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THE DEPLOYMENT OF ENERGY SOURCES AND THE INHERENT SOCIAL WELFARE COSTS

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Abstract

This study explores the long-run effect of renewable and non-renewable energy consumption on the welfare cost. The human welfare cost of ambient particulate matter exposure, occupational particulate matter exposure, and household air pollution were examined. The data of the Organization for Economic Cooperation and Development between period 1990 - 2019 were used. Contrary to non-renewable energy, conventional mean-based panel estimators showed that renewable energy has an insignificant link with the health cost of ambient particulate matter exposure. Moreover, renewable energy consumption significantly and negatively affected the health cost of household air pollution. Furthermore, renewable, and non-renewable energy consumption showed a statistically insignificant effect on the welfare cost of occupational particulate matter exposure. Quantile dynamics uncover a dependent inverted U-shaped relationship between non-renewable energy utilization and the health risks of occupational particulate matter exposure.

Keywords: Renewable energy, Non-renewable energy, Ambient, Welfare cost, Particulate matter.

1. Introduction

The industrialization is one of the major factors of increasing the concentrations of ambient particulate matter (PM). This is because PM emission usually originates from combustion processes which can be found in regular fossil fuel-powered machines such as automobiles as well as large-scale industrial processes such as power plants(Li *et al*., 2016). The size of PM determines its health hazard. The fine PM is less than 2.5μm in diameter ($PM_{2.5}$) to the coarser variants which have a diameter range between 2.5μm -10μm. It is generally the case that finer particles are more toxic because they can reach the lungs deeper (Thurston, 2016). Schwartz *et al.* (2018) employ causal modeling techniques and show that exposure to greater concentrations of $PM_{2.5}$ corresponds to the reduction in life expectancy. According to Sarkodie *et al.* (2019), the increase in $PM_{2.5}$ exposure has a decreasing effect on the life expectancy of individuals

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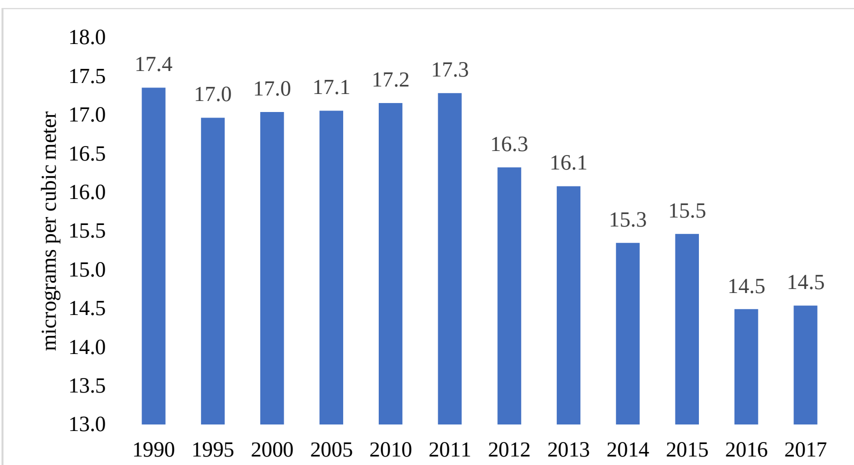
domiciled in North America, Europe, Central Asia, East Asia, and the Pacific region. Exposure to $PM_{2.5}$ can also be induced utilizing domestic cooking appliances using fossil fuels (Hanif, 2018b) follow-on the increased rate of mortality and morbidity rates. A remedy for such scenarios is the utilization of renewable energy sources instead which empirically shown an ameliorating effect on mortality and morbidity rates (Hanif, 2018a).

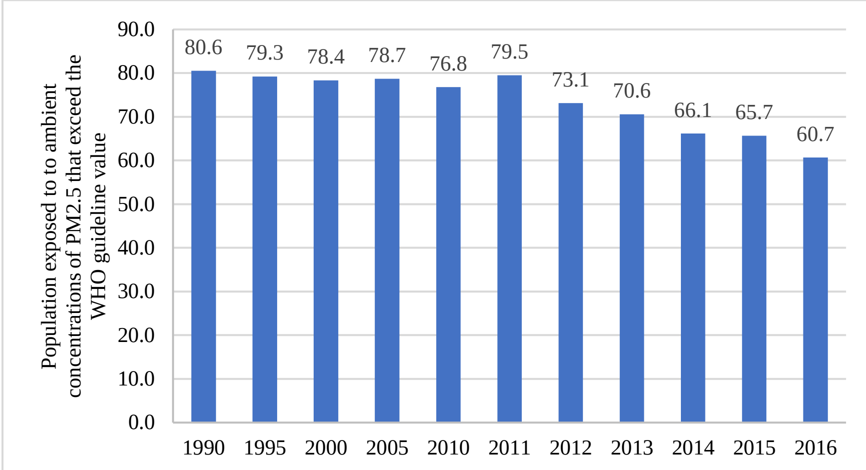
In addition, figure 2 illustrates the proportion of the population exposed to ambient concentrations of $PM_{2.5}$ exceeding the defined value by the World Health Organization (WHO). To explore the environment pollution consequences from energy consumption, Feng et al. (2019) used TMDN-DEA, a model of two-stage meta-frontier dynamic network data envelopment analysis. The study aimed to discover the environmental pollutions impact on mortality rate, tuberculosis rate, survival rate, and health expenditure efficiencies in 28 European Union (EU) countries and 53 non-EU countries between 2010 to 2014. The overall efficiency scores as well as the technology gap ratios of countries inside and outside the EU were assessed. In addition, the efficiencies of input and output variables in the production and health stage were estimated. Their findings signify that on average EU countries have achieved a higher efficiency than non-EU countries. Relatively EU countries possess higher energy efficiency whilst non-EU countries possess higher health efficiency. Health expenditures were observed to be lower in non-EU countries compared to the EU countries. The renewable energy was observed to be more efficiently consumed than the non-renewable energy. $PM_{2.5}$ were also found to be higher relative to the carbon dioxide (CO_2) efficiencies. What's more, children's mortality rates were deliberated to be higher than the adult's mortality rate for both EU and non-EU countries. The Organization for Economic Cooperation and Development (OECD) is an intergovernmental economic organization that works to build better policies and standard social lives within 38 member countries (OECD, 2021). The economies of the OECD are among the world most developed. Therefore, they would be the largest energy consumers. They also possess the necessary technology to remedy the risks associate with air pollution. This qualifies the member countries as a case study. Figure1 depicts the $PM_{2.5}$, air pollution, mean annual exposure in the OECD region between the years1990 and 2017.

Figure 1. $PM_{2.5}$, air pollution, mean annual exposure in the OECD region 1990- 2017.



This figure was created by the author and was based on the database of the World Bank Open Data (2021) In addition, figure 2 illustrates the proportion of population exposed to ambient concentrations of $PM_{2.5}$ exceeding the defined value by WHO.

Figure 2. proportion of the population exposed to ambient concentrations of $PM_{2.5}$ exceeding WHO value.



This figure was created by the author based on the database of the World Bank Open Data (2021).

The study serves as a framework to assess the impact of adoption of renewable or non-renewable energy, technology on the human welfare cost of ambient PM emissions, occupational, and household. This is important because the policy framework needed to mitigate the proliferation of PM emissions which may not be homogenous across the spectrum of the sources of these emissions. Therefore, there arises a need to empirically isolate —heterogeneously, the impact of renewable energy, non-renewable energy, and innovation on the human welfare cost of occupational, household, and ambient PM emissions. The human welfare cost of PM emissions is calculated as the disability adjusted life years (DALYS). It is a time-based measure that merges the years of life lost because of premature mortality and years of life lost due to time spent under conditions of less than full health, or the years of healthy life lost due to an underlying ailment or disability. It is a much more holistic way of measuring health risks because it combines both mortality and morbidity into a single unit. The study used data for OECD between the years 1990 and 2019. Table 1 summarizes the data sources and the measurements.

Table 1. Data sources and measurement

Variables	Measurement	Transformation	Source
Welfare cost of occupational particulate matter	Disability adjusted life years per capita.	Log transformed	OECD Statistics
Welfare cost of indoor air pollution	Disability adjusted life years per capita.	Log transformed	OECD Statistics
Welfare cost of ambient particulate matter	Disability adjusted life years per capita.	Log transformed	OECD Statistics
Patent applications	Number of patent applications per capita.	Log transformed	WDI
GDP per capita	Constant 2010 US Dollars	Log transformed	WDI
Population	Number of people at mid-year	Log-transformed	WDI
Renewable energy consumption per-capita	Tons of oil equivalent	Log-transformed	WDI

2. Background

The seminal paper of Grossman and Krueger (1991) discovered different mechanisms in which environmental degradation can be induced via the scale, technique, and composition effects of trade and foreign investment policy. These effects are however not limited to trade and foreign investment activities but also can be induced by various macro-economic variables. Studies further carried out to test the sources of energy, economic growth, and environmental degradation. Ang (2007) empirically uncovered economic growth exerts a long-run causal effect on energy use and environmental pollution. This comes with the implication that economic activities spur energy utilization and thus harming the environment. Liu and Hao (2018) empirically tested the types of energy source, economic growth, and carbon emissions along the belt and road. The study employed a panel dataset of 69 countries from 1970 to 2013. The result of panel Granger causality analysis was inferred a long-run bidirectional causalities amongst carbon emissions, energy use, industry value-added, and (gross domestic production) GDP per capita. However, by controlling sub-sample grouping, a unidirectional short-run causality flowed from GDP to renewable energy while long-run causality flowed in the inverse direction for only energy-importing countries. Nevertheless, for energy-exporting countries there exists a bi-directional causal relationship between energy use and GDP per capita in long-run. This implies that long-run energy conservation policies would affect economic growth in long-run for both importing and exporting countries. Additionally, Cai et al (2018) investigated the empirical relationship between clean energy, economic growth, and carbon emissions in the case of G7 countries. Their empirical analyses showed the existence of causality running from clean energy consumption to carbon emissions in Germany with feedback. Furthermore, a unidirectional causal flow is uncovered running from clean energy consumption to carbon emissions in the US. In the case of Germany, this may imply that clean energy consumption impacts the environmental quality and concerns about the quality of the environment further impact clean energy consumption. This thus brings about the bidirectional relationship in the German case. Concerning the association of health risks with economic activities and energy consumption studies have been carried out. Note that environmental pollution can cause a higher rate of societal mortality therefore the health risk perspective was deliberated. Rasoulinezhad *et al*. (2020) employed the generalized method of moments (GMM) estimation technique for the Commonwealth of Independent States (CIS) members within the period 1993–2018. The findings indicate that the highest variability of mortality could be attributed to CO_2 variability. Concerning fossil fuel consumption showed a significant influence on mortality rate due to cardiovascular disease (CVD), Diabetes Mellitus (DM), cancer, and Chronic Respiratory Disease (CRD). Furthermore, any enhancement in the human development index (HDI) exerts a negative effect on mortality increments from CVD, DM, cancer, and CRD in the CIS region. Recently, Koengkan *et al.* (2021) examined the impact of renewable energy consumption on reducing the outdoor air pollution death rate, in nineteen Latin America and the Caribbean countries, from 1990 to 2016. The econometric technique of quantile regression for panel data was applied. Their findings indicate a significant positive impact of economic growth and fossil fuel consumption on CO_2 emissions, whereas renewable energy consumption negatively impacts the CO_2emissions. Furthermore, fossil fuel consumption showed a positive impact on the mortality rate while economic growth had a negative effect. The model divulges the intake of renewable energy can 1) directly mitigate the outdoor air pollution death rates 2) indirectly lead to combinations sources of energy and less utilization of fossil fuels.

3. Method

The study adopted the analytical model of Stochastic Estimation of Impacts by Regression on Population, Affluence, and Technology (STIRPAT). The STIRAT model was developed by (Dietz and Rosa 1994) as a stochastic reformulation of the IPAT (Impacts of Population, Affluence, and Technology). The formula is an accounting equation. Therefore, the IPAT formulation cannot be employed for hypothesis testing since the strict proportionality of the effects of P, A, and Ton I have already assumed *a priori*. These core issues have properly addressed by the STIRPAT reformulation as it treats and relaxes these effects as parameters by proportionality restrictions imposed because of the IPAT identity. The standard STIRPAT model takes the following specification in "Eq. (1)".

$$I_i = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e_{it}\ . \qquad (1)$$

Let *P* symbolizes population using, affluence by *A*, and technology *T* which are multiplicative functions of environmental impact. *T* usually includes in the error term *e* because there is an unknown variable that can holistically capture technological effects. All variables have log-linearized to simplify the estimations. Thus, "Eq. (1)" takes the form as shown in "Eq. (2)" after log-linearization:

$$\ln I_{it} = a + b(\ln P_{it}) + c(\ln A_{it}) + e_{it}\,. \qquad (2)$$

In "Eq. (2)", *T* denotes technology which is impact per unit of consumption (*T=I/PA*) and is absorbed in the error term. However, technological change can be disaggregated into several components and directly impact upon impact per unit of consumption and their effects can be estimated independent of each other(York et al., 2003). The subscript *i* denotes countries and *t* symbolizing the year. Also, *b* and *c* capture the exponents of P and A respectively. The constant which scales the model is denoted by *a* while *e* denotes the idiosyncratic error term which is assumed to be an independently and identically distributed stochastic Gaussian process. The STIRPAT model has frequently been employed to analyze the environmental impact of human activity. However, this study adopted the human welfare cost of household, ambient and occupational PM exposure as impact variables. As such, the study captures the health impacts of human activity rather than the environmental impacts. The specific variables of the study are modeled in "Eq. (3)":

$$lhr_{it} = \beta_0 + \beta_1 lpop_{it} + \beta_2 lrgdp_{it} + \beta_3 lreng_{it} + \beta_4 lnreng_{it} + \beta_5 lpat_{it} + u_{it}. \qquad (3)$$

"Eq. (3)" denotes *lhr* as a health risk or human welfare cost associated with indoor, ambient, and occupational PM exposure for country *i* at time *t*. The population is denoted by *lpop*, affluence *A* which is the real GDP is represented by *lrgdp*. Renewable and non-renewable energy consumptions are denoted by *lreng* and *lnreng* respectively while *lpat* denotes patent applications. Renewable and non-renewable energy consumption can affect impact per unit consumption because they represent the utilization of clean and fossil fuel technologies, respectively. Patent applications represent new technological innovations and are expected to affect impact per unit of consumption. This effect, however, depends on whether the technological innovation aids the technique of production or increasing the scale of production. Let us assume production technique and output is constant; pollution provokes health risks that would increase if technological innovation enhanced the scale of production. Nonetheless, if the scale of production and the output is constant, the technological innovation that improves the technique of production through energy-saving methods reducing pollution threats health risks. Furthermore, u_{it} denotes the error term which is assumed to be independently and identically distributed across countries *i* and time *t*. Following (Shahbaz *et al.* 2016) both sides of "Eq. (3)" are normalized on the population in order to obtain per capita values for all the series. This renders a constant impact on the population in the model.

$$lhrk_{it} = \beta_0 + \beta_1 lrgdpk_{it} + \beta_2 lrengk_{it} + \beta_3 lnrengk_{it} + \beta_4 lpatk_{it} + u_{it}\,. \qquad (4)$$

In "Eq. (4)", *k* denotes that the variables were measured in per-capita values. Note that all the variables were normalized on the population before log-linearization.

Since OECD countries' pollution levels are distributed heterogeneously by specific economic realities; it makes sense to control for distributional heterogeneity when estimating the model parameters. To this end, this research follows (Koengkan et al. 2021) and adopts the method of moments quantile regression technique (MMQR) (Machado and Santos Silva, 2019) which controls for fixed effects across the conditional distribution of the model's dependent variable. Quantile regressions possess advantages over traditional mean-based estimation under specific circumstances. This condition can be explained as low sensitivity to outliers and the ability to isolate how the exogenous variables affect the endogenous variable across the different quantiles of the endogenous variables. This methodology becomes practical when conditional means relationships are weak or non-existent. A notable weakness of previous quantile estimation techniques was their inability to control unobserved heterogeneity across the panel cross-sections. The MMQR method corrects this weakness by allowing the individuals to have distribution wide effects rather than the mean shifting scenarios (Canay, 2011; Koenker, 2004). Another innovation of the MMQR technique is its ability to yield non-crossing estimates of the regression quantiles. The quantile framework is modeled in "Eq. (5)":

$$Q_Y(\tau|X_{it}) = \left(\alpha_i + \delta_i q(\tau)\right) + X'_{it}\beta + Z'_{it}\gamma q(\tau)\,. \qquad (5)$$

Where X'_{it} denotes a vector of study-specific independent variables while $Q_Y(\tau|X_{it})$ is indicative of the quantile distribution of the dependent variable *Y*. This distribution is conditional on the location of independent variables *X*.

The scalar coefficient which is analogous to the individual specific quantile-τ fixed effects is denoted by $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ and does not represent an intercept, unlike the traditional least square fixed effects. The scalar coefficients are time-invariant parameters whose heterogeneous impacts are allowed to have distribution-wide effects across the quantiles of the dependent variable *Y*. The τ-th sample quantile is denoted by $q(\tau)$ and its estimation is obtained in "Eq. (6)" via the solution of the optimization problem:

$$min_q \sum_i \sum_i \rho_\tau \left(R_{it} - (\delta_i + Z'_{it}\gamma\right)q. \tag{6}$$

Therefore, the check function is represented by "Eq. (7)":

$$\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}. \tag{7}$$

In this instance also, the model was specified separately for every three independent variables to ascertain to what extent the relationship between the independent variables and the dependent variables are heterogeneous.

4. Results

The summary statistics are reported in Table 2. The results show the mean value of non-renewable energy was greater than the mean value of renewable energy. This implies that non-renewable energy has a higher consumption rate than renewable energy in OECD economies. In addition, the human welfare cost associated with ambient PM exposure showed a higher mean value than the health impacts of both occupational and household PM exposure. Variables approximately follow a normal distribution. The per-capita human welfare cost of household air pollution (*ldhhapk*) had the highest standard deviation amongst other variables. This higher dispersion was also observed through its percentile distribution patterns from the lowest to the highest percentile. A careful observation of the percentiles of the distribution of *ldhhapk* showed that the bulk of this dispersion occurs from its median to its 90th percentile. The negative skewness of most of the variables (*lapmk, lopmk, lnrengk, lrgdpk* and *lpatk*) imply as a left-skewed distribution. The kurtosis values showed that per-capita non-renewable energy use has the thickest tails with the possibility of outliers at the extreme tails of its distribution. Excess kurtosis of 0.7 and 0.3 were also observed in per capita renewable energy use and per capita residents' patents, respectively.

Before estimating the model, it needs to uncover the existence of cross-sectional dependence in the data. The usual assumption in panel data analysis is that the error term is independent across cross-sections. This assumption usually does not hold in reality because of the existence of globally common shocks, such as the 2007 global financial crisis. Different countries heterogeneously can be affected, or country- induced shocks which can have regional spill-over effects such as the 1997 Asian financial crisis. The presence of the exemplified scenarios can be due to the existence of cross-sectional dependence in panel data. This cross-sectional dependency can greatly reduce the efficiency gains of panel data estimators which do not control for such effects (De Hoyos and Sarafidis, 2006).

Table 2. Summary statistics and correlation matrix

	lapmk	*lopmk*	*ldhhapk*	*lrengk*	*lnrengk*	*lrgdpk*	*lpatk*
Mean	-4.93	-7.18	-9.07	-1.12	1.00	26.57	-9.13
Median	-4.87	-7.20	-9.66	-1.18	1.07	26.53	-8.94
Maximum	-3.47	-6.34	-4.49	2.79	2.23	30.54	-5.71
Minimum	-6.93	-8.07	-12.41	-7.09	-2.17	22.77	-13.54
Std. Dev.	0.72	0.36	2.14	1.31	0.64	1.59	1.47
Skewness	-0.49	-0.25	0.49	0.07	-1.45	-0.06	-0.33
Kurtosis	2.84	2.82	1.96	3.70	6.99	2.83	3.36
Jarque-Bera	46.55	12.94	95.07	23.53	1127.20	2.04	24.98
Probability	0.00	0.00	0.00	0.00	0.00	0.36	0.00
P10	-6.00	-7.67	-11.48	-2.76	.156	24.27	-11.26
P25	-5.31	-7.39	-10.87	-1.98	.817	25.71	-9.87
P50	-4.87	-7.20	-9.66	-1.18	1.07	26.53	-8.94

P75	-4.38	-6.94	-7.23	-.20	1.38	27.66	-8.27
P90	-4.01	-6.71	-5.72	.54	1.68	28.58	-7.63
Observations	1110	1110	1110	1099	1109	1094	1046

Thus, the study employed the cross-sectional dependence test of Pesaran (2015) to ascertain the existence of cross-sectional dependence in the data and help to determine what type of testing and estimation procedure should be applied for the remaining empirical analysis. As reported in table 3, the null hypothesis of cross-sectionally dependent for only the welfare cost of occupational PM emissions (*lopmk*) was failed to reject. Panel cointegration and estimation techniques are robust to cross-sectional dependence, thus would be employed in the empirical analysis.

Table 3. Cross sectional dependence test

Variable	CD-test	mean ρ	mean abs (ρ)
Lapmk	110.17^{***}	0.78	0.84
Lopmk	-1.12	-0.01	0.64
ldhhapk	139.78^{***}	0.99	0.99
Lrengk	47.16^{***}	0.33	0.64
lnrengk	35.41^{***}	0.25	0.51
Lpatk	5.04^{***}	0.04	0.42
Lrgdpk	131.55^{***}	0.94	0.94

Note: "***" denotes statistical significance at the 1% level.

To ascertain the time-series properties of the variables, unit root tests were applied to avoid the incidence of spurious regression. This is because un-cointegrated non-stationary variables usually yield spurious results due to the existence of auto-correlation. As such, the usual practice would be to difference un-cointegrated non-stationary variables to uncover short-run relationships and to estimate cointegrated non-stationary variables at levels to uncover long-run relationships. Cross-sectional Im, Pesaran (2007) and Shin Test shortened to CIPS unit root test controls for heterogeneity in the autoregressive parameter of the Dickey-Fuller regression. Additionally, it controls for the presence of a single common factor that is unobserved and may have disparate factor loadings in the data. This mitigates the potentially distorting effects of cross-sectional dependence in the data. The test statistics follow a non-standard distribution under the null hypothesis of non-stationarity. Table 4 reports the importance of controlling for cross-sectional dependence in the test sequence. The results indicate that the null hypothesis for variable non-stationarity and the presence of a unit root at levels were rejected for two variables of *lrengk* and *lpatk* following Maddala and Wu (MW) specification which does not control for cross-sectional dependence. This result however does not hold for the CIPS specification which controls for the presence of a single unobserved factor and thus mitigates the existence of cross-country correlation. The null hypothesis for the presence of a unit root could not be rejected for all variables at levels under the CIPS specification. Both test specifications however supported the rejection of the null hypothesis for the presence of a unit root for all variables at first difference. Based on these results, we assume that all the variables are integrated of order one or I (1), which implies that they are non-stationary at levels but stationary at first difference. Following the unit root results, panel cointegration tests can be validly undertaken to ascertain the presence of long-run relationships.

Table 4. Unit Root Test

Variables	Level	1st Difference	Level	1st Difference
lapmk	28.58	134.1^{***}	6.96	-6.363^{***}
lopmk	70.72	296.2^{***}	4.85	-9.69^{***}
ldhhapk	28.75	301.97^{***}	13.90	-8.48^{***}
Lrengk	136.54^{***}	954.67^{***}	0.29	-20.89^{***}
lnrengk	34.47	997.67^{***}	0.17	-21.20^{***}
lrgdpk	48.48	401.59^{***}	0.83	-13.37^{***}

Lpatk	169.94***	746.55***	0.32	-19.30***

Note: "***" denotes statistical significance at the 1% level.

To uncover the existence of a long-run relationship amongst the variables, the panel cointegration tests were employed(Kao 1999; Westerlund 2007). Cointegration tests are vital to determine if the estimation of the long-run model parameters remains valid with non-stationary regressors.

If non-stationary regressors yield stationary errors, then the static ordinary least squares (OLS) estimator yields super-consistent estimates of the long-run parameters. In the first technique (Kao 1999), the null hypothesis for the cointegration test is the absence of cointegration for all the variables in all the panels while the alternative hypothesis is that the variables are cointegrated in all the panels. However, there are two versions of the test in the second technique (Westerlund 2007). In the first version of the test, the alternative hypothesis follows the cointegration does exist for the variables in all the panels while the second version stipulates the cointegration exists for the variables in some of the panels (Westerlund 2007). The second version was applied in this study. Before running the tests, the cross-sectional averages of each period were subtracted from the series of all the variables to mitigate the impact of cross-sectional dependence(Levin *et al.* 2002).

To estimate the long-run parameters, this paper employs both the fixed effects (FE), OLS, and the random effects (RE) generalized linear square (GLS) estimators. Both estimators employed the standard errors (Driscoll and Kraay 1998) which are robust to the effects of cross-sectional dependence and autocorrelation up to a specific lag. This can aid in mitigating the effects of cross-sectional dependence in the panel data estimators. To attain the objectives of this research there is a need to uncover to what extent the dependent and the independent variables are heterogeneous. To ascertain to what extent, the relationships between the independent variables and ambient, occupational, and indoor pollution are heterogeneous. These panel estimations were specified separately for the three independent variables. Additionally, to discriminate against which model would be preferred, the Hausman specification test was used. Cointegration tests summarized in table 5 evidenced that the cointegration was validated by four test statistics in the Kao (1999) specification for both the *lapmk* and *ldhhapk* models at the 5% significance levels. For the *lopmk* model, cointegration is validated by two test statistics (Kao 1999) specifications.

Table 5. Cointegration Test

Cointegration test	Statistics	*lapmk model*	*lopmk model*	*ldhhapk model*
Kao (1999)	Modified Dickey-Fuller t	3.16***	1.90**	2.47***
	Dickey-Fuller t	3.07***	-0.04	1.51*
	Augmented Dickey- Fuller t	0.42	-0.43	2.19**
	Unadjusted Modified	4.23***	3.22**	3.01***
	Unadjusted Dickey-Fuller t	4.63***	1.29*	2.13**
Westerlund (2007)	All Panels	-0.86	-1.65**	-1.26
	Some panels	-2.44***	-2.31**	-2.43***

Note: "***","**" and "*"denotes statistical significance at the 1% level, 5% and 10% levels respectively.

The Westerlund (2007) specification validates the presence of cointegration in some panels for all models. However, only in the *lopmk* model was cointegration validated for all panels. The results give sufficient evidence for the presence of cointegration in all models. The results from the fixed effects, OLS, and random effects GLS specifications were not too far apart for all models (see Table 6). Nevertheless, merely the *lapmk* model uncovers a statistically significant negative relationship between per-capita renewable energy consumption and *lapmk*. The same result of statistically insignificant was found in the FE-OLS specification. Overall, from the results can be implied that the human welfare cost of air pollution responds differently to renewable and non-renewable energy use depending on the type of pollution that stimulates the welfare cost. Yet the Hausman tests showed that the fixed effects estimator is the preferred estimator in all instances being efficient in the *lapmk* and *ldhhapk* models and consistent in the *lopmk* model. Thus, all inference discussions would be based on the fixed effects specification. In the first model, a one percent increase in per-capita non-renewable energy consumption was associated with a 0.226 % increase in the DALYS associated with ambient PM exposure. In addition, renewable energy consumption had no significant relationship with the disability adjusted life years associated with ambient PM exposure. Another notable observation was income significantly reduces the disability adjusted life years associated with ambient PM exposure. This outcome is consistent with Koengkan *et al.* (2021) which observes a negative effect of income (per-capita GDP) and outdoor air pollution death rates.

Table 6. Panel Estimation

	lapmk model		*lopmk model*		*ldhhapk model*	
Variables	FE-OLS	RE-GLS	FE-OLS	RE-GLS	FE-OLS	RE-GLS
lrengk	-0.01	-0.06***	0.00	0.00	-0.11***	-0.16***
lnrengk	0.23***	0.14*	-0.01	-0.03	-0.01	-0.09
lrgdpk	-0.94***	-0.78***	-0.06***	-0.05***	-2.33***	-2.15***
lpatk	0.09***	0.08***	0.07***	0.07***	-0.18***	-0.19***
lrengk	-0.01	-0.06***	0.00	0.00	-0.11***	-0.16***
Hausman RE-GLS—FE-OLS	RE-GLS—FE-OLS 6.80		FE-OLS—RE-GLS 11.23**		RE-GLS—FE-OLS 1.69	

Note: "***","**" ,"*"denotes statistical significance at the 1% level, 5% and 10% levels respectively.

Moreover, a positive relationship between residents' patent applications and the disability adjusted life years associated with ambient PM exposure was observed. A one percent increase in residents' patent application was explained by a 0.088% increase in the disability adjusted life years related to ambient PM exposure.

The dynamics change in the *ldhhapk* model wherein residents' patents were observed showed a statistically significant but negative relationship with the human welfare cost of household air pollution. Likewise, per-capita renewable energy consumption had a statistically significant and negative relationship with the human welfare cost of household air pollution. The dynamics change in the *ldhhapk* model wherein residents' patents were observed showed a statistically significant but negative relationship with the human welfare cost of household air pollution. Likewise, the utilization of renewable energy per-capita was statistically significant but negatively linked to the human welfare cost of household air pollution. On the other hand, the non-renewable energy consumption relationship with the human welfare cost of household air pollution was statistically insignificant. In the *lopmk* model, only income and patents had a significant relationship with the human welfare cost of occupational PM. Renewable and non-renewable energy consumption had a statistically insignificant relationship with the human welfare cost of occupational PM. The traditional mean-based specifications outcome implies that every single effect of renewable, non-renewable energies and residents' patents on ambient, indoor, and occupational air pollution were heterogeneous. This fulfills the objectives of this research. These relationships portend serious implications to environmental and health policies. The results from the mean-based estimations may not uncover all the latent distribution-wise information embedded in the model as it only isolates inferences based on the conditional mean. Due to this reason, the results of the method of moments quantile regression (MMQR) estimation outlined below uncovers a few latent dynamics hitherto unknown in the traditional mean-based estimators. Table 7 reveals a quantile dependent inverted U-shaped relationship of the human welfare cost in terms of particulate matter and the human welfare cost of household air pollution while non-renewable energy was consumed. It can also be observed that the negative effect of per-capita renewable energy consumption becomes barely significant ($p < 0.1$) at quantile 0.9 in the *lapmk* model. This comes with the implication that renewable energy consumption can only have some ameliorating effect on the welfare cost of ambient PM exposure at the most extreme quantile.

In countries with the highest disability adjusted life years associated with ambient PM exposure, renewable energy has a weak ameliorating effect. In the *lopmk* model, non-renewable energy consumption began to have an ameliorating effect on the human welfare cost of occupational PM at a quantile 0.75. This is to some extent consistent with Koengkan *et al.* (2021) outcome which uncovers a negative relationship between CO_2 emissions and outdoor air pollution death rates. Incidentally, real per-capita GDP only began to reduce the human welfare cost of occupational PM from the median quantiles, and the scale of this ameliorating effect increased across quantiles. Also, residents' patent applications increased the human welfare cost of occupational PM, and the scale of this effect increases across quantiles.

Table 7. Method of moments quantile regression estimate for all variables

Independent Variable	**Location**	**Scale**	**Quantiles**				
			0.1	0.25	0.5	0.75	0.9
lrengk	-0.01	-0.01	0.01	0.00	-0.01	-0.02	-0.02*
lnrengk	0.23***	-0.09***	0.38***	0.31***	0.22***	0.14***	0.09
lrgdpk	-0.94***	0.05***	-1.01***	-0.98***	-0.93***	-0.90***	-0.87***
lpatk	0.09***	0.01	0.07***	0.07***	0.09***	0.10***	0.10***
Constant	20.54***	-0.86**	21.91***	21.33***	20.44***	19.74***	19.27***
	Location	**Scale**	**Quantiles**				
			0.1	0.25	0.5	0.75	0.9
lrengk	0.00	-0.00	0.00	0.00	0.00	0.00	0.00
lnrengk	-0.03	-0.02	-0.00	-0.00	-0.03	-0.04*	-0.05**
lrgdpk	-0.06***	-0.04***	-0.01	-0.03	-0.07***	-0.10***	-0.12***
lpatk	0.07***	0.02***	0.04***	0.05***	0.07***	0.08***	0.09***
Constant	-4.83***	1.19***	-6.60***	-6.01***	-4.79***	-3.69***	-3.12***
	Location	**Scale**	**Quantiles**				
			0.1	0.25	0.5	0.75	0.9
Lrengk	-0.11***	-0.18	-0.08***	-0.09***	-0.11***	-0.13***	-0.14***
lnrengk	0.01	-0.17***	0.27***	0.19***	-0.02	-0.15**	-0.24***
lrgdpk	-2.33***	-0.031	-2.28***	-2.298***	-2.34***	-2.36***	-2.37***
lpatk	-1.18***	-0.01	-0.17***	-0.17***	-0.18***	-0.19***	-0.19***
Constant	51.00***	1.14*	49.26***	49.81***	51.18***	52.04***	52.61***

Note:

a"***","**" and "*"denotes statistical significance at the 1% level, 5% and 10% levels respectively.

b Bootstrap bias corrected and accelerated standard errors with 1000 Bootstrap replications and 1068 Jackknife replications are employed to mitigate cross-sectional dependence.

In the *ldhhapk* model, it was observed that per-capita renewable energy consumption had an ameliorating effect on the human welfare cost of household air pollution. This effect increased across quantiles. Similar to the *lopmk* model, there was a quantile- dependent inverted U-shaped relationship between *lnrengk* and *lopmk* with a saturation point at the fifth quantile.

In all the estimated models, real GDP per capita which indicates income had a negative relationship with the human welfare cost of exposure to all forms of pollution. With the implication that a higher income allows an individual to lead a healthier life with the ability to manage health-related risks.

Moreover, the fact that patent applications persuade occupational and ambient air pollution-related health risks while mitigating the health risks induced by household air pollution implies that innovation is channeled towards the development of safer appliances for home use. Innovations within occupational and ambient spaces are channeled towards equipment and devices which may induce air pollution and its associated health risks. The results of the study underpin the heterogeneous relationship between the independent and dependent variables across the different specifications employed. Therefore, developing policy frameworks to mitigate the heterogeneity of outdoor, indoor, and occupational air pollution need to be underlined.

5. Conclusion

This paper examined the usage of renewable and non-renewable energy, income, and patent on the human welfare cost of ambient, occupational, and household air pollution in OECD countries. Prior to this research (Feng *et al.* 2019; Hanif, 2018a; Koengkan *et al.* 2021; Rasoulinezhad *et al.* 2020) established the impact of renewable and non-renewable energy consumption on health indicators which capture mortality rates, life expectancy, and specific ailments such as tuberculosis in various locations. The novelty of this research lies in the fact that it employed a health indicator that incorporates both mortality and morbidity into a single variable. The health indicators employed to capture the DALYS associated with exposure to ambient and occupational PM as well as household air pollution. As such they embody holistically, the morbidity and mortality impact on human associated with the exposure to the aforementioned categories of air pollution. Various empirical techniques were employed to estimate the long-run relationship. Firstly, cross-sectional dependence tests showed that all the variables were cross-sectionally dependent except for the human welfare cost of occupational PM exposure. A second-generation unit root test indicated that all the variables were integrated at the first order or I (1). Panel cointegration tests uncovered sufficient evidence of a long-run relationship amongst the variables in the three specified models. The traditional mean-based panel estimation techniques revealed a statistically insignificant relationship between ambient PM exposure renewable energy consumption with the human welfare cost. However, non-renewable energy consumption had a positive relationship with the human welfare cost of ambient PM exposure. The finding is consistent with the Hanif (2018a) wherein it was uncovered that indoor and outdoor energy consumption had a positive and statistically significant relationship with mortality and tuberculosis in sub-Saharan African countries. It is also in line with the study of Koengkan *et al* (2021) in the sense that increased consumption of fossil fuel also caused higher air pollution and thus death rates in Latin America and the Caribbean countries.

Regarding the isolating quantile dynamics, it was discovered that renewable energy consumption had a negative relationship with the welfare cost of ambient PM exposure at the highest quantile. Consistent with Koengkan *et al* (2021), the negative relationship of renewable energy consumption with outdoor air pollution death rates become weakly significant at the median quantile and attains a strong significance at the 75th quantile. Additionally, PM exposure to renewable and non-renewable energy did not reveal a relationship with the human welfare cost. In addition, household air pollution as a result of renewable energy consumption had a negative relationship with the human welfare cost associated with it. This result is also consistent with the studies in the literature (Hanif, 2018a; Koengkan *et al.* 2021) wherein renewable energy consumption had a negative relationship with various health risks. However, non-renewable energy consumption had no impact on the human welfare cost of household air pollution. This result seems quite counterintuitive but when quantile dynamics were isolated, a positive relationship between the human welfare cost associated with ambient PM exposure and non-renewable energy consumption at lower quantiles was observed. At the median quantile, this relationship became insignificant and negative. This negative relationship started gaining statistical significance at higher quantiles. These dynamics can also be observed in the relationship between non-renewable energy consumption and the human welfare cost of occupational PM exposure (*lopmk*). A statistically weak and negative relationship between non-renewable energy consumption and *lopmk* was observed at quantile 0.75 following stronger statistical significance was obtained at quantile 0.90. These results are consistent with Ibrahim *et al.* (2021) where a U-shaped relationship between natural gas, petroleum, coal, and life expectancy was observed in a panel of sub-Saharan African countries. The difference between both studies however lies in the fact that Ibrahim *et al.* (2021) uncovers an empirical relationship based on lower and higher levels of the independent variables with regards to the mean values of the dependent variable. However, this research uncovers an empirical relationship based on the mean levels of the independent variables with regards to lower and higher quantiles of the conditional distribution of the dependent variable. Income was proxied as GDP per capita showed a negative relationship with all the categories of the human welfare cost of air pollution. This result is consistent with other studies in the literature (Feng *et al.* 2019; Hanif, 2018a; Koengkan *et al*. 2021) but is inconsistent with Rasoulinezhad *et al.* (2020) which uncovers a positive relationship between economic growth and mortality rates from specific diseases. One possible explanation is the differences in the measurement of economic growth. While this paper measured the economic growth as GDP per capita this intrinsically implies income. According to Rasoulinezhad *et al.* (2020) economic growth or the percentage growth of the GDP, implies the market size. The growth of the market may not implicitly be reliant on a rise in income but rather population growth may cause very serious implications for disease induced mortality rates. Another discovery is the positive relationship between technology which was examined by residents' patents and the human welfare cost of both ambient and occupational PM exposure. Our finding is in the same line with Ibrahim *et al* (2022) findings in which the residents' patents were negatively related to the human welfare cost of household air pollution.

5. 1. *Implications*

The human welfare cost of ambient, occupational, and household air pollution follows very different dynamics in their relationships with the independent variables. Thus, the development of an appropriate policy framework about mitigating their incidence may be entailed. Technological development can curtail the proliferation of ambient and occupational air pollution can be stimulated by governments and other relevant stakeholders. Note that the positive health impact of renewable energy can only be observed at the household level. This may be because renewable energy technologies have mostly been adopted by households or take up for households' consumption. The backup for the proliferation of renewable energy technologies per se in energy- intensive occupations with high-risk exposure to air pollution can be a pivotal element.

5.2. *Limitations*

There are a few limitations. Firstly, the data for occupational air pollution risk were not disaggregated to isolate segment differences. The reason is service and industrial sectors usually do not require the same level of energy intensity. Accordingly, air pollution exposure would be heterogeneous across different occupational endeavours. Secondly, the scope of this study was limited to OECD countries that have a higher concentration of advanced economies. Thus, the policy implications from this research may not be readily applied by other countries outside this scope. Although, studies have been undertaken in other regions, such as sub-Saharan African countries (Hanif, 2018a), Latin America, and the Caribbean (Koengkan *et al.* 2021) they do not capture the differences embodied in different measurements of health risks from air pollution. These studies utilize a broader definition of health outcomes. To develop policy frameworks that could incorporate the various regions of the world, a regional analysis at the global level can be done for future research.

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