



An empirical investigation of the underlying factors of recently declining air pollution in China

Emrah Eray Akça¹, Tayfun Tuncay Tosun²

¹ Department of Economics, Bartin University, Bartin, Türkiye

² Department of International Trade and Finance, Istanbul Aydin University, Istanbul, Türkiye

*Corresponding author E.mail: emrahakca@bartin.edu.tr

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Abstract

This study analyses the underlying factors of recently declining air pollution in China, utilizing annual time series data from 2000 to 2020 in the autoregressive distributed lag model approach framework. In the empirical setting, air pollution is represented by particulate matter (2.5) concentrations, known as the most detrimental ambient pollutant, and the empirical model includes several socioeconomic potential determinants of air pollution. The main motivation behind this study was the downward trend in air pollution in China as of the second decade of the 2000s. Although it is commonly accepted that the Air Pollution Prevention and Control Action Plan implemented by the Chinese State Council has been effective, the underlying factors of declining air pollution aren't clear. Based on this motivation, the study revealed the positive impacts of economic growth, industrialization, and foreign direct investment inflows on air pollution. In this respect, the overall results particularly emphasize the declining impact of an increase in medium- and high-tech exports on air pollution. In this context, to improve air quality further, the study suggests that China should transform its industrialization structure toward specialization in medium- and high-tech products and promote foreign direct investment inflows specialized in these products. This study provides additional policy recommendations for Chinese policymakers.

Keywords: Air Pollution, Industrialization, Foreign Direct Investment, Medium- and High-tech Exports, China.

Introduction

Environmental issues have been increasingly addressed globally, particularly as sustainable development goals propounded by the United Nations, and many countries have been striving to cope with environmental problems in their development paths. As a crucial indicator, particulate matter 2.5 (hereafter $PM_{2.5}$) concentrations, which are defined as the amount of fine particulate aerosol particles up to 2.5 microns in diameter, are the most detrimental air pollutants owing to their environmental prevalence and the wide range of adverse human health impacts

associated with exposure. $PM_{2.5}$ concentrations are measured in micrograms per cubic meter (μ g/m³) and consist of sulfates, nitrates, black carbon, and ammonium. The World Health Organization (WHO) set the particulate matter concentration at 10 μ g/m³ as a guide indicator in 2005, but this figure was updated to 5 μ g/m³ in 2021. PM_{2.5} concentrations exceeding the guideline value can lead to severe health risks, and exposure to these concentrations is more dangerous for elderly people, children, people with asthma, and people with severe health conditions such as cancer and diabetes. In addition, they have long-term effects on the respiratory and circulatory

systems, resulting in heart disease and deteriorated lung function (IQAir, 2022). UNEP (2023) reported that approximately four million people worldwide died from exposure to PM_{25} concentrations in 2019. All PM_{2.5} statistics provide significant insight into the nexus between air pollution caused by PM2.5 concentrations and economic development levels. Consistent with this insight, the report demonstrates that more than 90% of deaths from air pollution occur in low- and middle-income countries such as African, Central Asian, and South Asian nations. As a most likely paradoxical situation for the air pollutionincome level nexus, a significant statistic from the UNEP (2023) indicates that China was responsible for approximately 35% of PM2.5-related deaths worldwide in 2019. China has achieved extraordinary economic expansion due to the economic reforms that began in 1978 (Jiang et al., 2018; Hao et al., 2019). Over the period 1978-2021, China grew at a rate of 9.25%, on an annual average; on the other hand, these statistics were 2.99% and 2.37% for the world and Organization for Economic Cooperation Development (OECD) countries, respectively. Throughout this period, China exhibited much better growth than the world and the OECD averages, even during the COVID-19 emerged in China. While the world and the OECD experienced negative annual growth rates immediately after the 2008-09 global financial crisis and COVID-19, China grew positive. This spectacular economic expansion, however, has caused severe environmental pollution problems, particularly PM25-based air pollution, which was measured at 58.5 μ g/m³ in China in 2013 (more than 11 times the threshold value recommended by the WHO). In the same year, heavy smog was considerably observed in the northern and central areas of China, and concerns related to public health began to increase (Jiang et al., 2018; Cheng et al., 2023). The spread of smog waves resulting from PM_{2.5} concentrations has called for the Chinese government to intervene and take measures against intensified air pollution. Eventually, in 2013, the Chinese State Council put into force the Air Pollution Prevention and Control Action Plan (APPCAP), which aims to promote manufacturing technology in environmentally friendly industries through research and development, innovation, and the implementation of new technologies (Zhou and Tang, 2021). The APPCAP primarily controls air pollution by (i) rewarding firms with high energy efficiency and low emissions, (ii) providing business income tax in-

centives to high-tech companies with environmental protection projects, and (iii) offering financial support to air pollution control projects (Cheng et al., 2023). The APPCAP mapped out an ecologically friendly development route through technology and innovation. Among others, Huang et al. (2018), Feng et al. (2019), and Zhang et al. (2019) stated that APPCAP improved overall air quality and lowered mortality caused by PM_{2.5} concentrations in China. On the other hand, Ding et al. (2019) estimated the contribution of APPCAP to reducing PM₂₅ concentrations from 2013 to 2017 at a rate of 88.7%. Additionally, some studies have highlighted that energy transitions from fossil fuels to clean fuels have significantly improved the air quality in China (see Shen et al., 2021; Akça, 2024). Over 2019-2023, China has taken the lead in increasing its clean energy investment among all countries, with an increase of almost 185 billion US dollars, which is even greater than that of the European Union (International Energy Agency, 2023). In addition to the APPCAP and energy transition, other factors possibly led to a decrease in China's PM_{2.5} concentration from 58.5 $\mu g/m^3$ to 34.8 $\mu g/m^3$ (from maroon to red) over the period 2013-2020 (OECD, 2023). Nevertheless, despite all available air pollution preventive practices, the PM_{2.5} concentration in China is still much greater than the WHO guideline indicator. Drawing attention to the socioeconomic factors of the air pollution problem caused by PM25 concentrations in China, IQAir (2022) underlines that coal and other nonrenewable energy sources are still pervasive in China. This report also provides insight into China's prominent structural characteristics, such as being a rapidly industrializing nation with abundant natural resource reserves, industrial-oriented production and trade, and a large population, which may cause high PM_{2.5} concentrations. Numerous empirical studies have analyzed several socioeconomic factors, such as population density, urbanization, economic growth, industrial activity, trade openness, and natural resource abundance, to identify probable predictors of PM25 concentrations in China. Investigating the associations between air quality and socioeconomic factors within the framework of hypothesis-based approaches is crucial for more effective policy recommendations. In this context, empirical studies have tested the Environmental Kuznets Curve (EKC) hypothesis, expressing that, at the early stages of development, environmental degradation increases as the economy grows, but environmental recovery

growth reaches a threshold value begins as (Grossman and Krueger, 1996). Testing the EKC hypothesis for the rapidly expanding Chinese economy significantly advances the grasp of the knowledge about association between environmental quality and its determinants. In addition, the resource curse hypothesis by Auty (1993) contends that natural resource abundance negatively affects economic development through different channels. One of these channels may be related to environmental issues; therefore, this hypothesis might offer fundamental information on environmental degradation in a specific period for a natural resource-rich and rapidly growing developing country such as China. In addition, there are hypotheses based on foreign direct investment (FDI) inflows in countries that have grown with the significant contribution of FDI inflows, such as China. Contrasting approaches, the pollution halo hypothesis, and the pollution haven hypothesis analyze the environmental effects of FDI inflows. Supported by Talukdar and Meisner (2001), Wheeler (2001), and Perkins and Neumayer (2008), the pollution halo hypothesis claims that FDI inflows bring about lower carbon emissions and, consequently, emphasizes the qualified and environmentally friendly nature of FDI inflows. In contrast, empirically supported by Grimes and Kentor (2003), Cole (2004), Hoffmann et al. (2005), and Jorgenson (2007), the pollution haven hypothesis reveals that FDI inflows increase carbon emission levels and, consequently, emphasize the labor-intensive and polluting character of capital imported from abroad. The economic development path, with its dynamics and the course of PM2.5 concentrations, provides us with crucial sources of motivation to scrutinize the PM_{2.5}-related air pollution problem in China in conjunction with its level of economic development. Based on this motivation, this study reveals the primary factors contributing to considerably moderating the air pollution problem caused by $PM_{2.5}$:

China utilizing concentrations in appropriate econometric methods. The study's contributions to the literature are as follows(i) The best-fitting econometric techniques, as per the data features, are employed to provide robust results. (ii) This study provides evidence for the validity of the natural resource curse hypothesis from an environmental perspective for China. (iii) This study also hierarchically tests the pollution haven or pollution halo hypotheses for China. (iv) This study highlights the significance of medium- and high-tech exports in lowering PM25 concentrations through strengthening China's technological transformation in foreign trade. (v) Thus, based on the empirical findings, our study may also guide the policy-making process of nations with severe air pollution problems to improve air quality by revealing the factors reducing PM₂₅ concentrations in China. The remainder of the study is structured as follows: The material and methods employed in the empirical analysis are described in Section 2. The results and discussion are included in Section 3, and Section 4 provides concluding remarks.

Material and Methods

This study builds an econometric model to capture the underlying dynamics of PM2.5 concentrations utilizing China's annual time series from 2000 to 2020. Several factors could be incorporated into the econometric model; however, the data availability and analysis framework constrict the variable choice, particularly given that the PM_{2.5} concentration series consecutively started in 2000. However, after taking a glance at China's socioeconomic dynamics and transformation that happened as of the beginning of the 21st century, the most notable variables are included in the econometric model. These variables have also been argued on a global scale in recent years in the context of determinants of air quality. Herewith, the study estimates the following dynamic stochastic regression model (Equation [1]):

$InPM_{2.5_t} = \beta_0 + \beta_1 InGDPpc_t + \beta_2 InIND_t + \beta_3 InFDI_t + \beta_4 InMHTE_t +$ [1] $\beta_5 InREC_t + \beta_6 InCR_t + \beta_7 InRD_t + \varepsilon_t$

In Equation [1], ln refers to the natural logarithmic operator, and ε is the composite error term. The air pollution indicator PM_{2.5} is the dependent variable that shows mean population exposure to PM_{2.5} concentrations in China from 2000 through 2020,

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data for this variable are retrieved from the OECD (2023) database. The econometric model of the study involves seven independent variables thought to be conducive to changing $PM_{2.5}$ concentrations in China. The first independent variable is gross domestic product per capita (GDPpc) at constant 2015 prices and shows the economic growth path in US dollars. The second one, IND, represents the industrialization level and is measured as the value-added share of industry, including construction, in GDP. Another variable is foreign direct investment (FDI), measured as the share of net inflows in GDP. Medium- and high-tech exports (MHTE) are the shares of medium-

and high-tech manufactured exports in total manufac-

tured exports, and renewable energy consumption (REC) is the share of renewable energy in total final energy consumption. Coal rents (CR) are the difference between the value of both hard and soft coal production at world prices and their total costs of production and are expressed as a percentage of GDP. Finally, research and development expenditure (RD) represents gross domestic expenditures on research and development expressed as a percentage of GDP. All the independent variables are retrieved from the World Bank's (2023) World Development Indicators. In Table 1, descriptive statistics of all variables and the pairwise Pearson correlation matrix are presented.

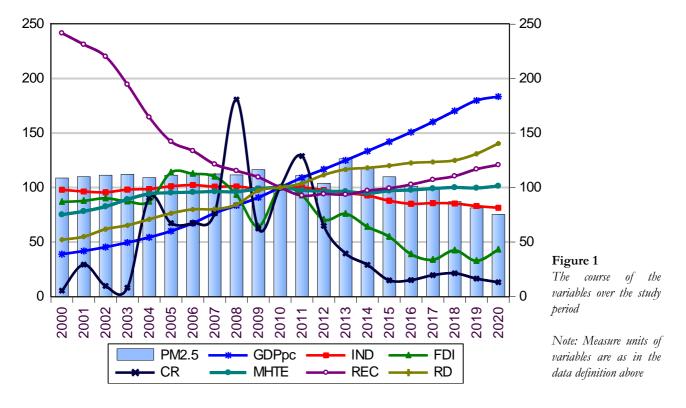
		Des	criptive sta	tistics (no	on-logarithmi	C			Table 1
Variables	М	[ean	Median		Std. dev.	Max.		Min.	Descriptive statistics and
$PM_{2\cdot 5}$		49.123	50.8	61	5.651	58.	481	34.841	pairwise
GDP _{pc}	5	858.151	5647.0	69	2720.203	10358	3.17	2193.897	correlations
IND		43.943	45.2	23	3.164	47.	557	37.843	
FDI		3.014	3.4	-75	1.052	4.	554	1.311	Note:
MHTE		57.103	58.3	44	4.329	61.	365	45.491	Measure uni of descriptiv
REC		16.401	14.1	41	5.858	29.	631	11.341	statistics are
CR		1.383	0.8	02	1.259	4.	953	0.147	in the data
RD		1.661	1.7	'14	0.464	2.	406	0.893	definition
		Pairwise co	orrelations b	etween v	variables (loga	rithmic)			above
Variables	PM _{2·5}	GDP _{pc}	IND	FDI	MHTE	REC	CR	RD	
PM _{2.5}	0.00	L -							
GDPpc	-0.53	0.00							
IND	0.75	-0.68	0.00						
FDI	0.66	-0.72	0.94	0.00					
MHTE	-0.33	0.76	-0.31	-0.38	0.00				
REC	0.11	-0.84	0.25	0.36	-0.87	0.00			
CR	0.31	0.02	0.58	0.47	0.43	-0.45	0.00		
RD	$PM_{2\cdot 5}$	0.98	-0.67	-0.71	0.83	-0.88	0.06	0.00	

According to the descriptive statistics, the mean $PM_{2.5}$ concentration was 49.123 µg/m³, of which the maximum value was 58.481 in 2013 and the minimum value was 34.841 in 2020. China paints a different image in the first and second decades of the 21st century in $PM_{2.5}$ concentrations. While the first decades testified to a modestly rising trend of $PM_{2.5}$ concentrations, in the second decades, especially as of 2013, China made substantial progress in reducing $PM_{2.5}$ concentrations. The GDP per capita of the Chi-

nese economy was 5 thousand 858 dollars on average over the period 2000–2020, together with a continuously increasing trend, and reached a value of almost 10 thousand 358 dollars in 2020. On the other hand, the mostly decreasing trend in industrialization may be interpreted as a change in the components of economic growth. The share of value added to industry in terms of GDP was, on average, nearly 44% and dropped to 37.8% in 2020. A similar situation is observed for net FDI inflows, which al-

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most constitute 3% of GDP from 2000 to 2020. While net FDI inflows corresponded to 4.5% of GDP in 2005, their share of GDP dropped to 1.3% in 2019. In contrast, medium- and high-tech exports period. during the relevant increase These corresponding to 57% of total manufacturing exports, on average, had a maximum value of 61.4% and a minimum value of 45.5% in 2000. Another salient statistic concerns renewable energy consumption, the mean value was 16.4% during the research period. Even if the absolute value of renewable energy consumption in China has increased, its share of total final energy consumption has decreased markedly since the beginning of the 2000s. Having a quite unsteady course, coal rents, on average, constitute nearly 1.4% of GDP, with a maximum value of approximately 5% in 2008. Finally, R&D expenditures gradually increased from 2000 to 2020, corresponding to 2.4% of the GDP in 2020. Figure 1 shows the course of the variables, which are scaled by the 2010=100 index, to observe the paths of the variables across the pertinent period. Accordingly, as of 2013, a continuous decrease in $PM_{2.5}$ concentrations was clear, and coal rents were generally quite unstable. Additionally, while the GDP per capita has consistently soared, the share of renewable energy consumption in total final energy has considerably decreased.



The results of pairwise correlations matter, especially in detecting multicollinearity problems among independent variables. In this respect, there is a high correlation between GDPpc, REC, and RD. Similarly, FDI is strongly correlated with IND, as are the correlations among MHTE, REC, and RD. $PM_{2.5}$ concentrations are positively correlated with IND, FDI, REC, and CR; on the other hand, they are negatively correlated with GDPpc, MHTE, and RD. Following these preliminary statistical analyses, strong proof of the underlying factors of $PM_{2.5}$ concentrations requires necessary empirical analysis.

Results and Discussion

By analyzing the underlying factors of the $PM_{2.5}$ concentration in China, this study follows the procedure of time series analysis. In this context, first, several unit root tests are conducted on the variables since doing so matters in determining the most fitting analysis techniques. Without detecting the stationarity of the variables, obtaining unbiased and efficient estimation results is unlikely warranted. For instance, in the case of nonstationary variables, ordinary least squares estimations have been spurious and cannot yield reliable results. Again, econometric models,

which involve variables with different stationary situations, require a method peculiar to this model characteristic. Hence, before passing to an estimation of the econometric model in Equation [1], the most commonly used unit root tests in the literature, the augmented Dickey-Fuller (ADF) and Philips–Perron (PP) tests, are performed to determine the integration degrees of all series, and the results are presented in Table 2.

			1	able 2.				
		AD	F	PP	Table 2			
Variables		Test stat.	Prob.	Test stat.	Prob.	Unit root test		
1 DM	Level	0.006[0]	0.948	0.167[2]	0.963	- Results		
$lnPM_{2.5}$	First Difference	-5.445[0]*	0.000	-5.328[2]*	0.000	NT-4 * ** 1 ***		
	Level	-3.915[0]*	0.001	-3.023[2]**	0.049	— Note: *, **, and *** indicate that the test		
$\ln \text{GDP}_{\text{pc}}$	First Difference					<i>statistics are significant</i>		
lnIND	Level	-0.906[0]	0.935	-0.985[1]	0.924	at the 1%, 5%, and		
	First Difference	-3.494[0]***	0.068	-3.468[1]***	0.072	10% levels, respectively.		
lnFDI	Level	-0.906[0]	0.765	-0.792[2]	0.799	The values in brackets		
	First Difference	-5.151[0]*	0.001	-5.209[2]*	0.000			
InMHTE	Level	-4.817[0]*	0.001	-4.619[2]*	0.002	length determined		
	First Difference					according to the Schwarz		
lnREC	Level	-2.947[0]***	0.058	-2.653[2]***	0.099	Information Criteria for		
	First Difference					ADF tests and show		
lnCR	Level	-2.514[0]	0.127	-2.487[2]	0.133	the bandwidth		
	First Difference	-6.024[0]*	0.001	-6.182[2]*	0.001	determined according to		
lnRD	Level	-2.393[0]	0.156	-2.393[2]	0.156	— the Barnet Kernel		
	First Difference	-3.312[0]**	0.028	-3.312[2]**	0.029	predictor for the PP test.		

According to both unit root test results, the variables GDPpc and REC are stationary at levels, and the other variables are stationary according to their first differences; i.e., all the variables are not integrated in the same order. These stationary characteristics of the variables cannot enable us to perform the ordinary least squares estimator, but the existence of a level relationship between the dependent variable and a set of regressors can be questioned by employing a variety of cointegration methods. In our case, we should apply the autoregressive distributed lag (ARDL) bounds testing approach originated by Pesaran et al. (2001) because the series is integrated at different orders. The bounds testing approach is based on standard F- and tstatistics, of which asymptotic distributions are nonstandard under the null hypothesis, referring to no level relationship between variables irrespective of whether the regressors are I (0) or I (1), by which the significance of the lagged levels of the variables in a univariate equilibrium correction mechanism is tested.

The ARDL cointegration approach has several advantages over other cointegration techniques (Odhiambo, 2009). First, the most important advantage is that there is no restrictive assumption on the variables, as they must be integrated in the same order. That is, the ARDL approach can be applied without considering whether the series are integrated of order zero or order oe. However, this feature of the ARDL approach does not eliminate the need to perform unit root tests because some series may be stationary at the second order, even if the possibility is quite low. Second, the ARDL approach is not as sensitive to sample size as other techniques are and may perform well in small samples. Third, the ARDL approach generally yields unbiased long-run estimates even when some of the regressors in the model are endogenous. In addition, long- and short-run coefficients may be synchronously estimated in the framework of the ARDL approach. Considering these advantages, the econometric model in Equation [2] is expressed in an ARDL form as follows:

$$\Delta InPM_{2.5_{t}} = \begin{pmatrix} \alpha_{0} + \sum_{i=1}^{m} \beta_{1i} \Delta InPM_{2.5_{t-i}} + \sum_{i=0}^{m} \beta_{2i} \Delta InGDPpc_{t-i} + \sum_{i=0}^{m} \beta_{3i} \Delta InIND_{t-i} + \sum_{i=0}^{m} \beta_{4i} \Delta InFDI_{t-i} \\ + \sum_{i=0}^{m} \beta_{5i} \Delta InMHTE_{t-i} + \sum_{i=0}^{m} \beta_{6i} \Delta InREC_{t-i} + \sum_{i=0}^{m} \beta_{7i} \Delta InCR_{t-i} + \sum_{i=0}^{m} \beta_{8i} \Delta InRD_{t-i} \\ + \beta_{9}InPM_{2.5_{t-1}} + \beta_{10}InGDPpc_{t-1} + \beta_{11}InIND_{t-1} + \beta_{12}InFDI_{t-1} + \beta_{13}InMHTE_{t-1} \\ + \beta_{14}InREC_{t-1} + \beta_{15}InCR_{t-1} + \beta_{16}InRD_{t-1} + \varepsilon_{t-1} \end{pmatrix}$$

$$[2]$$

In Equation [2], all variables are as defined in Equation [1], and Δ symbolizes the first difference operator. According to the ARDL approach procedure, in the first stage, based on the joint Fstatistic, bounds testing is performed for cointegration analysis. Because the asymptotic distribution of Fstatistics is nonstandard under the null hypothesis, which refers to no cointegration between variables, Pesaran et al. (2001) defined two sets of critical values for a given significance level, i.e., lower and upper critical values. Regarding the decision for cointegration, if the computed test statistic exceeds

the upper critical bounds, the existence of cointegration is confirmed. In contrast, there is no cointegration when the computed test statistic is lower than the lower critical bounds value. As a third alternative, computed statistics may fall into upper and lower bounds; thus, a clear inference concerning cointegration cannot be made. Thus, to pass to the estimation of parameter coefficients, first, the existence of cointegration must be affirmed. Ultimately, the study estimates the model in Eq. 2 as per the ARDL analysis procedure, and the results are exhibited in Table 3.

Predictors	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	
$\ln(CDD)$	0.079***						
$\ln(\mathrm{GDP}_{\mathrm{pc}})$	[0.033]						
ln(IND)		2.905*		2.354*	1.867*		
		[0.489]		[0.417]	[0.455]		
ln(FDI)	0.544**		0.253*			0.766*	
	[0.102]		[0.034]			[0.056]	
ln(MHTE)			-3.758*				
			[0.733]				
ln(REC)				0.149			
				[0.127]			
ln(CR)		-0.081***				-0.164*	
		[0.037]				[0.015]	
ln(RD)					-0.205		
					[0.155]		
Constant	1.287*	-3.106*	8.217*	-2.378*	-1.356	1.337*	
	[0.139]	[0.807]	[1.298]	[0.747]	[0.771]	[0.026]	
Selected	(A A 2)	(1,2,2)	(2, 4, 2)	(1, 2, 0)	(1,0,2)	(1,2,4)	
Model	(4,4,3)	(1,3,2)	(2,4,2)	(1,3,0)	(1,0,3)	(4,3,4)	
Ramsey	0.904 1.275		1.009	2 901	2 401	0 5 1 5	
Reset Test	0.894	1.375	1.009	2.801	2.491	2.515	
Bounds	DE 4E1* 4 200*		6.071*	2 (12***	2 7 4 2 4 4 4	1 47 1 544	
Test	25.451*	4.389*	6.271*	3.643***	3.743***	147.151*	

Empirical results based on the ARDL approach

Note: *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in [brackets].

As shown in Table 3, Equation [2] is hierarchically estimated to primarily avoid the multicollinearity problem. A review of the correlation coefficients between the independent variables in Table 1 reveals that most of the variables are strongly correlated with each other. This problem weakens the robustness of the estimation and most likely leads to biased and inefficient results. Therefore, explanatory variables are separately included in the estimation by considering their correlation relationships. Another reason for hierarchical estimation is the lack of a sufficient number of observations, which restricts the inclusion of all variables in the estimation simultaneously. The study estimates six different model specifications determined based on correlation results. For all the models, after ascertaining a suitable lag number, the ARDL models were selected according to the Akaike information criterion (AIC). The Ramsey Reset test results refer to the nonexistence of model specification mistakes for all the models. The results of bounds tests for cointegration show that all the model specifications are significant. In other words, null hypotheses are rejected because the computed Fstatistics are higher than the upper critical bounds values. This means that cointegration occurs among the examined variables for all the model specifications and enables us to estimate the long-run coefficients. The empirical findings of the six models are summa-

rized as follows: (i) GDP per capita is statistically significant but has a very low positive effect on PM₂₅ concentrations. These findings may be interpreted as follows: the Chinese economy did not all grow in an environmentally friendly way, and growth dynamics embody some polluting components, even though they had a weak spurring impact of economic growth on PM2.5 concentrations. However, this result does not enable us to make inferences regarding the position of the Chinese economy in the EKC pattern. To determine the extent of growth in the Chinese economy through the EKC path, the square of economic growth should be incorporated into the model. This is out of the scope of this research due to principally methodological limitations. (ii) In some way supporting this finding, in recent times, FDI has considerably contributed to the economic development path of China; FDI inflows are statistically significant and positively affect PM₂₅ concentrations. FDI inflows are statistically significant and give rise to greater PM2.5 concentrations, confirming that the pollution haven hypothesis is valid for China during the relevant period. (iii) Industrialization is statistically significant in all the model specifications and has a strong positive influence on the PM_{2.5} concentrations. As a result, industrialization is evaluated as the primary source of air pollution, proxied by PM2.5 concentrations in China. (iv) Medium- and high-tech exports are found to be significant and have a strong negative impact on PM₂₅ concentrations. This finding indicates that medium- and high-technology exports were the primary drivers of the declining trend in PM₂₅ concentrations over the relevant timeframe. As a result, one of the most important supporters of China's APPCAP policy is medium- and high-tech exports, which symbolize the technological transformation of China's foreign trade. This result may most likely shed light on the mystery of the declining trend in PM25 concentrations in China in recent years. On the other hand, (v) unexpectedly, renewable energy consumption is not one of the underlying dynamics of PM2.5 concentrations in China because it is found to be statistically insignificant. (vi) A similar evaluation may be made for R&D expenditures that have no significant impact on PM₂₅ concentrations. Recently, given that a considerable amount of research and development expenditures in the energy domain have been allocated for renewable energy, these insignificant findings are consistent with each other. Finally, (vii) the estimation results refer to

the statistically significant disincentive effect of coal rents on PM25 concentrations. Initially, this may be considered an unexpected and surprising result because coal is a nonrenewable energy source and is known as one of the most polluting factors of air in the literature. However, the study does not take coal production or consumption into account in a traditional style; instead, coal rents are considered owing to the particular need to seek a comprehensive answer to the question "Is the NRC hypothesis valid for China from an environmental perspective?". The results indicate that China eliminates the NRC hypothesis from an environmental perspective by utilizing rents from coal sources in the adoption and extension of a less-polluting production and trade structure.

Concluding remarks

At the beginning of the 2000s, as a notable emerging market economy, China significantly made progress in several components of its economic development path, such as GDP per capita, FDI inflows, and trade volume. However, in parallel with these achievements, increasingly rising concerns about air pollution in China have called for policymakers to take some steps. In return for this call, in 2013, the Chinese State Council put into action the APPCAP to promote manufacturing technology in environmentally friendly industries by rewarding firms with high energy efficiency and low emissions, providing business income tax incentives to high-tech companies with environmental protection projects, and offering financial support to air pollution control projects to promote innovation. Overall, on the one hand, the APPCAP has succeeded in alleviating air pollution; on the other hand, it has brought about some transformations in economic structure. Of course, these transformations have been reducing factors of air pollution. On the one hand, while this study accepts the positive role of the APPCAP in reducing air pollution, on the other hand, the question of 'what elements contributed to this achievement' has made a sensation. In this context, within the framework of the ARDL approach, this study analyzed the underlying factors of air pollution represented by PM_{2.5} concentrations in China for the period 2000-2020, most of which are likely highly associated with APPCAP. The analysis results strongly shed light on the factors influencing the decrease in PM_{2.5} concentrations. As important components of econo-

mic development, GDP per capita, industrialization, and FDI inflows act as air-polluting factors. In other words, improvements in these factors also lead to an unclear environment. From this window, either declining or structural transformation in these factors would lead to a cleaner environment. In recent years, a downward trend in PM2.5 concentrations may be attributed to a declining trend in industrialization and FDI inflows. However, since they are important components of the economic development process, structural transformation of these factors is necessary. In other words, the industrialization process and FDI inflows should be more environmentally friendly. In some way, guiding this argument, medium- and hightech product exports are strongly and negatively associated with PM2.5 concentrations. This means that both industrialization structures should focus on medium- and high-tech products and that FDI types specializing in medium- and high-tech goods should be encouraged. These recommendations seem to be applied within the APPCAP, which suggests a similar approach. Therefore, this plan should be strictly continued and even gone further. At the point of resource, coal rents may help to create a more qualified environment due to their negative impact on PM_{2.5} concentrations.

References

AHMAD F., DRAZ M.U., OZTURK I., SU L., RAUF A. (2020) Looking for asymmetries and nonlinearities: the nexus between renewable energy and environmental degradation in the Northwestern provinces of China. Journal of Cleaner Production 266: 1-17. https://doi.org/10.1016/j.jclepro.2020.121714

AKÇA E.E. (2024) Do renewable energy sources improve air quality? Demand-and supply-side comparative evidence from industrialized and emerging industrial economies. Environmental Science and Pollution Research 31(1): 293-311. https://doi.org/10.1007/s11356-023-30946-2

AUTY R. (1993) Sustaining development in mineral economies: The resource curse thesis. Oxford University Press, New York.

CHENG Y., DU K., YAO X. (2023) Stringent environmental regulation and inconsistent green innovation behavior: Evidence from air pollution prevention and control action plan in China. Energy Economics 120: 1-12. https://doi.org/10.1016/j.eneco.2023.106571

COLE M.A. (2004) Trade, the pollution haven hypothesis, and the environmental Kuznets curve: examining the linkages. Ecological Economics 48(1): 71-81. https://doi.org/10.1016/j.ecolecon.2003.09.007 DING D., XING J., WANG S., LIU K., HAO J. (2019) Estimated contributions of emissions controls, meteorological factors, population growth, and changes in baseline mortality to reductions in ambient PM 2.5 and PM2.5-related mortality in China, 2013-2017. Environmental Health Perspectives 127(6): 1-12. https://doi.org/10.1289/EHP4157

FENG Y., NING M., LEI Y., SUN Y., LIU W., WANG J. (2019) Defending blue sky in China: Effectiveness of the "Air Pollution Prevention and Control Action Plan" on air quality improvements from 2013 to 2017. Journal of Environmental Management 252: 1-13. https://doi.org/10.1016/j.jenvman.2019.109603

GRIMES P., KENTOR J. (2003) Exporting the greenhouse: Foreign capital penetration and CO2 emissions 1980-1996. Journal of World-Systems Research 9(2):261–275. https://doi.org/10.5195/jwsr.2003.244

GROSSMAN G.M., KRUEGER A.B. (1996) The inverted-U: what does it mean? Environment and Development Economics 1(1):119-122. https://doi.org/10.1017/S1355770X00000450

HAO Y., XU Y., ZHANG J., HU X., HUANG J., CHANG C. P., GUO Y. (2019) Relationship between forest resources and economic growth: Empirical evidence from China. Journal of Cleaner Production 214: 848-859. https://doi.org/10.1016/j.jclepro.2018.12.314

HOFFMANN R., LEE C.G., RAMASAMY B., YEUNG M. (2005) FDI and pollution: a Granger causality test using panel data. Journal of International Development: The Journal of the Development Studies Association 17(3):311-317. https://doi.org/10.1002/jid.1196

HUANG J., PAN X., GUO X., LI G. (2018) Health impact of China's Air Pollution Prevention and Control Action Plan: An analysis of national air quality monitoring and mortality data. The Lancet Planetary Health 2(7): 313-323. https://doi.org/10.1016/S2542-5196(18)30141-4

INTERNATIONAL ENERGY AGENCY (2023) World energy investment report. <u>https://www.iea.org/reports/</u> world-energy-investment-2023

IQAIR (2022) World air quality report. https://www.iqair.com/world-air-quality-report

JIANG P., YANG J., HUANG C., LIU H. (2018) The contribution of socioeconomic factors to PM2.5 pollution in urban China. Environmental Pollution 233: 977-985. https://doi.org/10.1016/j.envpol.2017.09.090

JORGENSON A.K. (2007) Does foreign investment harm the air we breathe and the water we drink? A cross-national study of carbon dioxide emissions and organic water pollution in less-developed countries, 1975 to 2000. Organization & Environment 20(2): 137-156. https://doi.org/10.1177/1086026607302153 ODHIAMBO N.M. (2009) Energy consumption and economic growth nexus in Tanzania: An ARDL bounds testing approach. Energy Policy 37(2): 617-622. https://doi.org/10.1016/j.enpol.2008.09.077

OECD (2023) Exposure to PM2.5 in countries and regions. <u>https://stats.oecd.org/Index.aspx?DataSetCode=</u> <u>EXP_PM2_5</u>

PERKINS R., NEUMAYER E. (2008) Fostering environment efficiency through transnational linkages? Trajectories of CO₂ and SO₂, 1980–2000. Environment and Planning A 40(12): 2970-89. <u>https://doi.org/10.1068/a4089</u>

PESARAN M.H., SHIN Y., SMITH R.J. (2001) Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics 16(3): 289-326. https://doi.org/10.1002/jae.616

SHEN Y., SU Z. W., MALIK M. Y., UMAR M., KHAN Z., KHAN, M. (2021) Does green investment, financial development and natural resources rent limit carbon emissions? A provincial panel analysis of China. Science of the Total Environment 755: 1-12. https://doi.org/10.1016/j.scitotenv.2020.142538

https://doi.org/10.1016/j.scitotenv.2020.142538

TALUKDAR D., MEISNER C.M. (2001) Does the private sector help or hurt the environment? Evidence from carbon dioxide pollution in developing countries. World Development 29(5): 827-840. https://doi.org/10.1016/S0305-750X(01)00008-0

UNEP (2023)Pollution action note-Data you need to know.

https://www.unep.org/interactive/air-pollution-note/

WHEELER D. (2001) Racing to the bottom? Foreign investment and air pollution in developing countries. The Journal of Environment & Development 10(3):225-245. https://doi.org/10.1177/10704965-0101003-02

WORLD BANK (2023) World Development Indicators. <u>https://databank.worldbank.org/source/world-</u> <u>development-indicators</u>

ZHANG X., XU X., DING Y., LIU Y., ZHANG H., WANG Y., ZHONG J. (2019) The impact of meteorological changes from 2013 to 2017 on PM 2.5 mass reduction in key regions in China. Science China Earth Sciences 62: 1885-1902.

https://doi.org/10.1007/s11430-019-9343-3

ZHOU L., TANG L. (2021) Environmental regulation and the growth of the total-factor carbon productivity of China's industries: Evidence from the implementation of action plan of air pollution prevention and control. Journal of Environmental Management 296:1-12.

https://doi.org/10.1016/j.jenvman.2021.113078