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Research Article

The relationship between air pollution and cardiovascular diseases in Türkiye

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ABSTRACT

The aim of this study was to determine the effect of air pollutant particles on the cardiovascular disease burden (CVDALY) in Türkiye. Particulate Matter 2.5 (PM 2.5) and Non-methane volatile organic compounds (NMVOC) were taken as the independent variable and CVDALY as the dependent variable. The variables were analyzed within the Panel Data Analysis and Machine Learning Approaches frame. Unidirectional Granger causality was determined from PM 2.5-NMVOC to CVDALY and revealed that they acted together in the long term. The regression analysis that was made using econometric and multivariate regression models revealed that generally 1 unit increase in PM 2.5 increased CVDALY by between 0.0021–0.0029 units; 1 unit increase in NMVOC increased CVDALY by between 0.00024–0.0004 units. In Machine Learning approach, it had been determined that if the PM 2.5 and NMVOC were reduced to 0.84- and 9.48 respectively; CVDALY would be decreased to 0.022. In other words, Machine Learning approaches results showed that reducing PM 2.5 by about 4.5 times and NMVOC by about 30% would be reduced CVDALY by about 39.6% from the current status of Türkiye. The empirical results showed that PM 2.5 - NMVOC increased CVDALY in Türkiye. From this perspective establishing and implementing policies to improve air quality in Türkiye could be an important approach in reducing cardiovascular diseases.

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INTRODUCTION

The development of industry, increasing population, prolonged life expectancy, and urbanization have brought air pollution to the fore, so air pollution has become one of the major problems threatening human health today. Air pollution occurs when the foreign substances in the air reach a certain density above the amount they should be. Sources of air pollution are based on natural and artificial (anthropogenic) causes. While natural causes are volcanic eruptions, forest fires, dust, and pollen; traffic, home heating, cooking, construction, industry, mechanical wear, power plants, agriculture, etc. are the artificial causes. The most important air pollutants particles are Azotoxides (NOx), Carbon monoxide (CO), Carbon Dioxide (CO_2), Hydrocarbons (HC), Ozone (O_3), Particulate Matter (PM), and Sulfur dioxide (SO_2). Many environmental factors affect our health. Even taking very low concentrations of these factors into the body by absorption/inhalation etc. adversely affects the life of living things and these environmental polluters can be increased the risk of diseases such as asthma, cancer, and heart disease [1]. Air polluters effect on the cardiovascular, respiratory and neurological systems. For example, PM exposure on the cardiovascular diseases are different like oxidative stress injuries, systemic inflammation, cardiac autonomic function or endothelial

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dysfunction [2]. It has been frequently studied in the literature that pollutants cause an increase in blood pressure, changes in heart rhythm such as arrhythmia, myocardial infarction due to thickening of the vessel wall, atherosclerosis, cardiac hypertrophy, increase in plasma viscosity, and thrombus formation [3–8]. Air pollutants increase epithelial permeability by damaging epithelial cells in the respiratory tract and cause a range of inflammatory effects such as cell inflammation and cytokine increase [3]. Air pollution causes a decrease in respiratory functions, exacerbation of asthma and chronic obstructive pulmonary disease (COPD), and developmental delay of the lungs. Depending on these, it may cause an increase in the cardiopulmonary death rate [3–5]. Air pollution can damage the brain through increased inflammation, oxidative stress, glial activation and cerebrovascular damage [9] and caused Parkinson's, Alzheimer's [4], ischemic stroke [3, 10] and mental retardation [3].

Air pollution is considered to be responsible for several million premature deaths worldwide each year [11, 12] and it is an important risk factor that threatens health in terms of shortening life span or increasing mortality [12, 13]. Air pollutants and health-related research focus mostly on single air pollutants [14, 15]. Besides this combined, air pollution from both O_3 and PM 2.5 was associated with 4.5 million deaths worldwide [13]. For example joint effects of cigarette smoking and simultaneous exposure to asbestos in lung cancer have also been reported by researchers [16, 17]. In the study examining the effects of NO_2, PM10, SO_2, and CO on cardiovascular diseases, only CO was associated with cardiovascular disease, ischemic heart disease, and hypertension [18].

Humans are exposed to many air pollutant particles in the inhaled air. This condition has limited results in air pollutants and disease-related research, as the effects of each pollutants cannot be measured separately. It is also difficult to determine the effects of multiple air pollutants on diseases. Besides this investigating the joint effect of multiple air pollutants effects on health has been evaluated by researchers recently [19, 20].

Studies showing the relationship between air pollutants and diseases are often carried out experimentally at the clinical level in the form of descriptive, regression and correlation studies. However, in parallel with the developing technology, public databases have been created where data on diseases are digitized. Many types of data can be accessed on these databases, such as the number of deaths from diseases, years of life lost due to diseases, incidence and prevalence of diseases. Although these data enable research from a health economics perspective using econometric methods, machine learning, and artificial intelligence algorithms, they have just begun to be researched in the literature. In the analyzes by using these methods and variables by switching from a single-pollutant approach to a multipollutant approach, better protection of public health against air pollution can be investigated. For this transition to be successful new methodological developments are needed in science's approach to air pollution studies were pointed out in the literature [19]. Machine learning and artificial intelligence algorithms can take their place in the literature as methodologies that enable the evaluation of the joint effects of independent variables that cause disease as new approaches.

Machine learning is a branch of artificial intelligence and consists of systems that make inferences from data with mathematical and statistical operations. Today, many different machine learning methods have emerged for the inference process. These methods are classification, regression, clustering and dimension reduction [21]. A machine learning method produces an output to predict, and the produced output is called "classification" if it is categorical, and "regression" if it is numerical. Clustering is explanatory modeling, which is the process of assigning similar observations to the same clusters. Machine learning, big data, and other similar new technologies can also be used to monitor disease patterns and predict their relevance to the economy, and may offer policy-making useful information in these areas in the future. Collectively, interdisciplinary synergies in policies, geriatric care, drug development, self-awareness, big data use, machine learning and personalized medicine will be a factor that provides the most opportunities for the elderly and maximizes their longevity in the upcoming period [22]. Linear regression analysis is an important analysis tool in the machine learning approach. It aimed to establish a linear relationship between two variable groups, dependent/response and independent/predictive variables, and to estimate new values over these variables. In recent years, Multivariate linear regression method is one of the most important techniques among linear regression techniques.

Multivariate linear regression models the relation between multiple dependent variables and independent variables simultaneously. The model can be easily derived as a maximum probability estimator under the assumption that the errors are normally distributed. After all, the model has a unique global minimum that can be given explicitly. Because of its simplicity, Multivariate linear regression is considered an important analysis tool in the social and natural sciences [23]. Besides this artificial intelligence algorithms can guide in revealing the relationship between health and the environment and making effective politic decisions.

The subject of this research is the relationship between cardiovascular disease and air pollutants. Air pollution directly affects the cardiovascular system through the respiratory system. One of the significant contributors to global cardiovascular deaths is air pollution; recent analyzes estimate that CVD causes 17.9 million deaths each year [24], with one-third of these deaths occurring before 70 years of age. Cardiovascular conditions are responsible for 40–60% of premature deaths from air pollution [25, 26]. Numerous epidemiological studies have shown that cardiovascular problems caused by short-term exposure to PM increase morbidity and mortality; confirmed sensitization in older adults with CVD or diabetes [27–29]. In addition, long-term exposure to PM can greatly increase the risk of CVD;

Table 1. Defining variables

Variables	Unit	Source	Abbreviation
Particulate Matter 2.5	Kilograms per capita	https://stats.oecd.org/	PM 2.5
Non-methane volatile organic compounds	Kilograms per capita	https://stats.oecd.org/	NMVOC
The burden of cardiovascular diseases	Per capita	http://ghdx.healthdata/	CVDALY

it can reduce life expectancy by several years [30, 31]. In this context, epidemiological studies related to the cardiovascular system and air pollutants are reported frequently and provided the relationship between cardiovascular diseases and air pollutants [32–34].

This study, considering the potential of air pollution's significant health effects investigated the burden of cardiovascular disease attributable to air pollution at the Türkiye level. The European Environment Agency (EEA) stated that 97.2 percent of the urban population in Türkiye is exposed to unhealthy levels of PM10 [35]. Based on available evidence, Türkiye appears to be one of the countries in Europe with a high rate of premature deaths due to air pollution and according to current data, 28924 people died prematurely in 2010 in Türkiye due to exposure to particulate matter (PM) and ozone in the outdoor environment was indicated [36]. From this perspective to reveal air polluters' impact on the burden of cardiovascular diseases in Türkiye, the hypothesis was identified as follows:

H_1: Air pollution has been increasing the cardiovascular disease burden.

MATERIALS AND METHODS

In this section, the information about the variables used in the study, the analysis methods and tools used in the analysis, and the limitations of the study were evaluated under 3 (three) sub-headings. In this study with a different perspective, it was aimed to evaluate the relationship between cardiovascular health and air pollution using the econometric (time series analysis) and Machine Learning approaches (ML) methodology out of clinical experimental research also. First of all, it was aimed to show the effect of the joint effect of air pollutants on cardiovascular disease by defining the relationship between variables with econometric analysis, testing the obtained results through machine learning, and harmoniously evaluating the results. Therefore it is thought that the findings obtained by econometric and ML analyses at the empirical level will enrich the health-related literature in terms of methodology.

Variables

In this study, PM 2.5 and Non-Methane Volatile Organic Compounds (NMVOC) air pollutants were the independent variables; CVDALY was the dependent variable showing the deterioration in cardiovascular health and the information of the variables were given in Table 1. This study includes the regular data on PM 2.5 and NMVOC between 1990 and 2017 in Türkiye.

In the cardiovascular literature, especially PM 2.5 was studied. Particulate matter is defined according to its aerodynamic diameter. PM10 and PM 2.5 are particles smaller than 10 μm and 2.5 μm respectively. Pollutant sources that cause the formation of particulate matter; industrial processes, domestic heating processes and traffic [37].

NMVOC is a compound of many chemical species that may lead to secondary organic aerosol formation as pollutants and cause an increase in tropospheric ozone concentrations [38–40]. Some types of NMVOCs are toxic substances and can directly harm human health [41]. Disability-adjusted life years (DALY) is a health metric that measures the years of healthy life lost due to illness and injury, and it shows the sum of the years of life lost due to premature death and illness. In this study, the DALY criterion, which evaluates the years of life lost due to cardiovascular disease and the years of life spent with this disease, was used and was abbreviated as CVDALY in the study.

Statistical Analysis

Statically analyses were made under five headings. In the first section, descriptive statistics were given and the significance of the econometric model of this study was carried out by using the Least Squares Method. In the second section, unit root tests were done to determine the stationarity levels of the variables; then the lag length of the established econometric model was revealed and the causality relationships between the variables were analyzed with the Granger causality test. In the fourth section, the effect of air pollutants on cardiovascular disease burden was estimated by FMOLS and DOLS tests. In the last stage, Machine Learning Regression method was used to predict the burden of cardiovascular diseases according to the minimum level of PM 2.5 and NMVOC. The details of the methods used in the analysis and the findings obtained were given in the title of the results. The statistical analyses for econometric evaluations "Eviews 10" and for Machine Learning Approaches "Phyton" program were used.

Limitation of This Study

The year range for the data belonging to variables were between 1990 and 2017, so the time has been accepted as an important constraint for this study. Using of two variables of air pollutants (PM 2.5-NMVOC) in the study could be considered as the second limitation and the methodology used in the research was also considered as another limitation.

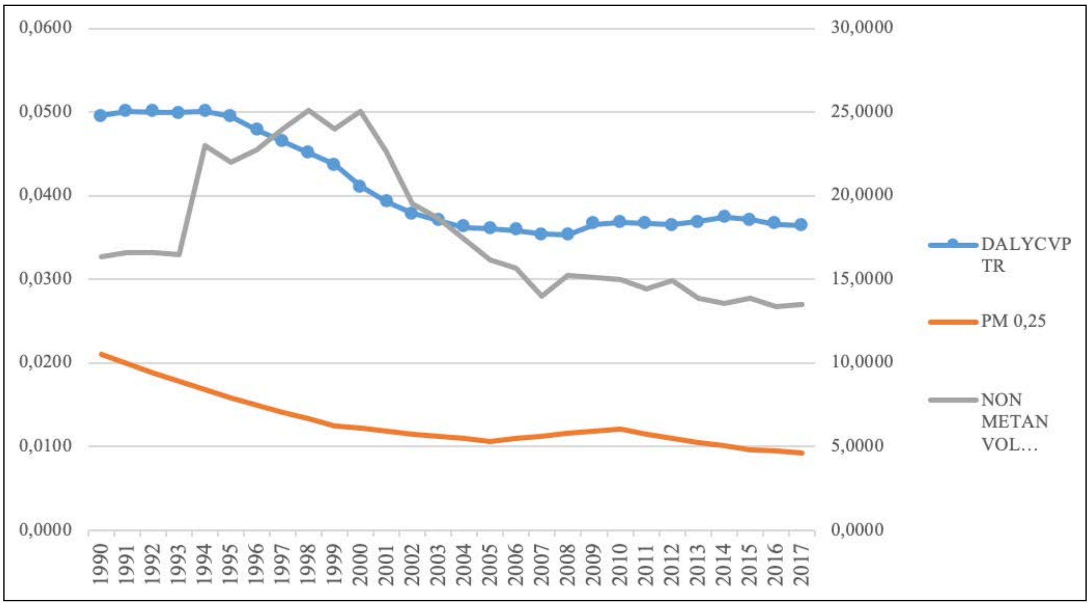

Figure 1. CVDALY, PM 2,5 and NMVOC by years, 1990–2017.

Table 2. Results of least squares

Dependent variable	Independent variable	Coefficient	Prob.	R^2	Adjusted R^2	F-statistic	Prob(F-statistic)
	PM 2.5	0.002949	0.0000				
CVDALY	NMVOC	0.000412	0.0030	0.8997	0.8917	112.1060	0.0000
	C	0.014567	0.0003				

: Significance at level 1%. Jarque Bera Normality Test: 0.261945; Ramsey Reset Test: 0.0313; Breusch-Godfrey Serial Correlation LM Test: 0.0712; Breusch-Pagan-Godfrey: 0.1354; ARCH: 0.1586 Wald Test: c(PM 2.5)=0.002949 p=0.0000 c(NMVOC)=0.000412 p=0.0000.

RESULTS

CVDALY mean in Türkiye was 0.04±0.01 (min: 0.03; max: 0.05); PM 2.5 mean was 6.46±1.62 (min: 4.64; max: 10.48); NMVOC mean was 17.81±4.01 (min: 13.38; max: 25.07) between 1990–2017 (Fig. 1).

The Econometric Model

The equation for the econometric model was set up as follows:

*CVDALY = C(1)*PM2.5 + C(2)*NMVOC + C(3)*

In Table 2, the value of R and R^2 was 89% that the explanatory power of the econometric model was good. Besides this result the relationship between the variables was found to be significant ($p<0.01$). At the same time, diagnostic tests (Jarque Bera Normality Test; Ramsey Reset Test, Breusch-Pagan and ARCH Tests) explaining the relationship between the variables and the model confirm the significance of the model. For this reason, the model established in the study was considered significant.

Panel Unit Root Tests

In Table 3, panel unit root test results were given while null hypothesis in unit root tests indicates the existence of unit root in variables; the alternative hypothesis states that there is no unit root in the variables. In Table 3, the stationarity of the variables was found at the level.

Granger Causality Analysis

By using the Granger Panel Causality test, the causality relationship between the series has been tried to be determined. A statistically strong relationship between variables; this relationship does not mean that it means causality. The statistically, while the relationship is considered as an expression of an association, the concept of causality is primarily based on a theoretical explanation [42].

In Granger causality analysis, primarily all the series must be stationary at the same level, so the level-individual intercept model was used according to unit root test results. Then the second presumption was to determine the lag length of the model. The VAR model was set up for determine the lag lengths of the variables. In Table 3, the maximum length of the variables AIC and HQ tests were found in the 4th length and LR and SC tests were found in the 1st length and FPE tests were found in the 3rd length. Table 3 presents the results showing the delay length and the causal relationship between the estimated and predicted equation in the VAR model. The lag lengths obtained in the research were defined in the VAR Model, and since the diagnostic tests (unit root, correlation, etc.) that test the significance of the results obtained in causality analyzes were found to be significant at the 4th length, the research was carried out on the 4th lag length.

Table 3. Results of granger casuality tests

A. Results of unit root tests					
Variables	**Levin, Lin and Chu**	**Breitung t-stat**	**IM, Pesaran and Shin W-stat**	**ADF**	**PP**
CVDALY-PM2.5-NMVOC					
Level					
Individual effects	0.0000*	–	0.0033**	0.0050**	0.0516***
Individual effects and individual linear trends	0.0109**	0.3898	0.0068**	0.0154**	0.7390
None	0.0403**	–	–	0.3091	0.0004*
1. diff.					
Individual effects	0.0255**	–	0.0063**	0.0040*	0.0034*
Individual effects and individual linear trends	0.0468**	0.0374**	0.0302**	0.0178**	0.0184**
None	0.0007*	–	–	0.0000*	0.0000*
2. diff.					
Individual effects	0.0000*	–	0.0000*	0.0000*	0.0000*
Individual effects and individual linear trends	0.0000*	0.0000*	0.0004*	0.0004*	0.0000*
None	0.0000*	–	–	0.0000*	0.0000*

*, **, ***: Significance level at 1%; 5%; 10% respectively.

B: VAR lag order selection criteria						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	29.26580	NA	2.05e-05	-2.283982	-2.135874	-2.246734
1	134.3048	173.5427*	4.88e-09	-10.63520	-10.04277*	-10.48621
2	145.1050	15.02632	4.38e-09	-10.79174	-9.754983	-10.53100
3	156.8363	13.26153	3.92e-09*	-11.02925	-9.548168	-10.65676
4	167.8489	9.576110	4.29e-09	-11.2042*	-9.278847	-10.72002*
5	175.7811	4.828307	7.98e-09	-11.11140	-8.741672	-10.51542

*: Indicates lag order selected by the criterion; LR: Sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

C: Granger casuality/block exogeneity wald tests			
Nul hypothesis	**Prob.**	**Condition**	**Description**
PM 2.5 ≠> CVDALY	0.0001*	Rejected	PM 2.5 was the Granger cause of the CVDALY
NMVOC ≠> CVDALY	0.0000*	Rejected	NMVOC was the Granger cause of the CVDALY
CVDALY ≠> PM 2.5	0.7006	Received	CVDALY was not the Granger cause of the PM 2.5
NMVOC ≠> PM 2.5	0.9953	Received	NMVOC was not the Granger cause of the PM 2.5
CVDALY ≠> NMVOC	0.0513	Received	CVDALY was not the Granger cause of the NMVOC
PM 2.5 ≠> NMVOC	0.3813	Received	PM 2.5 was not the Granger cause of the NMVOC

JB Normality test:0.9497; VAR Residual Serial Correlation LM Tests:0.6430; VAR satisfies the stability condition between 0.180447–0.923563; * significance level at 1% and in the estimation 4th lag length was used.

Johansen Cointegration Test

The effects of air pollutants on the cell epithelium take time depending on the intensity of exposure to the agent. The effects of continuous and small amounts of exposure appear in many years. Especially in chronic diseases, diseases develop in the long term due to exposure to the agent. It should not be ignored that questioning long-term relationships through cointegration tests will also provide important evidence in the analyses carried out on these diseases and their factors. From this perspective having verified that the series were nonstationary and same order integration as I(0), it was tested whether there exists any long-run equilibrium relationship between the variables by using Johansen cointegration tests (Table 4). According to the Johansen cointegration result there was at least one cointegration relationship between variables; that showed CVDALY- PM 2.5-NMVOC acts together in the long term.

Table 4. Cointegration –DOLS-FMOLS test results

A. Johansen Cointegration Test Results				
Unrestricted cointegration rank test (trace)	**Eigenvalue**	**Trace statistic**	**Critical value**	**Prob**
No deterministic trend - Lags interval (in first differences): 1 to 4				
None*	0.5848	39.6065	35.1927	0.0157*
At most 1	0.4560	19.3871	20.2618	0.0656**
At most 1	0.2086	5.3835	9.1645	0.2440
Linear deterministic trend - Lags interval (in first differences): 1 to 4				
None*	0.5413	31.6934	29.7970	0.0299*
At most 1	0.4432	13.7669	15.4947	0.0896**
At most 1	0.0128	0.29855	3.8414	0.5848

*, **: Significance level at 5%; 10% respectively. JB Normality test: 0.013; VAR Residual Serial Correlation LM Tests: 0.9011; VAR Residual Heteroskedasticity Tests: 0.6945; VAR satisfies the stability condition between 0.225647–0.897363.

B: Panel DOLS and FMOLS estimations results				
The dependent variable: CVDALY				
	DOLS		**FMOLS**	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**
PM 2.5	0.002122	9.697258	0.002703	8.482802
	(0.0000)		(0.0000)	
NMVOC	0.000249	4.733593	0.000362	3.220116
	(0.0002)		(0.0037)	
	R: 0.99 R^2: 0.98		R: 0.88 R^2: 0.87	
	JB Normality test 0.5143		JB Normality test 0.2487	

Notes: Probability values are in parenthesis. In the DOLS estimation method, lead and lag were set as 1.

Dynamic Least Square (DOLS)-Fully Modified Ordinary Least Square (FMOLS) Tests

Panel DOLS and FMOLS tests are commonly used tests in cointegrated panel tests. In this study, the relationship between variables was estimated using dynamic least squares (DOLS) and fully modified ordinary least squares (FMOLS) techniques (Table 4).

According to the DOLS coefficient estimation results, PM 2.5 and NMVOC were effective on CVDALY positively and 1 unit increase in PM 2.5 increased CVDALY by 0.0021 units; 1 unit increase in NMVOC increased CVDALY by 0.00024 units ($p<0.00$). According to the FMOLS coefficient estimation results, PM 2.5 and NMVOC were effective on CVDALY and 1 unit increase in PM 2.5 increased CVDALY by 0.0027 units; 1 unit increase in NMVOC increased CVDALY by 0.00036 units ($p<0.00$). In summary, the main findings obtained from FMOLS and DOLS forecasting methods confirm the positive impact of PM 2.5 and NMVOC effective on CVDALY.

Machine Learning Method

This study tried to determine the independent variables (PM 2,5 -NMVOC) effects on the dependent variable (CVDALY) by using the ML method. The Least Squares Method results by using the ML approach was shown in Table 5. According to Table 5, the dependent and independent variables' coefficients gave consistent results with econometric results as in Table 2 and Table 4.

According to the ML estimation result, PM 2.5 and NMVOC were effective on CVDALY, and 1 unit increase in PM 2.5 increased CVDALY by 0.0029 units; 1 unit increase in NMVOC increased CVDALY by 0.0004 units. In summary, the main findings obtained from ML forecasting methods confirm the positive impact PM 2.5 and NMVOC effective on CVDALY as the results of the econometric model (Table 4).

Regression analyses provided important evidence in revealing the relationship between the dependent and independent variables, but evaluations made within the framework of this evidence may lead to more rough estimates. However methods such as ML approaches have only just begun to be studied in the literature, they could be helpful to determine the joint effect of independent variables on the dependent variable. As a matter of fact, in this study, the ML method was used to determine the joint effect of PM 2,5 and NMVOC on CVDALY.

Table 5. OLS results by machine learning method

Dependent variable	Independent variable	Coefficient	Prob.	R^2	Adjusted R^2	F-Statistic	Prob(F-statistic)
CVDALY	PM 2.5	0.0029	0.0000*				
		(0.000)					
	NMVOC	0.0004	0.0000*	0.900	0.892	112.8	3.07e-13
		(9.48e-05)					
	C	0.0146	0.0000*				
		(0.002)					

Jarque Bera Normality Test: 2.650; *: Significance level at 1%.

B: Machine learning regression estimations results	
PM 2.5	=0.84
NMVOC	=9.48
CVDALY ML estimation value	=0.02206693
Multi Regression Score	0.8966072524192289
r2 socre	0.8966072524192289
MAE	0.0018798910197996026
RMSE	0.0019494894486548
Explain Varians Score	0.8797690050363055

Omnibus: 12.505 Durbin-Watson: 0.312; Prob(Omnibus): 0.002 Jarque-Bera (JB): 2.650. Skew: 0.190 Prob (JB): 0.266; Kurtosis: 1.542.

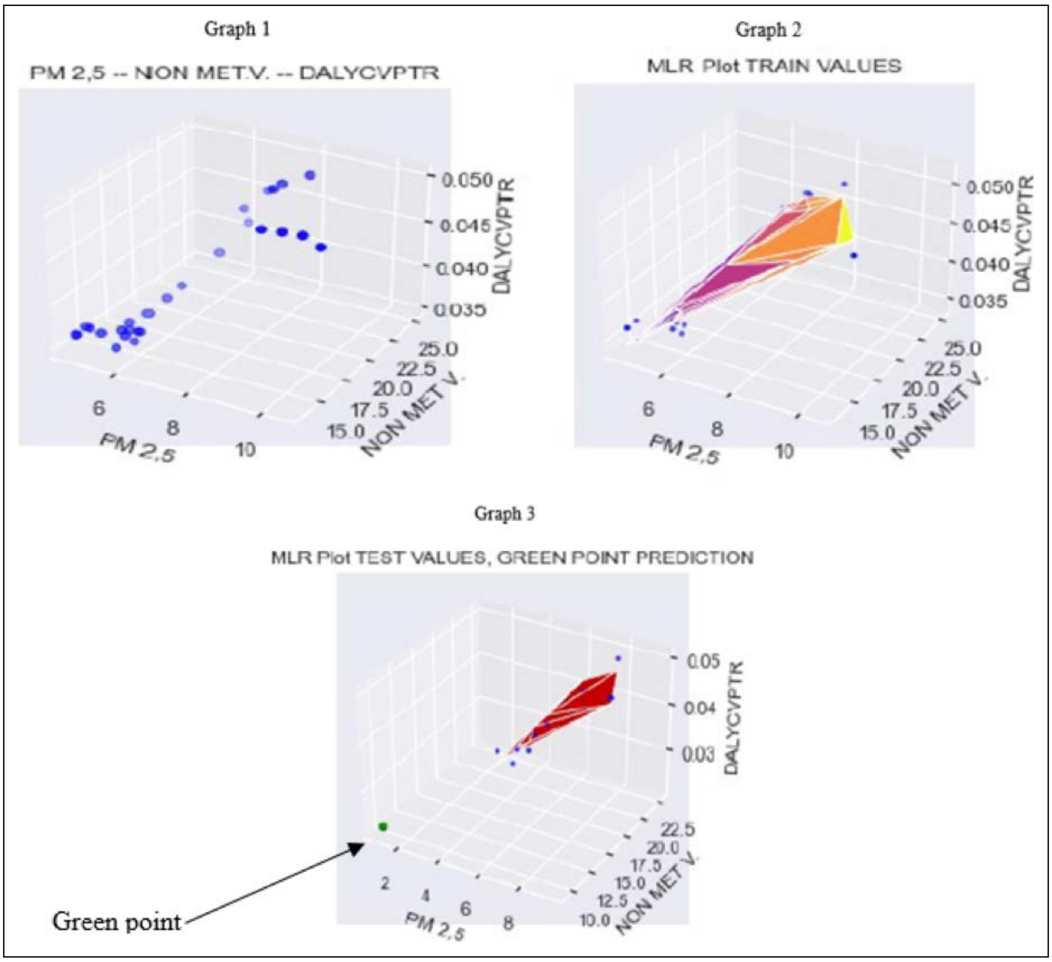

Figure 2. CVDALY-PM 2.5 – NMVOC MLregression model.

In the study, regression analyses showed that PM 2,5 and NMVOC increased CVDALY. Therefore by using the ML methods to find the answer to the question that how CVDALY would be affected as a result of reducing these two air polluters together; first of all, assuming that it was not possible to completely destroy the particles in the air, it was thought that it would be appropriate to determine the country where the particles in the study were at the lowest level for the analysis. As a matter of fact, the country with the lowest values of PM 2.5 and NMVOC in 2017 among the countries with data on air pollutants was Sweden. When to defined these values to the ML method -the current PM 2.5 (4.64) and NMVOC (13.49) value in Türkiye was reduced to Swedens' PM 2.5 (0.84) and NMVOC (9.48) values- CVDALY was decreased from 0.0364 to 0.022 in Türkiye (Table 5 section B). In other words, ML approaches results showed that in Türkiye reducing PM 2.5 by about 4.5 times and NMVOC by about 30% would be reduced CVDALY by about 39.6%.

In Figure 2, the first graph shows the regression relationship between the variables; while revealing the relationship of independent variables with the dependent variable perly in the second graph; the point indicated as green in the 3rd graph showed the joint effect of the reduced PM 2.5 and NMVOC value together on CVDALY.

DISCUSSION

In this study, PM2.5 and NMVOC air pollutants were discussed in order to determine the effect of air pollution on cardiovascular diseases in Türkiye. In this context, data from the years 1990–2017 were used. In general, while the CVDALY has decreased by approximately 27% from 2017 to 1990; PM 0.25 and NMVOC also decreased by 56%, and 17% respectively. In econometric evaluation, the unidirectional Granger causality relationship from PM 2.5 to CVDALY; and the unidirectional Granger causality relationship from NMVOC to CVDALY were revealed. The cointegration test results show the long-term relationships between PM 2.5 - NMVOC –CVDALY as showing long term relationships. Generally, a 1 unit increase in PM 2.5 increased CVDALY by between 0.0021–0.0029 units; a 1 unit increase in NMVOC increased CVDALY by between 0.00024–0.0004 units. ML approach results showed that in Türkiye reducing PM 2.5 by about 4.5 times and NMVOC by about 30% would reduce CVDALY by about 39.6% (reduced to Swedens' air polluter values). Within the framework of these findings the hypothesis identified as "Air pollution has been increasing the cardiovascular disease burden" was received in this study.

A research project involving 25 European cities has shown that complying with the WHO's 10 μg/m^3 standard for average annual PM 2.5 concentration may increase the average life expectancy of people aged 30 and over by up to 22 months [43]. Estimates, based on further analysis of the concentration of particles in the air, predict that deaths, particularly from outdoor air pollution, may reach up to 8.9 million in a year [25] and estimated that reducing air pollution to WHO air quality guidelines worldwide will increase life expectancy by 0.6 years [12].

In Australia, a 38% reduction in PM10 led to a 17.9% reduction in cardiovascular diseases and a 22.8% reduction in respiratory diseases, and an 11.4% reduction in overall mortality. In addition, it has been shown that this decrease is more effective with a 19.6% decrease in cardiovascular diseases and a 22.9% decrease in respiratory diseases in winter [44]. The ban on coal burning in Durbin Ireland resulted in a 71% reduction in black smoke dust (smoke) and a 34% reduction in sulfur dioxide in the air, and this reduction caused decrease in cardiovascular disease by 7%, respiratory disease by 13% and overall mortality by 8% in this city [45].

CONCLUSION

The results obtained from this study confirmed the relationship between air pollutants and the burden of cardiovascular diseases. PM 2.5 and NMVOC are foreseen as significant threats to public health and showed the need to reduce air pollutants which are one of the causes of the burden of cardiovascular diseases in Türkiye.

Besides this, the analysis of data using the econometric methodology and machine learning approaches also showed that it is possible to evaluate the health-related literature, which was studied in experimental clinic research, from out of the clinic with a different perspective. Therefore the use of econometric and machine learning models to monitor disease models and predict their relationship to the burden of diseases can guide the development of health policies. Therefore it is also thought that this study will contribute to the health and artificial intelligence-related literature. However, it should be noted that there are uncertainties in assessing the health effects of multiple air pollutants arising from various factors such as econometric calculations, measurement errors, and the degree of relationships between pollutants. It is also worth noting that more epidemiological studies are needed to verify whether econometric models and ML approaches are reliable.

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DATA AVAILABILITY STATEMENT

The author confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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