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RESEARCH PAPER

The Impact of Socioeconomic and Meteorological Factors on PM2.5 Concentrations in the United States: An ARDL Bounds Testing Approach

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Abstract

The threat of air pollution in the form of fine particulate matter (PM2.5) has been increasingly becoming serious around the world. To address this problem, an accurate understanding of its determinants is needed. This study investigates the impact of both natural and socioeconomic factors on PM2.5 concentrations in the United States (US). To this end, we apply an ARDL bounds testing approach using monthly data over the period from 2000 to 2021. Our findings support the existence of long-run relationship among the variables. Further, the results suggest that, in both the long and short term, energy consumption worsened PM2.5 pollution. However, there exists an inverse relationship between economic growth and PM2.5 concentrations only in the long term, which contrasts with what was found in the short term. Besides, industrialization exerts a negative impact on PM2.5 concentrations only in the short term. Regarding the natural factors, the results provide significant evidence that wind speed mitigates PM2.5 concentration contrary to temperature. However, no significant impact exists for precipitation and relative humidity. The results of Toda-Yamamoto causality test indicate the presence of a unidirectional causality running from economic growth and energy consumption to PM2.5 concentration at 5% significance level, and from industrialization and wind speed to PM2.5 at the 10% significance level. In light of these findings, some policy implications are recommended for U.S. policymakers.

Keywords: ARDL Model, Causality Test, Meteorological Conditions, PM2.5 Concentrations, Socioeconomic Factors.
JEL Classification: C1, C5, O1, Q5.

1. Introduction

Clean air is essential for human comfort, health and well-being (Luo et al., 2017). However, in recent decades, the development of the world economy has led to a series of environmental issues, particularly air pollution, which has increasingly become a serious hazard. In fact, almost all of the global population (99%) lives in places where the air quality does not reach the WHO criteria (WHO, 2022). The harmful impacts of air pollution have made it a hotspot of both public interest and scientific research. Particulate matter (PM) is widely considered as a major component of air pollution. Amongst PM, PM2.5, which is fine particulate matter with an aerodynamic diameter of less than 2.5 µm, is particularly important as it may present a higher risk to human health compared to PM10 (particles with an aerodynamic diameter of fewer than 10 µm) (Abd Aziz et al., 2018). Indeed, it has been recognized as a Group 1 carcinogen by the International Agency for Research on Cancer (IARC) and the World Health Organization (WHO) (Hamra et al., 2014) due to its adverse effects on humans. The robust connection between ambient PM2.5 concentrations and human health has been confirmed by epidemiological studies.

Researchers have confirmed that exposure to particulate pollution has been associated with increased risks of lung cancer, cardiovascular disease mortality, kidney disease risk, and ischemic heart disease mortality (Pope et al., 2011; Bowe et al., 2017; Thurston et al., 2016). More dangerously, according to the Global Burden of Disease study, ambient PM2.5 was the fifth leading risk factor for mortality in 2015, causing 4.2 million deaths, or 7.6% of total deaths worldwide (Cohen et al., 2017), which shows that PM2.5 is a truly global threat and not a simply regional air pollution issue. Not only does air pollution poses a severe threat to human health, but also negatively impacts sustainable development; indeed, according to the Organization for Economic Cooperation and Development (OECD), air pollution could lead to 6 to 9 million premature deaths per year by 2060 and cost 1% of global GDP (OECD, 2016). Hence, the attention of researchers is turning more and more toward PM2.5mitigation issues.

Considering the seriousness of PM2.5 pollution and the urgent necessity to implement efficient abatement policies, numerous studies have been dedicated to the identification of the factors driving PM2.5 concentrations, and further research is ongoing in this area. It has indeed been empirically found that natural factors such as meteorological conditions, vegetation coverage, and topography influence PM2.5 concentrations (Luo et al., 2017). Among these influencing factors, meteorological conditions are among of the most essential factors as they can affect PM2.5 concentrations via diffusion and dilution capacities (Liu et al., 2020). Therefore, a more reliable and comprehensive understanding of the PM2.5 pollution problem can be achieved by taking meteorological factors into account (Yang et al., 2017). However, in addition to these conditions, it is crucial to emphasize that PM2.5 pollution is not only a natural phenomenon, but additionally it is a man-made one resulting from human socio-economic activities (e.g., energy consumption, population growth, economic development) (Ji et al., 2018), that has been the dominant factor as PM2.5 is mainly originated from the combustion of fuels such as wood, coal, oil, and the emission of motor vehicle exhaust (Shou et al., 2019).

Briefly, the factors that impact PM2.5 concentrations involve socioeconomic and natural conditions. Nevertheless, there is a lack of extensive research on their joint influences, as researchers generally focus on one-sided factors such as either natural or socioeconomic factors. Using only one perspective can result in inaccurate analytical results. Thus, to better assess the influencing factors on PM2.5 mitigation, both natural and socioeconomic factors were considered and interpreted in this study. It may also be noted that most studies are mainly conducted at the scale of a city within a country (Chen el al., 2018) or a few large cities around the world (Han et al., 2016). Research on PM2.5 concentrations has rarely been performed at a country scale. Furthermore, many studies have focused on heavily polluted developing countries, such as China (Zhang et al., 2019; Zhou et al., 2018), while only a few have included developed economies.

To achieve the above objectives, this study uses the United States (US). The US presents an interesting case study since it is the largest consumer of primary energy in the world, with a 15.8% share in 2020 (BP, 2021). Moreover, it is one of the developed economies where per capita fossil fuel consumption is 60,167 kWh in 2020, which keeps the United States in the first place, followed by China, 23,674 kWh (4th), and India, 5,7888 kWh (9th)[1]. Keeping that in mind, the U.S. case needs to be thoroughly examined to ensure its environmental future by effectively controlling air pollution through a combination of diligent scientific research and reasonable policy implementation. Therefore, it will be useful to understand the factors that contribute to PM2.5 pollution.

As a matter of fact, the purpose of this paper is to determine the impact of socioeconomic and meteorological factors on PM2.5concentration, over the period January 2000 to December 2021. To the best of our knowledge, the impact of socioeconomic and natural factors on PM2.5 pollution has not been tackled jointly in the case of the United States. We aim to make the two following contributions to the literature: first, we extend the study to the country level, whereas previous research has been primarily limited to the city level, and second, we provide an

[1]. Retrieved from here.

empirical analysis of a developed economy in which we determine the links between socioeconomic, meteorological, and PM2.5 concentration factors. Given that many developing countries are adopting the strategies and policies of developed countries like the United States, the challenges facing the U.S. economy, therefore, merit detailed study.

The remainder of this paper is organized as follows. Section 2 presents a brief review of the literature. While Section 3 discusses the data and methodological framework. Empirical results and discussions are presented in Section 4, while the final section draws the conclusion of our empirical research and provides some policy recommendations.

2. Literature Review

So as to enhance environmental quality, it is necessary to identify the main influencing factors responsible for air quality deterioration. A growing body of literature has devoted considerable effort to analyzing the factors leading to the increase of PM2.5 levels, given their severity and the urgent need for effective mitigation measures. This literature can be divided into two categories: studies on socioeconomic factors and studies on meteorological conditions.

2.1 Socioeconomic Factors

For many years, exploring the relationship between economic growth and environmental quality has always piqued the interest of researchers. Literature on the subject is voluminous and continues to grow. Many of them use the Environmental Kuznets Curve (EKC) model as the primary empirical framework. The EKC hypothesis was first proposed by Grossman et al. (1991), their major conclusion was that pollution increases with an increase in revenues in the early stages of economic development and then decreases at higher levels of income in the later stages of economic development. As stated above, at higher income levels, people begin to attach more importance to the environment. In other words, only wealthy societies can afford to be concerned about environmental issues; poor societies must devote most of their resources to necessities (Baldwin, 1995).

Borhan et al. (2012) examined the impact of GDP on pollution in ASEAN 8 using data from 1965 to 2010, and discovered that as GDP rises, pollutant emissions rise first, but once GDP reaches a certain level, pollutant emissions begin to decline. As we can see, a country's economic level has a major impact on polluting emissions.

Industrialization and energy consumption were also a major driver of environmental degradation that had attracted attention in the empirical literature. For example, Zhao et al. (2018) investigated the relationship between GDP per capita, energy consumption, urbanization process, industrialization structure, and the amount of possession of civil vehicles and PM2.5 concentrations, over 1998 to 2016, using the auto-regressive distributed lag (ARDL) approach. The findings support the evidence that GDP per capita was the greatest factor affecting PM2.5, followed by total energy consumption, urbanization, industrialization activity, and the amount of ownership of civil vehicles.

Li et al. (2016) used a panel data model to investigate the effect of economic growth, urbanization, and industrialization on PM2.5 concentrations in China at the prefecture-level from 1999 to 2011. The findings indicated that industrialization was the most important factor influencing PM2.5 concentrations in the total panel, the industry-oriented panel, and the service-oriented panel. A study also conducted by (Chen el al., 2018) has examined the relationship between energy consumption, energy intensity, economic growth, urbanization, and PM2.5 concentrations by categorizing countries into four panels based on income levels. The empirical outcomes evidenced that energy consumption was the most important factor influencing PM2.5 concentrations in lower-middle-income and low-income countries. Furthermore, recent studies, such as this by Xu et al. (2019) examined the socioeconomic determinants driving the observed spatiotemporal variations in air quality using the Air Pollution Index (API) and Air Quality Index (AQI). API is based on SO2, NO2, and PM10, whereas AQI is based on six atmospheric pollutants, which include SO2, NO2, PM10, PM2.5, CO, and O3. They found out that vehicle volume, energy consumption, secondary sector proportion, and GDP per capita all have contributed to significant rises in air pollution. Population growth has also been identified as a cause of environmental problems since Malthus (1798) made the link, and the matter has been debated since. Population growth raises demand for land, food, transportation, energy, natural resources, and environmental infrastructure, which may intensify human and socioeconomic activities, contributing to ambient air pollution (Sarkodie et al., 2019). In general, research on air quality and population reveals that population is positively associated with air pollution, but the association holds only for some examined pollutants and not others (Cramer, 1998; Cramer and Cheney, 2000; Cole and Neumayer, 2004).

Previous studies have documented that population is positively associated with PM2.5. For example, Lou et al. (2016) showed that population density was a particularly important factor that had the potential to influence the accumulation of PM2.5. Indeed, a 1% increase in population density can result in a 0.214% increase in the daily growth rate of PM2.5. Lou et al. (2016) and Fang and Yu (2021), also have found that PM2.5 pollution is higher in more populated cities due to life and production activities and their relationship to emissions of polluting gases. It is therefore understood that higher population levels lead to higher energy consumption and higher emission.

2.2 Meteorological Factors

In addition to socioeconomic factors, meteorological factors also have a statistically significant impact on PM2.5 pollution as they can contribute to at least a 16% decrease in PM2.5 levels (Yang et al., 2011). To date, many studies have been conducted on the relationships between PM2.5 concentration and meteorological conditions. For instance, Pateraki et al. (2012) also showed that the concentration of PM2.5increased with the increase of air temperature. Moreover, other empirical studies observed that wind speed contributed to diluting pollutant concentrations in the air by carrying airborne particles into the atmosphere in parallel with nearby cities. The higher the wind speed, the better the quality of urban air. Similarly, Zhang et al. (2016) found also that precipitation was conducive to facilitate the dispersion of air pollutants and had a significant negative effect on PM2.5 pollution. Chen et al. (2018c) analyzed the impact of meteorological factors on local PM2.5 concentrations in 188 monitoring cities across China and showed that meteorological effects on PM2.5 concentrations exhibit significant seasonal and regional variations. According to Bai et al. (2019) relative humidity has a positive effect on air pollution, which indicates that the higher the relative humidity, the lower the air quality. In addition, Jing et al. (2020) found that temperature was the main impacting factor throughout the whole year, as it can explain 27% of PM2.5 concentrations.

Recently, Cifuentes et al. (2021) found that the use of only meteorological variables does not represent the variation of hourly concentrations of PM2.5, since this pollutant is related with on-road sources emissions. Similarly, Park et al. (2021) noticed that meteorological conditions (i.e., wind and turbulent motion at the surface) were vulnerable to PM2.5 concentrations. Further, considerably decreased PM2.5 pollutants were mostly affected by synoptic rather than local conditions. Li et al. (2021) showed that the synoptic pattern and topography can affect PM2.5 concentration in Northeast China.

More recently, Gao et al. (2022) revealed that the level of PM2.5 exhibits considerable seasonal discrepancies in PM2.5 concentration and its variations. Further, they noted that the aerosol optical thickness corrected for humidity, and the relative humidity in the atmosphere exhibits a high effect on PM2.5 concentration.

3. Data and Methodology

3.1 Data

Socioeconomic and meteorological factors were both considered to identify the determinants of PM2.5. Our data are composed of monthly time series covering the period from January 2000 to December 2021 with a total of 264 observations for each variable. Daily PM2.5 concentrations were aggregated to monthly averages and used as a proxy to measure environmental quality. For socio-economic factors, given the availability of data and previous research, real gross domestic product, industrial production index, and total primary energy consumption were ultimately selected for inclusion in the study. We selected temperature, precipitation, relative humidity, and wind speed as meteorological variables. All the meteorological and socioeconomic indicators and their descriptions are presented in Table 1.

Table 1. The Description of Variables

Variable	Symbol	Measurement	Source
Dependent variable			
Air pollution	PM2.5	Particulate matter (PM2.5) (μg/m³)	EPA
Independent Variables			
Economic growth	EG	Real gross domestic product (Chained 2012 USD)	YCharts
Energy consumption	EC	Total primary energy consumption (Quadrillion Btu)	EIA
Industrialization	IPI	Industrial production index	FRED
Precipitation	Precip	Mm	NASA
Relative humidity	RH	kPa	NASA
Temperature	Temp	°C	NASA
Wind speed	WS	m/s	NASA

Note: EPA= Environmental Protection Agency, EIA= Energy Information Administration, FRED= Federal Reserve Bank of St. Louis, NASA= NASA POWER Data Access Viewer. Sources: EPA, YCharts, EIA, FRED and NASA.

3.2 Methodology

The empirical analysis is principally based on the ARDL model and the causality test of Toda and Yamamoto (1995), however, prior to the estimation of the models, we begin by investigation the integration proprieties of the variables under consideration.

3.2.1 Stationarity Analysis

The stationarity test is a prerequisite for time series analysis, as it prevents spurious regression problems. Hence, the unit root was first examined using the Augmented Dickey and Fuller (ADF), the Phillips and Perron (PP), and Kwiatkowski Phillips Schmidt and Shin (KPSS) tests.

3.2.2 ARDL Model

To assess the short-run and long-run relationship between PM2.5 and the independent variables, the Autoregressive Distributed Lags (ARDL) model was used in this study. Two key contributions in this context are Pesaran and Shin (1999) and Pesaran et al. (2001). The ARDL method has been extensively utilized as it provides several advantages over traditional statistical methods for assessing cointegration and short/long-term relationships. There are different cointegration methods given in the literature (Engle and Granger, 2015; Johansen and Juselius, 1990; Johansen, 1991). Although these studies make a significant contribution to the body of research on cointegration or long-run equilibrium relationships, their application remains limited. For example, the Engle and Granger test is only used for two variables, and these must be integrated in the same order, which makes it unusable for multivariate cases.

In this regard, the ARDL bounds testing approach proposed by Pesaran et al. (2001) was adopted to address these shortcomings and verify cointegration. This approach can be utilized to test for a level relationship for variables that are either I(0) or I(1) or a combination of both. This allows us to overcome the pre-testing problems associated with the standard cointegration analysis that requires the classification of the variables into I(0) and I(1). Nevertheless, ARDL cannot be used with non-stationary variables integrated of order two I(2). Moreover, compared to conventional cointegration approaches, it is possible to set various lags for each of the variables in the model (Pesaran et al., 2001), making it more flexible. Besides, the majority of cointegration techniques are sensitive to sample size, but the ARDL technique provides consistent and robust outcomes for small sample sizes (Pesaran and Shin, 1999; Pesaran et al., 2001).

To apply the bound test procedure, the following ARDL will be estimated to find the cointegration relationship between PM2.5, EG, EC, IPI, Precip, RH, Temp and WS. We specify the following unrestricted error correction models (UECM):

$$\begin{aligned}\Delta PM2.5_t = {} & \lambda_0 + \theta_1 PM2.5_{t-1} + \theta_2 EG_{t-1} + \theta_3 EC_{t-1} \\ & + \theta_4 IPI_{t-1} + \theta_5 Precip_{t-1} + \theta_6 RH_{t-1} \\ & + \theta_7 Temp_{t-1} + \theta_8 WS_{t-1} + \sum_{i=1}^{p} \alpha_{1\mathrm{i}}\, \Delta PM2.5_{t-i} \\ & + \sum_{i=0}^{q} \alpha_{2\mathrm{i}}\, \Delta EG_{t-i} + \sum_{i=0}^{r} \alpha_{3\mathrm{i}}\, \Delta EC_{t-i} \\ & + \sum_{i=0}^{s} \alpha_{4\mathrm{i}}\, \Delta IPI_{t-i} + \sum_{i=0}^{t} \alpha_{5\mathrm{i}}\, \Delta Precip_{t-i} \\ & + \sum_{i=0}^{u} \alpha_{6\mathrm{i}}\, \Delta RH_{t-i} + \sum_{i=0}^{v} \alpha_{7\mathrm{i}}\, \Delta Temp_{t-i} \\ & + \sum_{i=0}^{w} \alpha_{8\mathrm{i}}\, \Delta WS_{t-i} + \varepsilon_t\end{aligned} \tag{1}$$

where: the variables are all specified as before; Δ designates the first difference operator; λ_0 is the intercept; ε_t is the stochastic error term; the summation signs denote the short-term dynamics; θ_i represents the long-run coefficients; p, q, r, s, t, u, v and w denote the optimal lags. The optimum lagged orders of equation (1) were chosen based on the Akaike Information Criterion (AIC).

Having estimated equation (1), we now proceed to identify the existence of the long-run relationship between the variables. The ARDL boundary test approach is based on the F-test values which consists of critical values of the lower and upper bounds, I(0) and I(1) respectively, founded on the following null and alternative hypothesis.

$H0: \theta 1 = \theta 2 = \theta 3 = \theta 4 = \theta 5 = \theta 6 = \theta 7 = \theta 8 = 0$

(No levels relationship)

$H1: \theta 1 \neq \theta 2 \neq \theta 3 \neq \theta 4 \neq \theta 5 \neq \theta 6 \neq \theta 7 \neq \theta 8 \neq 0$

(Evidence of levels relationship)

The null hypothesis of no cointegration is rejected if the calculated F-statistic surpasses the upper critical bounds or accepted if the F-statistic falls under the lower critical bounds. However, if the F statistics is in-between the upper bound and lower bound critical value then, the decision is inconclusive. Thus, it is necessary to know more about the order of integration of the variables before making a conclusive inference (Pesaran et al., 2001). Once the long run relationship between PM2.5 and the independent variables is confirmed, the next stage requires the estimation of the long run model described in equation (2).

$$\begin{aligned} PM2.5_t = \lambda_0 &+ \sum_{i=1}^{p} \theta_{1i} PM2.5_{t-i} + \sum_{i=0}^{q} \theta_{2i} EG_{t-i} + \sum_{i=0}^{r} \theta_{3i} EC_{t-i} \\ &+ \sum_{i=0}^{s} \theta_{4i} IPI_{t-i} + \sum_{i=0}^{t} \theta_{5i} \Delta Precip_{t-i} \\ &+ \sum_{i=0}^{u} \theta_{6i} \Delta RH_{t-i} + \sum_{i=0}^{v} \theta_{7i} \Delta Temp_{t-i} \\ &+ \sum_{i=0}^{w} \theta_{8i} \Delta WS_{t-i} + \varepsilon_t \end{aligned} \tag{2}$$

Finally, the Error Correction Model is given below (equation 3), where Δ indicates the first difference operator and the ECM_{t-1} and δ_1 denote the error correction term and the speed of adjustment in long-run equilibrium after short-run shocks, respectively. The ECT must be negative and significant to affirm the long-run relationship among the variables.

$$\begin{aligned} \Delta PM2.5_t = \psi_0 + \delta_1 ECM_{t-1} &+ \sum_{i=1}^{p} \alpha_{1i} \Delta PM2.5_{t-i} \\ &+ \sum_{i=0}^{q} \alpha_{2i} \Delta EG_{t-i} + \sum_{i=0}^{r} \alpha_{3i} \Delta EC_{t-i} \\ &+ \sum_{i=0}^{s} \alpha_{4i} \Delta IPI_{t-i} + \sum_{i=0}^{t} \alpha_{5i} \Delta Precip_{t-i} \\ &+ \sum_{i=0}^{u} \alpha_{6i} \Delta RH_{t-i} + \sum_{i=0}^{v} \alpha_{7i} \Delta Temp_{t-i} \\ &+ \sum_{i=0}^{w} \alpha_{8i} \Delta WS_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

3.2.3 Diagnostic Tests

Different testing methods have been implemented to measure the consistency of the ARDL model and the reliability of its results. The stability of the model will be determined by the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests, which were both proposed by Brown et al. (1975). Furthermore, the functional form will be determined by the Ramsey Regression Specification Error Test (RESET) (Ramsey, 1969) which tests if non-linear combinations of the fitted values can describe the explanatory variable under the null hypothesis that, the model is correctly specified. We will also use the Breusch-Godfrey LM serial correlation for autocorrelation. In addition, the Breusch-Pegan-Godfrey heteroscedasticity test and the ARCH test will also be used to test for the presence of heteroscedasticity.

3.2.4 Causality

Given that the ARDL approach attempts to determine the existence of cointegration among variables, but with no information concerning the direction of that relationship, this study uses the causality testing method of Toda and Yamamoto (1995), where we estimated a vector autoregression (VAR) model which is formulated in levels.

The main advantage of Toda and Yamamoto (1995) test is its appropriateness even if the order of integration of variable is not the same. The basic idea of the Toda and Yamamoto (1995) procedure is to intentionally add additional lags in the estimation of a VAR. More specifically, the estimation process consists of two steps, where after determining the maximum integration order (d_{max}) of the inherent variables, we run an unrestricted level VAR model and determine the lag length k. Residual and stability tests were performed to guarantee that the residuals of the estimated model are serially independent and that the model is stable over the sample period. This was followed by the use of the Wald procedure to test the Granger causality of the ($k + d_{max}$) th-order VAR.

4. Results and Discussion

4.1 Descriptive Summary and Correlation

Before performing some unit root tests, we proceed to some preliminary analyses of our data series. Table 2 details the initial descriptive statistics of the data used for estimation, whereas Fig.1 exhibits the time plots of the variables analyzed in the study. The Table indicates that PM2.5 has a minimum value of 5.633 and maximum of 16.771 over the period under consideration. The minimum and maximum values of industrialization are 84.202 and 104.166, respectively. Regarding the climatic variables, the relative humidity has the highest average (73.709), while the lowest average value is the wind speed (4.634). In addition, we found that wind speed had the lowest standard deviation compared to the other climate variables. Subsequently, the statistic of skewness reveals that, the variables industrialization, relative humidity, temperature and wind speed are negatively skewed meaning these variables are skewed to the right compared to a normal distribution. Whereas PM2.5, Precipitation and GDP are skewed to the left. Additionally, according to the kurtosis results, the distributions of all variables are platykurtic (kurtosis values less than 3), except for precipitation and relative humidity, which have leptokurtic distributions (kurtosis values greater than 3). Since none of the kurtosis and skewness values for these variables meet the conditions for normality. We confirm that the series is not normally distributed. Furthermore, the Jarque-Bera (JB) statistic, one of the most used tests of normality, is consistent with the prior results as it rejects the null hypothesis that the data are normally and identically distributed.

Table 2. Descriptive Statistics of the Data

	PM2_5	EG	EC	IPI	PRECIP	RH	TEMP	WS
Mean	10.114	16125.51	8.151	96.657	3.014	73.709	14.463	4.634
Median	9824821	15818.48	8.057	98.022	2.515	74.97	14.975	4.62
Maximum	16.771	19850.65	9.664	104.166	14.44	88.19	32.61	6.26
Minimum	5.633	12870.36	6.513	84.202	0.04	44	-3.71	2.78
Std. Dev.	2.396	1865.161	0.542	4.844	2041573	8.009	9.542	0.745
Skewness	0.352	0.12	0.438	-0.471	1.457	-1.2	-0.079	-0.044
Kurtosis	2.411	2.037	2.893	2.183	7.157	4.799	1.711	2.288
Jarque - Bera	9.259	10.837	8.582	17.084	283.475	98.987	18.547	5.661
Probability	0.01	0.004	0.014	0	0	0	0	0.059

Source: Research finding.

Table 3. Correlation Matrix

Correlation probability	PM2 5	EG	EC	IPI	PRECIP	RH	TEMP	WS
PM2_5	1.00							
EG	-0.718***	1.00						
EC	0.354***	0.008	1.00					
IPI	-0.385***	0.695***	0.233***	1.00				
PRECIP	-0.193***	0.056	-0.36***	0.036	1.00			
RH	-0.131**	0.154**	0.142**	0.055	0.314***	1.00		
TEMP	0.008	0.018	-0.451***	0.004	0.397***	-0.391***	1.00	
WS	-0.262***	-0.028	-0.048	-0.028	-0.088	0.101	-0.561***	1.00

Source: Research finding.

Note: (***) and (**) denote the rejection of the null hypothesis at 1% and 5%, respectively.

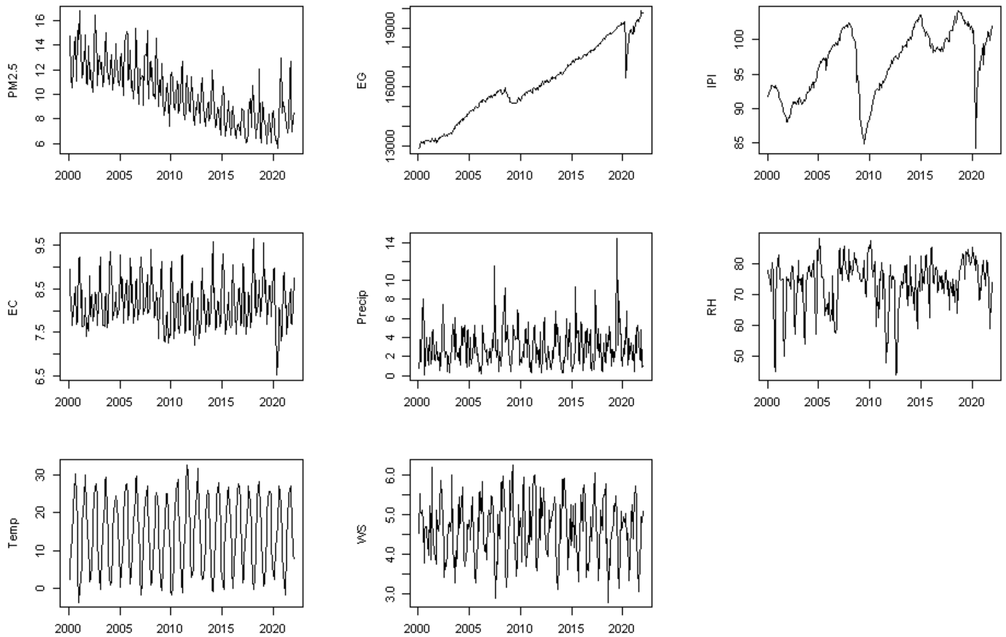

Figure 1. Time Series Plots The Variables
Source: Research finding.

In Table 3, we display the correlation matrix between variables under consideration. As shown in the table, a significant negative relationship is observed between PM2.5 and the variables economic growth, industrialization, precipitation, relative humidity, and wind speed for the sampled period. However, for the case of energy consumption, as a priori expectation, a positive statistical association is seen with PM2.5.

4.2 Stationarity Analysis

This study adopts the augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski -Phillips-Schmidt-Shin (KPSS) test as unit root tests to confirm whether the studied variables were stationary at level, first difference or both. The results are given below in Table 4.

Table 4. The Results of Unit Root Tests

Variables	At Level		At First Difference		Outcome
	Intercept	Intercept and Trend	Intercept	Intercept and Trend	
Phillips-Perron					
PM2_5	-8.0005**	-10.4548***	-42.0052***	-42.7551***	*I(0)*
EG	-0.0878	-3.7665**	-16.8784***	-16.8555***	*I(0)/I(1)*
EC	-9.1643***	-5.2914***	-30.3580***	-30.1914***	*I(0)*
IPI	-2.1430	-2.6754	-12.9017***	-12.8744***	*I(1)*
PRECIP	-12.1426***	-12.1280***	-44.0221***	-43.9216***	*I(0)*
RH	-7.4315***	-7.4825***	-53.9948***	-54.0350***	*I(0)*
TEMP	-6.7052***	-6.6946***	-8.1404***	-8.1264***	*I(0)*
WS	-7.5845***	-7.5568***	-41.3206***	-41.1428***	*I(0)*
Augmented Dickey-Fuller					
PM2_5	-1.6927	-1.8818	-6.4942***	-6.6043***	*I(1)*
EG	-0.2626	-3.4008*	-14.3581***	-14.3383***	*I(0)/I(1)*
EC	-4.1768***	-4.1801***	-4.1687***	-4.1601***	*I(0)*
IPI	-2.0335	-2.5719	-11.9947***	-11.9716***	*I(1)*
PRECIP	-12.1720***	-12.1584**	-12.4812***	-12.4534***	*I(0)*
RH	-7.6511***	-7.7473***	-10.4290***	-10.4116***	*I(0)*
TEMP	-2.6948*	-2.6907	-15.2937***	-15.2569***	*I(0)/I(1)*

WS	-3.7096***	-3.7015**	-14.4934***	-14.4646***	*I(0)*
Kwiatkowski -Phillips-Schmidt-Shin					
PM2_5	2.1286***	0.2595***	0.1157	0.0795	*I(1)*
EG	2.0732***	0.1616**	0.0675	0.0538	*I(1)*
EC	0.1186	0.0636	0.0829	0.0411	*I(0)*
IPI	0.8980***	0.0726	0.0362	0.0363	*I(1)*
PRECIP	0.1021	0.0489	0.0877	0.0507	*I(0)*
RH	0.2259	0.0802	0.2094	0.2045**	*I(0)*
TEMP	0.0127	0.0095	0.0114	0.0070	*I(0)*
WS	0.0546	0.0523	0.1138	0.1103	*I(0)*

Source: Research finding.
Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%.

With reference to Table 4, we note that the results of the tests are roughly similar for most of the considered cases. More interestingly, even if some differences exist regarding the identification of the order of integration, none of the used tests reveal that the level of integration exceeds 2. Particularly, some among the variables in our study are stationary at level I(0) stationary, while others are stationary at first difference I(1). So that the ARDL approach is a suitable technique to apply for the cointegration analysis (Pesaran et al., 2001).

4.3 ARDL Bound Testing

According to the ARDL method, selecting the appropriate lag length for each of the variables is very essential. Therefore, using AIC lag length criteria, the (3,6,2,5,0,0,4,1) model is used for the estimating the long run relationship. Now that it has been proved that none of the variables are I(2) or beyond, we will proceed to the next stage of analysis to see if there is evidence of a long-run relationship among the variables. This can be done using the bounds testing approach provided by Pesaran et al. (2001). The ARDL bounds estimation tests the null hypothesis that no long run association exists. Decision rule is to reject H0 if the computed F-statistic lies above the upper bound of Pesaran test statistic table (the variables are co-integrated). The results of the ARDL bound test of cointegration are displayed in Table 5.

It is apparent from the results that the value of F-statistic of our model is greater than the upper bound of Pesaran test statistic at 1% level of significance.

Accordingly, we strongly reject the hypothesis of no co-integration, proving the existence of a long-run relationship between PM2.5 and the selected independent variables over the period considered.

Table 5. Bound Test for Cointegration

F-statistic	4.185182	
K	7	
Significance Level	**Bound Critical Values**	
	Lower Bound I(0)	**Upper Bound I(1)**
10%	1.92	2.89
5%	2.17	3.21
2.5%	2.43	3.51
1%	2.73	3.9

Source: Research finding.

4.4 Estimation Short-Run and Long-Run Relationships

4.4.1 Long-Run Relationships

Given that the variables have a co-integrating relationship, we can consequently estimate the short- and long-term dynamic relationships between the variables. Table 6 depicts the long-run results.

Table 6. Long-run Coefficients of ARDL

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EG	-0.001004***	0.000145	-6.935433	0.0000
EC	1.532038*	0.844782	1.813532	0.0711
IPI	0.005008	0.061910	0.080887	0.9356
PRECIP	-0.133651	0.124057	-1.077335	0.2825
RH	0.043997	0.034710	1.267583	0.2062
TEMP	0.061702	0.078987	0.781170	0.4355
WS	-0.878573	0.545000	-1.612059	0.1083
C	13.66031	8.640153	1.581027	0.1153

Source: Research finding.

Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%.

The estimated results of the long run relationship reveal that, economic growth has a negative impact on PM2.5 concentrations, which is justified by both the sign and the statistical significance of its coefficient, implying that when the economy is expanding PM2.5 concentrations are managed efficiently. This signifies that economic growth has been conducive to enhancing the quality of the environment in the United States during the study period. These results are consistent with Jiang et al. (2022).

On the contrary, we observe a positive relationship between energy consumption and $PM_{2.5}$, which means that energy consumption stimulates environmental pollution. Our findings reliably accept that the estimated coefficient is equal to 1.532038 and it is statistically significant. This is to be expected, given that the United States is the world's largest consumer of fossil fuels. The results on energy consumption corroborated the findings of Gupta et al. (2022) and Zhao et al. (2018). They found that higher energy consumption degrades environmental quality in the long run. This result is an incentive for policy makers to work on reducing PM2.5emissions. Similar to energy consumption, industrialization degrades the quality of the environment in the long run as, although as the results show, its coefficient is insignificant. In addition, as expected, temperature and relative humidity are positively correlated with PM2.5 concentrations, nevertheless they are also insignificant. Whereas the coefficient value is not significant. Regarding precipitation and wind speed, the results show that they both have an inverse relationship with PM2.5. This is justified by the fact that the estimated coefficients are equal to -0.878573 and 0.061702, respectively. The sign of these two variables is negative as expected, but both coefficients are not statistically significant.

4.4.2 Short-Run Relationships

After examining the long-run relationship of the variables, we will now analyze the short-run relationship of this model. Table 7 summarizes the short run results. These results show a strong positive relationship that is significant in the short as well as the long term, as indicated by a coefficient of 1.388173. Therefore, energy consumption is the largest contributor to PM2.5. This result is consistent with previous studies that have shown that the consumption of non-renewable energy sources such as coal and oil increases PM2.5 concentrations and thus degrades environmental quality. In contrast to the long run estimate, which showed a negative and significant impact of economic growth on PM2.5, the short run estimate validates a significant but positive relationship between the two variables, signifying that in the short term, PM2.5 concentrations increase with economic growth. As for industrialization, there is an inverse relationship with PM2.5 concentrations in the short term. This could be explained by the fact that optimizing the industrialization alleviates PM2.5 pollution. Regarding meteorological factors, the coefficient of temperature was found to be positive and significant at least than 5% level. This result indicates that temperature rises are likely to raise PM2.5 concentrations. Therefore, temperature was found to exert appositive effect on air pollution. In the case of wind speed, as for the long term, there is an inverse statistical relationship with PM2.5. The results show that the estimated coefficient is equal to -0.60, suggesting that increasing wind speed leads to a reduction in PM2.5 concentrations. The reason for this is that the higher the wind speed, the greater the dilution and diffusion of the pollutants in the air (Liu et al., 2019). Low wind speed, on the other hand, limits the diffusion of PM2.5and causes it to concentrate on the surface (Li et al., 2017). Lastly, the coefficient of cointEq or ECM (-1) is negative, as expected, and statistically significant, indicating the presence of a long-term relationship among the variables of the study. The value of ECT coefficient is -0.386978, which indicates a rapid and strong adjustment to equilibrium. In other words, about 38% of the disequilibrium in the short run converges back to the long run equilibrium monthly.

Table 7. Short-run Coefficients of ARDL

ECM Regression				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(PM2_5(-1))	-0.254940	0.055808	-4.568146	0.0000
D(PM2_5(-2))	-0.191105	0.043980	-4.345233	0.0000
D(EG)	0.001026*	0.000616	1.665731	0.0971
D(EG(-1))	0.000514	0.000618	0.831604	0.4065
D(EG(-2))	0.000666	0.000625	1.066525	0.2873
D(EG(-3))	-1.64E-05	0.000625	-0.026186	0.9791
D(EG(-4))	-0.001176	0.000626	-1.879147	0.0615
D(EG(-5))	-0.002050	0.000414	-4.947946	0.0000
D(EC)	1.388173***	0.137380	10.10459	0.0000
D(EC(-1))	0.853865	0.161464	5.288282	0.0000
D(IPI)	-0.291333***	0.100870	-2.888209	0.0042
D(IPI(-1))	-0.019891	0.097417	-0.204185	0.8384
D(IPI(-2))	-0.036433	0.095450	-0.381698	0.7030

D(IPI(-3))	0.105573	0.095905	1.100812	0.2721
D(IPI(-4))	0.354849	0.098403	3.606069	0.0004
D(TEMP)	0.065624***	0.015955	4.113075	0.0001
D(TEMP(-1))	-0.025384	0.018827	-1.348247	0.1789
D(TEMP(-2))	-0.023125	0.018474	-1.251736	0.2119
D(TEMP(-3))	0.044161	0.016467	2.681805	0.0079
D(WS)	-0.604840***	0.102283	-5.913403	0.0000
CointEq(-1)	-0.386978***	0.061980	-6.243597	0.0000
R-squared	0.641195			
Adjusted R-squared	0.610916			
Durbin-Watson stat	2.048688			

Source: Research finding.
Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%.

4.5 Diagnostic Tests of the Model

In this study, to verify the robustness and fitness of our model we used serial correlation (Breusch-Godfrey Serial Correlation LM test), heteroscedasticity (Breusch-Pagan-Godfrey test and ARCH test) and Ramsay's Reset stability tests. The results are reported in the Table 8.

Table 8. Diagnostic Tests

Test	F-statistic	Probability
Breusch-Godfrey Serial Correlation LM test	0.715331	0.3986
Breusch-Pagan-Godfrey test	1.380823	0.1041
ARCH test	1.043122	0.3081
Ramey’s RESET test	2.61669	0.0752

Source: Research finding.

Based on the test results, we can conclude that the model is free from autocorrelation, heteroskedasticity, and it is well specified. Finally, to check the stability of the long-term of the coefficient of the estimated variables in the model, the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests are used. The graphs of the CUSUM (Fig. 2) and CUSUMSQ (Fig. 3) show that, both plots lie within the 5% critical bound, indicating that, the estimated coefficients of the model are stable for the period 2000-2021 at the 5% level of significance.

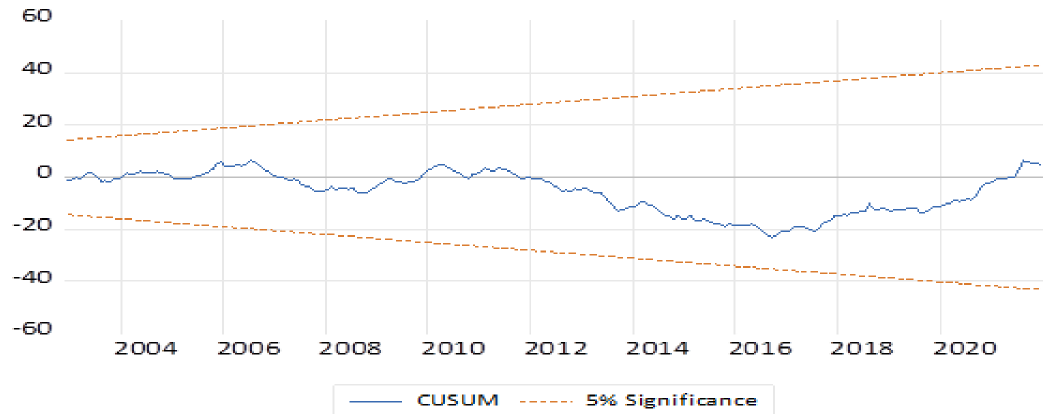

Figure 2. CUSUM Plot
Source: Research finding.

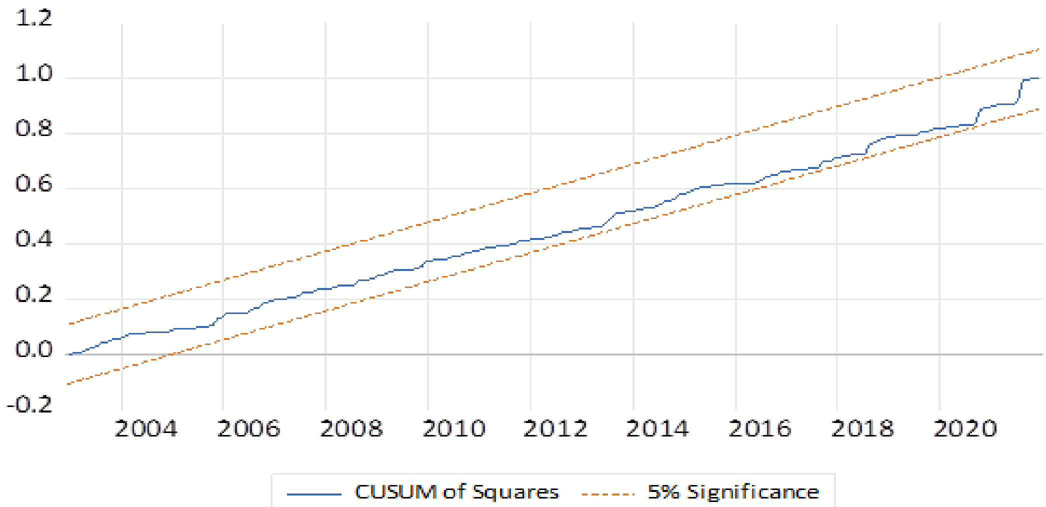

Figure 3. CUSUMSQ Plot
Source: Research finding.

4.6 Toda-Yamamoto Test Results

The final step of the investigation is to test the existence of a causal relationship between the variables; indeed, the direction of causality may be informative about the role of socio-economic and meteorological factors in reducing

PM2.5emissions. Therefore, to explore the causality and directions between the selected variables, this study used the test of Toda-Yamamoto (1995). It has been used in this study for it is suitable in the case of stationary series at different orders and in the presence of cointegration. Toda-Yamamoto's (1995) approach includes the following steps:

The first step in the Toda- Yamamoto causality test is to specify the maximum integration order (dmax). As a result of the performed ADF, PP and KPSS unit root tests, we found that the maximum order of integration was I(1). Therefore, (dmax) is determined to be 1. Then, it is required to select the appropriate lag length (k). In this context, the optimal lag length is chosen as 11 to ensure that the model is free of serial correlation.

After checking the adequacy of the VAR model, the Toda-Yamamoto causality test was performed. The findings of the test are displayed in the table 9 below.

Table 9. Toda-Yamamoto Causality Test

Independent variables	**Dependent variables**							
	PM2.5	**EG**	**EC**	**IPI**	**Precip**	**RH**	**Temp**	**WS**
PM2.5		0.8025	0.3302	0.9446	0.0545	0.0076	0.6905	0.8914
EG	0.0019		0.3499	0.0038	0.4584	0.2042	0.5993	0.8582
EC	0.0139	0.4041		0.9680	0.2826	0.0031	0.1919	0.0027
IPI	0.0739	0.4238	0.1067		0.2001	0.0412	0.7913	0.9426
Precip	0.6720	0.0000	0.3465	0.0013		0.0135	0.3114	0.4305
RH	0.8030	0.0176	0.1055	0.0863	0.2580		0.9328	0.1823
Temp	0.2924	0.0793	0.0002	0.6850	0.0214	0.2313		0.3470
WS	0.0907	0.0356	0.0985	0.1384	0.5201	0.0080	0.6168	

Source: Research finding.

As presented in Table 9, we can confirm that there is evidence of causality. More precisely, there is a unidirectional causality initiating from economic growth and energy consumption to PM2.5 concentration at 5% significance level. An equivalent trend of unidirectional causality is witnessed triggering from industrialization and wind speed to PM2.5 at the 10% significance level.

5. Conclusion and Policy Recommendation

This study examines the impact of meteorological and socioeconomic factors on PM2.5 concentrations in the United States, from January 2000 to December 2021, using the ARDL approach to cointegration. Prior to the application of modelling approach, the integration proprieties of the variables were investigated by performing the Augmented Dickey Fuller, Philipps-Perron, and Kwiatkowski-Phillips-Schmidt-Shin unit root tests.

Our findings support the existence of long-run relationship among the variables. Furthermore, from a meteorological perspective, the estimation results revealed that the coefficient of temperature has a positive and significant only in the short term, indicating that rises in temperature lead to increases in PM2.5 concentrations. In contrast, wind speed exerts a statically negative correlation with PM2.5 concentrations, suggesting that the greater the wind speed, the better the dilution and diffusion of pollutants in the air. Besides, no significant impact exists for precipitation and relative humidity.

Regarding the socioeconomic factors, the results suggest that, in both the long and short term, energy consumption worsened PM2.5 pollution. However, there exists an inverse relationship between economic growth and PM2.5 concentrations only in the long term, which contrasts with what was found in the short term. Besides, industrialization exerts a negative impact on PM2.5 concentrations only in the short term.

Finally, the analysis of the Toda Yamamoto test reveals the existence of a unidirectional causality running from economic growth, energy consumption, industrialization and wind speed to $PM_{2.5}$.

Based on the empirical findings, this study provides some important policy implications. First, since precipitation, wind speed, relative humidity, and temperature have quite different influences on PM2.5 concentrations, different air pollution reduction goals and targets should be set according to different meteorological conditions. Second, regarding energy consumption and economic growth, both are key variables influencing $PM_{2.5}$. Therefore, policy makers must very carefully balance the relation between attenuating PM2.5 concentrations and minimizing energy consumption as well as boosting economic growth when formulating policies to manage PM2.5 concentrations. Moreover, in the U.S. economy, the use of renewable energy sources has been greatly promoted in recent years. Yet, this alternative energy in the country is not quite sufficient. Even though the consumption of fossil fuels is being curtailed, this is still not enough. Therefore, the government should encourage the application and popularization of green energy such as wind and solar energy by providing substantial subsidies and incentives for the use of renewable energy and by giving more tax exemptions to companies that use clean energy to realize green economic development. Lastly, unlike in developing countries, increasing GDP in developed countries, such as in our case the United States, can lead to growth with lower PM2.5 concentrations, so policies that promote economic growth are also beneficial in terms of improving air quality.

Our analysis has some limitations in that it proves the internal validity of the findings in the context of the United States. Therefore, more investigation is necessary to ascertain whether our outcomes, related to the main drivers of PM2.5 concentrations, can be generalized to other countries. Furthermore, future studies could extend our framework by investigating the potential asymmetric cointegration between the variables under consideration.

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