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Air Pollution and Solar Photovoltaic Power Generation: Evidence from South Korea

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ABSTRACT

Solar energy, with its declining costs and enhanced efficiency, is a viable alternative to traditional fossil fuels. However, its effectiveness is compromised by atmospheric and meteorological conditions, particularly air pollution, which reduces solar radiation and panel efficiency. This study estimates the impact of air pollution on solar photovoltaic (PV) power generation in South Korea, a rapidly industrializing nation with high levels of air pollution and a growing focus on renewable energy. Using hourly power generation data from 2006 to 2013 and addressing potential endogeneity of PM10 with an instrumental variable approach, we find that a 10 mg/m^3 increase in PM10 reduces solar power generation by 2.17 MWh, resulting in an estimated annual economic loss of approximately USD 2.2 million during the study period. These findings highlight the urgent need to mitigate air pollution to enhance solar power efficiency and maximize the social benefits of renewable energy.

1. Introduction

The global shift toward renewable energy is critical for addressing climate change and ensuring a sustainable energy future. The adoption of renewable energy can be influenced by various factors, including policy support, population demographics, and the influence of traditional energy sectors (Bourcet, 2020; Escoffier et al., 2021). Among renewable energy options, solar energy has emerged as a leading contender in this transition, primarily due to improvements in efficiency and declining costs of solar panels. Innovations in solar cell technology, such as the development of new semiconductor materials, enhanced cell designs, and refined manufacturing techniques, have led to higher energy conversion rates, allowing solar panels to generate more electricity from the same amount of sunlight (Green et al., 2019; Yang et al., 2017).

Furthermore, the decreasing costs of solar photovoltaic (PV) systems have played a pivotal role in their widespread adoption and increased cost-effectiveness. Policies aimed at supporting renewable energy deployment, such as feed-in tariffs, tax incentives, and renewable portfolio standards, have spurred demand and investment in solar PV technology (Jacobsson and Bergek, 2011; Sovacool and Dworkin, 2014). Technological advancements, including improvements in solar cell efficiency, manufacturing processes, and materials, have further contributed to cost reductions in PV modules and system components (Creutzig et al., 2017; Breyer et al., 2018). Additionally, economies of scale resulting from increased production volumes and market competition have further driven down costs (Feldman et al., 2012; REN21, 2021). Collectively, these factors have transformed solar PV into a competitive and cost-effective energy option, challenging traditional perceptions of its affordability and viability.

However, despite its promise, solar power generation faces significant variability due to atmospheric and meteorological conditions, potentially impacting its cost-effectiveness and reliability. Air pollution, in particular, poses a critical challenge to solar power deployment. It diminishes both solar radiation reaching the Earth's surface and the efficiency of solar panels themselves. This occurs through two primary mechanisms: scattering, where air pollution particles disperse sunlight, reducing the amount reaching solar panels, and absorption, where these particles directly absorb a portion of the solar radiation. Both mechanisms lead to decreased power output (Kawajiri et al., 2011; Li et al., 2017; Sweerts et al., 2019).

While previous studies have examined the relationship between air pollution and solar power generation, there remains a lack of consensus, particularly concerning South Korea. Research conducted in other countries, such as China (Li et al., 2017), India (Ghosh et al., 2022), and Malaysia (Mekhilef et al., 2012), with differing geographic, climatic, and industrial contexts, may not be directly applicable to the South Korean situation. Moreover, prior studies within South Korea have often been limited in scope or methodology, with some neglecting to address

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potential endogeneity issues, as exemplified by the study by Son et al. (2020) which focused on only two regions.

This study aims to address this gap by providing robust estimates of the impact of air pollution, specifically PM10, on solar power generation in the South Korean context. We seek to quantify the magnitude of PM10's effect on solar power generation, investigate whether this impact varies over time or exhibits lagged effects, and assess the economic implications of reduced solar power output due to air pollution.

To answer these questions, we utilize a comprehensive dataset consisting of hourly nationwide data for solar power production, air pollution, and meteorological conditions from 2006 to 2013. To address potential endogeneity and autocorrelation issues, we employ the Newey-West instrumental variable regression model, using wind direction as an instrument for PM10. This approach allows us to obtain unbiased estimates of the causal relationship between air pollution and solar power generation.

Our study makes several key contributions to the literature. First, it provides novel and unbiased estimates of the impact of air pollution on solar power generation in South Korea, a country with unique geographical, climatic, and industrial characteristics. Second, it employs a robust econometric methodology to address endogeneity concerns, ensuring the validity of our findings. Third, it quantifies the economic consequences of reduced solar power generation due to air pollution, providing valuable insights for policymakers.

By addressing these research questions and offering robust empirical evidence, our study aims to inform policy discussions and support the development of effective strategies to promote the use of solar energy and reduce air pollution in South Korea and other countries facing similar challenges in transitioning to renewable energy sources.

2. Background

2.1. Solar PV system in South Korea

The adoption and deployment of solar PV systems in South Korea have been significantly influenced by a range of government policies designed to promote renewable energy and reduce greenhouse gas emissions. Numerous major policies, including subsidies, tax incentives, and regulatory frameworks, have played a vital role in shaping the adoption of solar PV systems in the country. While most of these initiatives were primarily implemented after 2010 and thus fall outside the scope of this research, it's important to acknowledge their contribution to the current solar energy landscape.

Before 2010, one key aspect of the policy landscape was the provision of subsidies and financial incentives to stimulate investment in solar PV technology. Park and Koo (2018) highlight the instrumental role of government subsidies in driving the uptake of solar PV systems among households and businesses. A notable example is the feed-in tariff (FIT) scheme introduced in 2002. The FIT aimed to accelerate solar energy adoption by offering long-term contracts to solar power producers, guaranteeing a fixed price for electricity fed back into the grid. This policy provided a stable and attractive return on investment, thereby fostering the growth of the solar energy sector. Indeed, the FIT scheme led to a substantial increase in solar power capacity, from 5.9 MW in 2003 to 730 MW in 2011, and a corresponding rise in the number of PV companies.

However, the rapid expansion fueled by the FIT scheme also led to concerns about its financial sustainability. To manage the growth and associated costs, the government introduced capacity caps in 2010 and 2011. Ultimately, due to the escalating financial burden of the FIT subsidies, the scheme was replaced in 2012 with the Renewable Portfolio Standard (RPS). The RPS aims to increase the share of renewable energy in the country's energy mix by mandating that a certain percentage of electricity generation comes from renewable sources (Alsharif et al., 2020).

2.2. Air pollution in South Korea

South Korea has faced significant air pollution challenges stemming from various sources, including industrial activities, vehicle emissions, and transboundary pollution from China (Crawford et al., 2021). Notably, the concentration of fine particulate matter (PM2.5) in Seoul often exceeds the World Health Organization's guidelines, reaching levels approximately twice the recommended limit (Trnka, 2020). PM10, another key air pollutant relevant to this study, also exhibits elevated concentrations at times, primarily originating from similar sources as PM2.5.

While South Korea generally experiences lower average air pollution levels compared to countries like Malaysia and India, it experiences substantial spikes during the winter and spring. These spikes are attributed to a combination of factors, including increased energy generation for heating, changes in atmospheric circulation patterns, the influx of Asian dust storms, and occasional temperature inversions (Kim, 2019; Seo et al., 2018; Lee et al., 2004).

Consequently, the impact of air pollution on solar PV power generation in South Korea can vary seasonally and with changing weather conditions. This study carefully considers these temporal and meteorological factors to isolate and analyze the specific effects of ambient particulate matter on solar power generation.

3. Conceptual framework

This section presents a conceptual framework for understanding the impact of air pollution on solar photovoltaic power generation. It outlines the physical mechanisms affecting the energy conversion process of solar panels, supported by relevant studies.

The primary mechanism we focus on is the reduction of solar radiation reaching the ground due to air pollution. Particulate matter, such as PM10, scatters and absorbs sunlight, diminishing the amount that reaches the Earth's surface and consequently reducing solar panel output and energy conversion efficiency. Studies have shown significant reductions in solar radiation due to air pollution, with decreases of over 20 % reported in China (Li et al., 2017) and up to 52 % in India (Ghosh et al., 2022).

Another mechanism is the deposition of particulate matter on solar panels, creating a barrier that hinders sunlight from reaching the photovoltaic cells. This "soiling effect" reduces panel efficiency and power output. Research has demonstrated efficiency reductions of up to 28.7 % due to pollution (Chaichan et al., 2015), with the impact varying based on factors like panel tilt angle and accumulation levels (Zhou et al., 2019). While soiling is a concern in regions with high pollution and low rainfall, South Korea's high annual precipitation mitigates this issue, making it less relevant to our study.

Additionally, meteorological conditions can influence solar panel efficiency. High temperatures can decrease efficiency, while high humidity can lead to moisture buildup on panels, also hindering performance. Studies have confirmed the impact of ambient temperature on solar power output (Karagulian et al., 2015).

Lastly, the specific type of solar panel can affect its susceptibility to air pollution's impacts. Some panels may be more resistant to soiling or tolerant to atmospheric changes (Zhou et al., 2019). However, during our study period (2006–2013), variations in panel types in South Korea were relatively limited due to the nascent stage of solar power development, minimizing this concern.

We focus primarily on the reduction of solar radiation in the context of South Korea. This is a pressing issue in many regions, and Korea offers a unique case study. Its high precipitation minimizes soiling concerns, and its small size and relatively uniform meteorological conditions facilitate controlling for weather-related variables. Furthermore, using data from 2006 to 2013 allows us to capture the early stages of solar power generation in Korea, avoiding potential biases associated with recent data that may include energy storage systems not typically measured as "generation."

In summary, by focusing on the reduction of solar radiation and controlling for meteorological conditions, we aim to isolate the impact of air pollution on solar power generation in South Korea. This approach is supported by the specific context of Korea, where soiling is less of a concern and panel type variations are minimal during the study period.

4. Data

This study utilizes three primary datasets: hourly-level power generation data by source from the Korea Power Exchange (KPX), meteorological data from the Korea Meteorological Administration (KMA), and air quality data from the Korea Environment Corporation (KECO). The research period spans from 2006 to 2013. The power generation data covers all power sources, including solar photovoltaic (PV) power generation, and is nationwide. The meteorological and air quality data are also nationwide and collected from a network of stations across the country.

The KPX provides hourly-level information on power generation by source for the entire country. The dataset contains a total of 70,128 hourly observations. The power generation data is disaggregated by the power source, including coal, natural gas, nuclear, hydroelectric, and solar PV. For this study, we focus on solar PV power generation data.

The KMA dataset provides hourly-level information on meteorological variables such as precipitation, temperature, wind speed, cloud cover, and solar radiation. We utilize meteorological data collected from 90 stations across the country, covering all regions. The meteorological data are collected from the observatory stations managed by the KMA (KMA, 2023). We aggregate the meteorological data by averaging the hourly values from all stations to obtain a nationwide hourly average for each meteorological variable.

The KECO dataset provides hourly-level information on air pollutants such as PM10, NO2, and SO2. We utilize PM10 data, a primary pollutant known to affect solar PV power generation. The dataset covers 53 stations across the country. The air quality data are collected from the observatory stations managed by the KECO (KECO, 2023). Similar to the meteorological data, we aggregate the air quality data by averaging the hourly values from all stations to obtain a nationwide hourly average for PM10.

It is worth noting that although the KECO dataset includes information on PM2.5, this study uses PM10 as the primary air pollutant for analysis. This is because PM10 is known to have a more significant impact on solar PV power generation than PM2.5 (Bergin et al., 2017; Li et al., 2017). Additionally, KECO began collecting PM2.5 data relatively recently, since 2015, which means that the dataset does not cover the entire study period from 2006 to 2013. Therefore, PM10 data allows for a more comprehensive analysis over the entire study period. However it's important to acknowledge that PM2.5 also plays a role in affecting solar radiation and future research could explore its impact alongside PM10 when data availability allows.

Overall, the datasets used in this study provide a reliable and comprehensive source of information on power generation, meteorological conditions, and air quality in South Korea. The data enable us to examine the impact of air pollution on solar PV power generation with a high degree of accuracy.

The use of meteorological variables such as sunshine duration, cloud cover, precipitation, wind speed, and temperature is crucial in analyzing solar power generation. These variables influence solar power output in various ways: sunshine duration directly affects the amount of solar energy available, cloud cover reduces the solar radiation reaching the panels, and temperature and humidity can impact the efficiency of the solar cells. Previous studies have identified the importance of these variables in determining the performance of solar power generation systems (Gow and Manning, 1999; Green et al., 2019; Reno et al., 2012).

Table 1 provides descriptive statistics for the variables used in this study. The data covers hourly observations from 2006 to 2013 in South Korea. The total number of observations is 64,846. The mean value of solar energy production during the study period is 42.38 MWh, with a minimum value of 0.00 MWh and a maximum value of 451.32 MWh. The standard deviation of 77.23 MWh indicates substantial variability in solar power generation, with some hours having very high or very low generation levels.

Table 1
Descriptive statistics.

	Observation	Mean	SD	Min	Max
Solar power generation	64,846	42.38	77.23	0.00	451.32
PM10	64,846	52.72	34.82	7.80	872.85
Sunshine duration	64,846	0.26	0.34	0.00	1.00
Precipitation	64,846	0.16	1.21	0.00	63.90
Temperature	64,846	12.95	10.06	−13.77	34.04
Wind speed	64,846	1.28	0.97	0.01	7.06
Cloud cover	64,846	5.72	3.12	0	10

Notes: Solar power generation is measured in megawatt per hour (MWh), PM10 concentration is measured in microgram per cubic meter (μg/m^3), sunshine duration is measured in hours, precipitation is measured in millimeters, temperature is measured in Celsius (°C), and wind speed is measured in meters per second (m/s).

The key explanatory variable in this study is PM10, which has a mean concentration of 53.03 μg/m^3 (micrograms per cubic meter), with a standard deviation of 34.16 μg/m^3. It is worth noting that the mean PM10 concentration exceeds the annual mean limit of 20 μg/m^3 recommended by the World Health Organization (WHO) and 15 μg/m^3 by the United States Environmental Protection Agency (EPA).

The mean value of sunshine duration is 0.26 h, with a minimum of 0 and a maximum of 1, indicating that, on average, solar panels received sunlight for 15.6 min per hour. On the other hand, the mean value of cloud cover is 5.72, with a minimum of 0 and a maximum of 10, suggesting that, on average, around 57.2 % of the sky was covered by clouds during the study period.

These descriptive statistics offer insights into the key variables and underscore the challenges of maximizing solar power generation in South Korea, given the relatively low sunshine duration and periods of high PM10 levels.

5. Empirical strategy

We exploit wind direction as an instrumental variable (IV) to address the potential endogeneity of the PM10 measure. Endogeneity can arise from various sources, including measurement errors, omitted variables that affect both PM10 and solar power generation, and potential simultaneity between these variables.

Air pollution is a complex issue arising from diverse sources such as vehicular emissions, industrial activities, and natural phenomena. Its spatiotemporal variability poses challenges for accurate measurement and analysis in empirical models. One of the main issues with air pollution as an independent variable is endogeneity, occurring when unobserved factors simultaneously affect both air pollution and the dependent variable, leading to biased estimates. Several previous studies have highlighted the importance of controlling for endogeneity in models investigating the impact of air pollution on various outcomes, including health (Currie and Neidell, 2005), education (Graff-Zivin and Neidell, 2013), and energy production (Kuang et al., 2023). Therefore, it is crucial to address potential endogeneity issues to obtain accurate estimates of air pollution's impact on different outcomes.

Our baseline model is represented by the following equation:

$$Y_t = \alpha + \beta_1 PM10_t + \beta_2 SD_t + \beta_3 X_t + \beta_4 f(t) + \varepsilon_t \tag{1}$$

where Y_t represents solar power generation at time t, $PM10_t$ represents the concentration of particulate matter smaller than 10 μm in diameter at time t, SD_t is sunshine duration at time t, and X_t includes other meteorological variables (precipitation, temperature, wind speed, and cloud cover) at time t. The function $f(t)$ incorporates both linear and quadratic terms of the time trend variable t to control for potential non-linear time trends over the research period.

We choose wind direction as an IV for two primary reasons. First, it has been established as a plausible instrument that satisfies the relevance and exogeneity criteria required for IV analysis. Wind direction is primarily determined by natural factors and is unlikely to be directly correlated with unobserved factors affecting solar power generation, such as changes in technology or policy (Currie and Neidell, 2005; Deryugina et al., 2019; Graff-Zivin and Neidell, 2013).

Second, a significant portion of air pollution in Korea originates from China and is transported by prevailing winds. China is a major source of transboundary air pollution in Asia, and studies have shown that pollutants emitted there can travel long distances, impacting air quality in neighboring countries (Crawford et al., 2021). Specifically, research has indicated that up to 48 % of fine particulate matter in Korea can be attributed to pollution from China (Crawford et al., 2021; Kim, 2019).

Following the IV approach outlined in Deryugina et al. (2019), we utilize wind direction (WD) as an instrumental variable to address the endogeneity of PM10 levels. We employ a two-stage least squares (2SLS) model:

$$PM10_t = \alpha_0 + \alpha_1 WD_t + \alpha_2 SD + \alpha_3 X_t + \alpha_4 f(t) + \epsilon_t \tag{2}$$

$$Y_t = \beta_0 + \beta_1 \widehat{PM10}_t + \beta_2 SD + \beta_3 X_t + \beta_4 f(t) + \varepsilon_t \tag{3}$$

where $\widehat{PM10}_t$ is the predicted value of $PM10_t$ from the first-stage regression.

To account for potential autocorrelation and heteroscedasticity in the error terms, we employ the Newey-West estimator (Newey and West, 1987). This estimator is commonly used in time-series analysis to produce robust standard errors when the errors are correlated over time or have unequal variances. The Newey-West adjustment for standard errors is defined as:

$$Var(\beta) = (X'X)^{-1}(X'\widehat{\Omega}X)(X'X)^{-1} \tag{4}$$

where X is the design matrix of independent variables. To account for the correlation between the error terms at different lags, the variance estimates are calculated using the following formula:

$$X'\widehat{\Omega}X = X'\widehat{\Omega}_0 X + \frac{T}{T-k}\sum_{l=1}^{L}\sum_{t=l+1}^{T}\left(1 - \frac{l}{L+1}\right)\widehat{e}_t\widehat{e}_{t-l}\left(\mathbb{x}_t'\mathbb{x}_{t-l} + \mathbb{x}_{t-l}'\mathbb{x}_t\right) \tag{5}$$

where $\mathbb{x}_t$ represents the row of the X matrix observed at time t, k is the number of parameters, T is the number of observations, L is the number of lags, and $\widehat{\Omega}_0$ is the Newey-West weighting matrix (Greene, 2003). We use the Bartlett kernel to construct the weighting matrix, which assigns decreasing weights to observations with increasing separation.

To assess the presence of autocorrelation, we examine the correlogram of the residuals. Fig. 1 reveals statistically significant autocorrelation up to five lags. Therefore, we conduct two analyses: a robustness check controlling for autocorrelation up to five lags ($l = 5$) and our primary analysis controlling for autocorrelation up to 15 lags ($l = 15$), following Greene's (2003) rule of thumb of setting l to the integer of $T^{\frac{1}{4}}$, where T represents the sample size.

The use of the Newey-West estimator is crucial in this study to ensure unbiased coefficient estimates and accurate statistical inference in the presence of autocorrelation and heteroscedasticity.

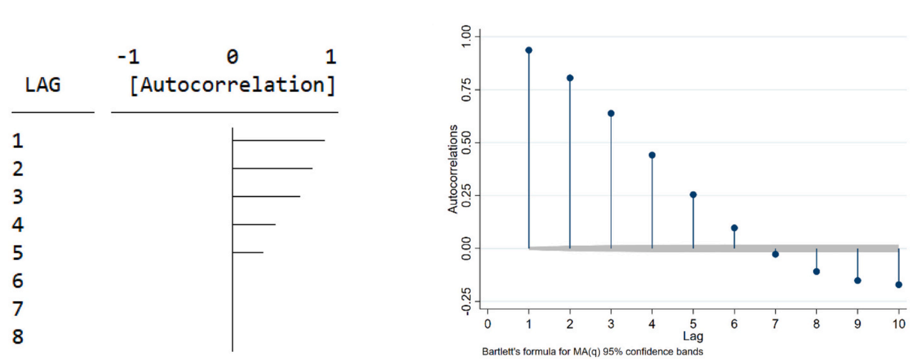
6. Results

Table 2 shows the regression results indicating that PM10 and sunshine duration are significantly related to solar power generation. In particular, PM10 has a negative coefficient estimate in all four models, with estimates ranging from −0.009 in Column (1) to −0.028 in Column (4). This suggests that an increase in PM10 concentration in the air is

Table 2
OLS regression results.

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
PM10	−0.009	−0.147***	−0.085***	−0.028***
	(0.007)	(0.008)	(0.007)	(0.006)
Sunshine duration		159.047***	159.444***	92.941***
		(0.988)	(1.012)	(1.040)
Precipitation			−0.586***	−0.550***
			(0.088)	(0.101)
Temperature			−0.311***	0.568***
			(0.053)	(0.070)
Temperatureˆ2			0.037***	0.026***
			(0.003)	(0.003)
Wind speed			1.971***	1.015***
			(0.273)	(0.222)
Cloud cover			1.387***	−2.481***
			(0.057)	(0.072)
f(T)	No	No	No	Yes
Time FE	No	No	No	Yes
Adjusted R2	0.000	0.501	0.513	0.683
Observations	64,846	64,846	64,846	64,846

Notes: Columns (1)–(4) use robust standard errors to correct for heterogeneity in errors. The model controls for quadratic terms ($t + t^2$) to account for potential time trends. Time fixed effects are also included, consisting of hour-of-day, day-of-week, and month-of-year fixed effects, to control for unobserved heterogeneity. The estimates are based on Ordinary Least Squares (OLS) regression models.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.



(a) Autocorrelation coefficients (b) Autocorrelation plots

Fig. 1. Autocorrelation analysis of hourly solar power generation.

associated with a decrease in solar power generation. On the other hand, sunshine duration has a positive coefficient estimate in all models, with estimates ranging from 92.941 in Column (4) to 159.444 in Column (3). This indicates that an increase in sunshine duration is associated with an increase in solar power generation.

Interestingly, in Column (3), we observe a negative coefficient estimate for ambient temperature, suggesting a counterintuitive relationship with solar power generation. This finding aligns with Son et al. (2020), who also reported a negative association between temperature and solar PV output. However, this contradicts previous studies that documented a positive relationship (Kawajiri et al., 2011; Dubey et al., 2013). Our results underscore the critical importance of controlling for time trends and time-fixed effects when estimating this relationship. Failure to do so can lead to biased estimates with misleading signs. Notably, in Column (4), where time trends and time-fixed effects are incorporated, the temperature coefficient becomes positive, consistent with the established understanding that solar power generation generally increases with rising temperatures.

When analyzing the impact of PM10 on solar power generation, it is important to recognize that its effects may not be instantaneous. Weather conditions, including air pollution levels, can influence solar power output with a time lag. To capture these dynamic effects, we examine the lagged impacts of PM10 and sunshine duration on solar power generation using a distributed lag model. Given the time series nature of our data and the potential for autocorrelation, we employ the Newey-West estimator with 15 lags for the standard errors. This lag selection adheres to Greene (2003)'s rule of thumb, setting the number of lags to the integer value of $T^{\frac{1}{4}}$, where T represents the sample size, to effectively address autocorrelation concerns.

Table 3 presents the cumulative lagged effects of PM10 and sunshine duration on solar power generation. The results reveal a subtle weakening of the negative impact of PM10 on power generation over time, with the coefficient estimate decreasing slightly from −0.029 at lag01 to −0.030 at lag05, suggesting a stabilization of the effect after an initial period. In contrast, sunshine duration demonstrates a strong, immediate positive effect on solar power generation, with coefficient estimates ranging from 92.71 at lag01 to 78.51 at lag05, indicating a diminishing impact over time.

Importantly, our results indicate that the impacts of PM10 and sunshine duration on solar power generation may not persist indefinitely. The effect of PM10 stabilizes after an initial period, while the impact of sunshine duration diminishes over time. This observation emphasizes the importance of considering the temporal dynamics of these relationships when assessing their influence on solar power generation.

Table 4 presents the instrumental variable (IV) regression analysis results, employed to address potential endogeneity concerns with PM10 in the earlier OLS models. Column (1) showcases the results from the two-stage least squares (2SLS) model, while Columns (2) and (3) display the results of the Newey-West 2SLS model with varying lag specifications for the Newey-West standard errors.

Both the 2SLS and Newey-West 2SLS models consistently reveal a negative and statistically significant (at the 1 % level) coefficient estimate for PM10. This indicates that a 1 mg/m^3 increase in PM10 concentration leads to a 0.217 MWh decrease in solar power generation. Notably, these PM10 coefficient estimates are markedly larger than those obtained from the OLS models presented in Tables 2 and 3, suggesting potential bias in the OLS estimates due to endogeneity. The greater magnitude of the PM10 coefficients in the 2SLS models emphasizes the importance of controlling for endogeneity to achieve unbiased estimates of the relationship between PM10 and solar power generation.

In contrast, the coefficient estimate for sunshine duration remains positive and statistically significant across all models, affirming that increased sunshine duration positively impacts solar power generation. The consistency of these coefficient estimates (around 91.06) between the 2SLS and OLS models further supports the robustness of our findings.

We assess the strength of our instruments using the *KP F statistic*. In Table 4, both models demonstrate *KP F statistics* well above the recommended threshold of 10, with values of 130.91 and 189.81, respectively. This indicates the robustness of our chosen instruments and minimizes the risk of weak instrument bias. Further details on the first-stage model are available in Table A.1.

The Wu-Hausman test, employed to test for PM10 endogeneity, yields *p*-values of 0.00 in both models, providing strong evidence of endogeneity. This confirms the potential bias in OLS estimates and underscores the necessity of IV models for obtaining unbiased estimates in this context.

Based on our findings, a 10 mg/m^3 increase in PM10 concentration results in a 2.17 MWh reduction in hourly solar power generation. Over the 2006–2013 study period, this translates to a total loss of 152.2 GWh. Utilizing the retail cost of solar-generated electricity during this timeframe, we estimate the annual average cost of this reduced generation per 10 mg/m^3 increase in PM10 to be approximately 240 million KRW

Table 3
Cumulative lagged effects of PM10 and SD.

	(1) Lag01	(2) Lag02	(3) Lag03	(4) Lag04	(5) Lag05
PM10	−0.029**	−0.030**	−0.030**	−0.030**	−0.030**
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
Sunshine duration	92.71***	93.34***	89.65***	84.17***	78.51***
	(2.90)	(3.11)	(3.17)	(3.20)	(3.20)
Weather controls	Yes	Yes	Yes	Yes	Yes
f(T)	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	61,903	60,478	59,156	57,857	56,577

Notes: The regression model used for this table is the Newey-West time series model. Lags for Newey-West standard errors (SE) are set to the integer value of $T^{\frac{1}{4}}$, where T represents the sample size. Weather controls include precipitation, temperature, cloud cover, and wind speed, along with quadratic terms $(t + t^2)$ to capture potential time trends. Time fixed effects, including hour-of-day, day-of-week, and month-of-year effects, are included to address unobserved heterogeneity. All specifications are estimated using the distributed lag model, and the coefficients for PM10 and sunshine duration are linearly cumulative. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Instrumental variable regression results.

	(1)	(2)	(3)
Dep. Var.: Solar power generation	2SLS	Newey-West 2SLS	Newey-West 2SLS
PM10	−0.217***	−0.217***	−0.217***
	(0.037)	(0.072)	(0.074)
Sunshine duration	91.06***	91.06***	91.06***
	(1.11)	(2.19)	(2.77)
Weather controls	Yes	Yes	Yes
f(T)	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
KP F statistic	130.91	189.81	189.81
Wu-Hausman test	27.156	25.714	25.714
	(0.000)	(0.000)	(0.000)
Lags for Newey-West SE	0	5	15
Observations	64,846	64,846	64,846

Notes: Lags for Newey West standard errors (SE) are set to the integer value of $T^{\frac{1}{4}}$, where T represents the sample size. The Wu-Hausman test is conducted to check for the endogeneity of the endogenous regressor, PM10. The p-value for the Hausman test is reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Robustness checks.

	(1)	(2)
Dep. Var.: Solar power generation	Newey-West 2SLS (Sunrise-Sunset Hours)	Newey-West 2SLS (Sunshine Duration Hours)
PM10	−0.315***	−0.290***
	(0.105)	(0.101)
Sunshine duration	73.69***	77.27***
	(3.66)	(3.45)
Weather controls	Yes	Yes
f(T)	Yes	Yes
Time FE	Yes	Yes
KP F statistic	139.75	144.74
Wu-Hausman test	23.939	24.019
	(0.000)	(0.000)
Lags for Newey West SE	13	13
Observations	34,649	37,711

Notes: Lags for Newey West standard errors (SE) are set to the integer value of $T^{\frac{1}{4}}$, where T represents the sample size. The Wu-Hausman test is conducted to check for the endogeneity of the endogenous regressor, PM10. The p-value for the Hausman test is reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(or 2.23 million USD). These figures highlight the substantial economic impact of air pollution on solar power generation and emphasize the urgent need for pollution reduction measures to ensure the sustainable and cost-effective production of renewable energy.

7. Robustness checks

Solar power generation is intrinsically linked to sunlight availability. Consequently, incorporating data from all 24 h of the day might introduce bias due to omitted variables. This bias can stem not only from the inclusion of nighttime hours, even with hourly fixed effects, but also from seasonal variations in daylight duration. To address this potential bias, we restrict our analysis to two specific time windows: 1) daylight hours, defined as the period between sunrise and sunset each day, and 2) hours with detected sunshine radiation, focusing exclusively on periods when solar power generation is feasible.

Table 5 presents the results of these robustness checks. Column 1 displays regression results using only data from daylight hours, while Column 2 focuses on hours with detected sunshine radiation. In both cases, we employ the Newey-West estimator with 13 lags for standard errors, reflecting the reduced sample size due to the restricted time windows (the number of lags is adjusted from 15 in Table 4 to 13 in Table 5 based on the new sample size, adhering to Greene's (2003) rule of thumb). The results from both columns remain consistent and statistically significant, mirroring the findings in Table 4 and confirming the substantial negative impact of ambient PM10 concentration on hourly solar power generation. Notably, after controlling for daytime hours, the estimated effects are considerably larger in magnitude compared to the full 24-h dataset, highlighting the importance of accounting for sunlight availability in our analysis.

8. Conclusion

This study provides robust evidence of the detrimental impact of air pollution, particularly PM10, on solar power generation in South Korea. Our findings reveal that elevated PM10 concentrations lead to reduced solar panel efficiency, decreased power output, and increased costs. These results underscore the critical need to mitigate air pollution to foster the growth of renewable energy and achieve South Korea's ambitious renewable energy targets.

Policymakers are urged to prioritize the implementation of stringent air pollution control measures. This could include mandating the adoption of advanced emission control technologies in industries, promoting the use of cleaner fuels, and implementing stricter vehicle emission standards. Additionally, targeted incentives, such as tax breaks or subsidies, could be employed to encourage the adoption of electric or hybrid vehicles. Such proactive measures would not only facilitate the expansion of renewable energy but also contribute to a healthier and more sustainable environment for South Korea.

Furthermore, our findings highlight the importance of international cooperation in addressing transboundary air pollution. The significant impact of wind direction on PM10 levels in South Korea underscores the necessity of collaborative efforts with neighboring countries to mitigate pollution sources. Joint initiatives to implement effective pollution control measures and promote clean energy adoption can create a more favorable environment for solar power generation and foster sustainable development across the region.

In conclusion, this study enhances our understanding of the intricate relationship between air pollution and solar power generation in the context of South Korea. Our findings emphasize the critical role of air quality management in ensuring the reliable and sustainable production of solar energy, a key component in achieving the country's renewable energy goals. Future research could build upon these findings by extending the analysis to other geographical contexts, investigating the impact of specific air pollutants, exploring the role of technological advancements in mitigating air pollution's effects on solar panels, and examining the distributional consequences of air pollution on solar power generation across different socioeconomic groups. Additionally, future studies could explore the potential synergies between air pollution reduction policies and renewable energy promotion strategies to maximize their combined benefits and pave the way for a cleaner and more sustainable energy future.

While this study offers valuable insights, it is not without limitations. The use of nationwide time-series data, lacking specific solar PV locations, limits our ability to pinpoint the precise effects of air pollution and weather conditions at a localized level. Furthermore, although we controlled for various weather variables, unobserved factors might still influence solar power generation. Additionally, the study does not consider other factors that can affect solar power adoption and operation, such as policy incentives, economic conditions, and technological progress. Future research could address these limitations by utilizing more granular data, employing advanced econometric techniques to account for unobserved heterogeneity, and incorporating a broader range of factors that influence solar power systems.

CRediT authorship contribution statement

Moon Joon Kim: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Appendix

Table A1
First-stage regression results.

	(1)	(2)
Dep. Var.: PM10	2SLS	Newey-West 2SLS
Wind direction		
	Reference: NNW	Reference: SSE
North	−0.0589	−7.3436***
	(0.4776)	(0.8887)
North Northeast	−2.7936 ***	−10.0785***
	(0.4812)	(0.8750)
Northeast	−4.2388***	−11.5237***
	(0.4695)	(0.86215)
East Northeast	−4.4617***	−11.7466***
	(0.4688)	(0.8576)
East	−0.4167	−7.7016***
	(0.7074)	(0.8999)
East Southeast	2.0898***	−5.1951***
	(0.5715)	(0.9297)
Southeast	7.3448***	0.0599
	(0.9878)	(0.9626)
South Southeast	7.2849***	(ref)
	(0.8380)	
South	4.7378***	−2.5471***
	(0.6245)	(0.9076)
South Southwest	5.5217***	1.7632**
	(0.5391)	(0.8567)
Southwest	6.9034***	−0.3815
	(0.5107)	(0.8390)
West Southwest	9.5411***	2.2562***
	(0.5837)	(0.8434)
West	11.3870***	4.1020***
	(0.7456)	(0.8427)
West Northwest	8.9847***	1.6998**
	(0.6219)	(0.8186)
Northwest	3.0785***	−4.2065***
	(0.4468)	(0.8106)
North Northwest	(ref)	−7.2849***
		(0.8389)
Weather controls	Yes	Yes
f(T)	Yes	Yes
Time FE	Yes	Yes
F statistic	130.91	189.81
Observations	64,846	64,846

Notes: The dependent variable for the first-stage regression is PM10, and the instrument used is wind direction consisting of 16 wind directions. In Column 1, the reference wind direction is set as North Northwest, while in Column 2, the reference wind direction is set as South Southeast. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107924

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