is negatively associated with the mortality rate in the Euro Union countries relative to non-Euro countries. In addition, non-renewable energy...
exhibits mortality-reducing properties in both sub-samples but with higher elasticity in non-Euro countries. Lastly, the results from the GMM estimations affirm the persistency of infant and under-5 mortality rates.

Some policy recommendations, stakeholders may consider that implementing technological advancement in particle traps, preheated catalytic converters and electronic vehicle controls may affect emissions-related air pollution. In addition, the enforcement of emission-tailored legislation can also contribute to a decrease in emission-related pollution. Although we have found that non-renewable energy consumption reduces the mortality rate, it should be noted that renewables can curb the effects of carbon emissions and, therefore, increase both health and environmental quality. Besides, excessive extraction of non-renewable resources can make a country vulnerable to shocks. To improve the environment, renewable energy sources can be used instead of non-renewables to reduce the emission of hazardous air pollutants. Hence, promoting green solutions to attain a friendly and sustainable environment in European countries is essential. Green solutions involve replacing fossil fuel or non-renewable resources with renewable energy technologies and obtaining energy efficiency. On a broader scale, to mitigate the adverse effects of infant and under-5 mortality rate emissions, European countries should decrease carbon emissions and drive energy consumption that maximises human welfare. As carbon emissions pose health threats to the region, European countries should design effective programs to reduce carbon emissions by undertaking energy-efficient policies, such as introducing carbon credit or carbon capture programs, banning black carbon-generating fuels, and gradually shifting from fossil fuels to other sources such as hydropower, wind, and solar. It is also recommended that the countries enhance human welfare by continually improving access to high-quality education, sanitation, and health facilities for all. As such, sustainable improvement of income of the people and investment in sectors such as sustainable urbanisation, health, and primary and secondary education should be a priority for Europe to minimise infant mortality rates. By reducing human beings’ exposure to respiratory and cardiovascular diseases that arise from fossil fuel burning, renewables offer significant positive benefits to the health sector. Since our objective was to look at the effect of carbon emissions on health, we did not include regulatory control in our model. For further studies, the role of regulatory authority on the health-environment dynamics may be taken up [13, 75–91].

**Appendix**

Table 8  Distributional effects of carbon emissions and non-renewable energy consumption on infant mortality rate

| Variables                      | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   | (7)   | (8)   | (9)   | (10)  | (11)  |
|-------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| lnCO2PC                       | 0.340*** | 0.349*** | 0.350*** | 0.354*** | 0.356*** | 0.358*** | 0.361*** | 0.363*** | 0.366*** | 0.369** | 0.371** |
| lnENUPC                       | −0.261 | −0.264 | −0.272** | −0.281** | −0.292** | −0.300** | −0.308** | −0.317** | −0.320** | −0.323** | −0.326** |
| lnSECF                        | −0.252 | −0.250* | −0.246** | −0.243** | −0.246** | −0.251** | −0.261** | −0.272** | −0.281** | −0.291** | −0.302** |
| INFL                          | 0.007* | 0.007** | 0.006*** | 0.005*** | 0.006*** | 0.007*** | 0.007*** | 0.007*** | 0.008*** | 0.008*** | 0.008*** |
| lnBSAN                        | −3.668*** | −3.693*** | −3.720*** | −3.749*** | −3.779*** | −3.820*** | −3.864*** | −3.902*** | −3.949*** | −4.003*** | −4.041*** |
| lnURB                         | −3.164*** | −3.164*** | −3.163*** | −3.162*** | −3.161*** | −3.160*** | −3.159*** | −3.158*** | −3.157*** | −3.155*** | −3.154*** |
| Observations                  | 407   | 407   | 407   | 407   | 407   | 407   | 407   | 407   | 407   | 407   | 407   |

Standard errors in ()

* p < 0.1; ** p < 0.05; *** p < 0.01
Table 9: Distributional effects of carbon emissions and nonrenewable energy consumption on under-5 mortality rate

| Variables | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     | (9)     | (10)    | (11)    |
|-----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| lnCO2PC   | 0.322*** | 0.325***| 0.328***| 0.331***| 0.335***| 0.340***| 0.345***| 0.349***| 0.355***| 0.362** | 0.366** |
|           | (0.114)  | (0.101) | (0.088) | (0.078) | (0.064) | (0.060) | (0.069) | (0.083) | (0.110) | (0.144) | (0.167) |
| lnENUPC   | -0.239   | -0.245  | -0.252* | -0.258**| -0.266**| -0.276**| -0.287**| -0.295**| -0.307* | -0.322  | -0.331  |
|           | (0.192)  | (0.170) | (0.149) | (0.131) | (0.115) | (0.109) | (0.123) | (0.142) | (0.186) | (0.242) | (0.280) |
| lnSECF    | -0.265*  | -0.262* | -0.258**| -0.255**| -0.250***| -0.244***| -0.238**| -0.233**| -0.226  | -0.218  | -0.213  |
|           | (0.155)  | (0.130) | (0.116) | (0.098) | (0.083) | (0.078) | (0.088) | (0.100) | (0.115) | (0.150) | (0.170) |
| INFL      | 0.006*   | 0.006** | 0.006** | 0.006***| 0.006***| 0.006***| 0.006***| 0.006***| 0.006***| 0.006***| 0.006***|
|           | (0.002)  | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| lnBSAN    | -3.693***| -3.716***| -3.741***| -3.766***| -3.796***| -3.834***| -3.877***| -3.908***| -3.956***| -4.011***| -4.047***|
|           | (0.956)  | (0.849) | (0.742) | (0.653) | (0.574) | (0.543) | (0.614) | (0.719) | (0.924) | (1.201) | (1.394) |
| lnURB     | -3.214***| -3.214***| -3.215***| -3.216***| -3.217***| -3.219***| -3.221***| -3.222***| -3.224***| -3.226***| -3.227***|
|           | (0.717)  | (0.637) | (0.557) | (0.490) | (0.430) | (0.407) | (0.407) | (0.407) | (0.407) | (0.407) | (0.407) |
| Observations | 407       | 407       | 407       | 407       | 407       | 407       | 407       | 407       | 407       | 407       | 407       |

Standard errors in ()
* p < 0.1; ** p < 0.05; *** p < 0.01

Author Contribution: BNA conceptualised and designed the study and analysed and interpreted the data. AKT supervised and improved the paper and did data analysis. MIS interpretation of results and writing reviewing and editing. SU interpretation of results and writing reviewing and editing. All authors read and approved the final manuscript.

Availability of Data and Material: Data will be made available upon request to the first author.

Code Availability: Codes will be made available upon request to the first author.

Declarations

Ethics Approval: Not applicable.

Consent to Participate: Not applicable.

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