Increase in domestic electricity consumption from particulate air pollution

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Abstract:

Accurate assessment of environmental externalities of particulate air pollution is crucial to the design and evaluation of environmental policies. Current evaluations mainly focus on direct damages resulting from exposure, missing its indirect co-damages through the feedback and interactions among the externalities, human behaviors, and technologies. Our study provides an empirical assessment of such co-damages using customer-level daily and hourly electricity data of a large sample of residential and commercial consumers in Arizona, United States. We use an instrumental variable panel regression approach and find that particulate matter air pollution increases electricity consumption in residential buildings as well as in retail and recreation service industries. Air pollution also reduces the actual electricity generated by distributed solar panels. Lower-income and minority ethnic groups are disproportionally impacted by air pollution and pay higher electricity bills associated with pollution avoidance, stressing the importance of incorporating the consideration of environmental justice in energy policy making.

Keywords: Co-damage; Air pollution; Electricity consumption; Solar energy; Inequitable outcomes

Introduction

Air pollution has been resulting in negative externalities in multiple aspects which calls for policy interventions to address the associated damages. Policymakers and research are widely concerned about increases in mortality risk which are direct damages induced by pollution as well as co-damages in terms of other welfare losses. These damages are generated via different channels including physical and mental health impact on human beings, decreases of labor productivity[1,2], declines of subjective well-being[3], harm on cognitive competence [4,5], disturbance on ecosystem health[6], diminished value of local environmental amenities and properties[7], rises in household medical expenditure, etc. Accurate assessment of such externalities is crucial to estimating the social cost of pollution for the design and evaluation of policies such as a Pigouvian tax that imposes the polluters for such external cost for pollution control, or a cap-and-trade program that establishes a market issuing allowances to internalize such cost[8]. While direct pollution damages are often measured in existing studies, there are not many discussions in the literature about the magnitude of the co-damages. A key challenge to quantify these co-damages, however, is to understand the feedback and interactions among pollution, human behaviors [9], and technologies. People can mitigate exposure to environmental risks by taking various avoidance behaviors, such as adjusting outdoor activities [10,11] and purchasing facemasks and air purification systems in the short term [9,12], and migrating to new living locations in the longer term [13]. Avoidance behaviors alleviate the negative health impact by pollution [14] but come at a cost, for example spending less time for outdoor activities[10,15], and may lead to further impacts such as increased energy consumption due to a shift from natural to mechanical ventilation[16], increased needs for heating or air-conditioning or other activities such as watching TV[17,18] in residential buildings. The commercial buildings may also be affected via further complexities if individuals choose to work remotely due to air pollution to avoid exposure during commuting[19]. However, on the other hand commercial buildings might have better indoor air quality due to better ventilation [20] so that people can stay in commercial buildings for longer period of time. These two effects can cancel out, and thus we hypothesize that air pollution does not have a statistically significant impact on commercial buildings as a whole. Such effects and the consequential extra environmental damage are, however, hardly addressed explicitly and quantitatively in the current studies, and thus lead to biases in the damage evaluation. Our paper fills in this gap in literature.

While electricity demand is driven up by pollution averting behaviors, air pollution can further affect electricity supply in the opposite direction. High concentrations of particulate matters reduce solar electricity generation due to the changed solar irradiance. The emissions of aerosols can attenuate solar radiation by scattering and absorbing sunlight before it reaches the solar panel [21], and thus reduces photovoltaic performance [22,23]. Large particulate matters can also generate dust on top of solar panels. In areas with severe air pollution such as China, the potential of solar PV generation decreased on average by 11–15% between 1960 and 2015 [22]; the decrease of point-of-array irradiance can even reach 35% in the most polluted areas [23]. Such interaction adds another dimension to the complexity of assessing pollution externalities. Existing studies take a dominantly engineering perspective that relies on computer simulations to calculate the change in solar irradiance due to air pollution or field experiments to measure the changes in electricity generation of a few solar panels in response to air pollution. While providing critical estimation on the relationship between particulate pollution and solar electricity generation in certain refined meteorological and geographical conditions, these studies fall short in evaluating how much actual solar generation is affected at a large scale. Our paper contributes on the empirical ground and serves a crucial reference for policy making.

As pollution co-damages are closely related to both demand-side human behaviors and supply-side solar power generation, the distribution of these co-damages would raise environmental justice concerns. Lower-income households or minority ethnic groups can be more vulnerable to the impact of air pollutions. Individuals from these groups usually reside in locations with higher air pollution levels [24]. Moreover, they may live in affordable houses and buildings that are aged, not insulated well, equipped with fewer energy-efficient appliances, and thus lead to higher energy-related expenditures [25,26]. The increased electricity bills due to more indoor hours, therefore, translate into a larger proportion of the household income compared to their higher-income or non-minority counterparts. This constraints other essential expenditures on medical services by lower-income and minority households, thus leading to further adverse health impacts [27]. Our analyses incorporate the equity aspects of pollution co-damages to provide necessary implications for policy design towards environmental justice.

This article demonstrates how the interactions among air pollution, human defensive behavior, and energy supply system can influence the estimates of negative externalities caused by air pollution. Using consumer-level daily and hourly electricity consumption data and solar panel generation records in Phoenix metropolitan, Arizona during 2013-2018, we testify how particulate air pollution, indicated by concentrations of both PM10 and PM2.5 (particulate matter 10 micrometers or less in diameter, and 2.5 micrometers or less, respectively), triggers consumer avoidance behaviors as well as lowers the generation of solar energy. Our sample covers 4,313 residential buildings and 17,422 commercial buildings. A variety of demographic and socio-economic characteristics are associated with the consumer data set, based on which we further explore the heterogeneity of the co-damages associated with income and ethnicity. Estimates can be biased by endogeneity issues due to reverse causality (i.e. air pollution induces changes in energy consumption as well as solar electricity generation, which in turn also affects the air quality) and missing variables (e.g. unobservable characteristics of the local economy and physical environment can affect the air quality and energy consumption simultaneously). To address the endogenous biases, we use wind direction as an instrumental variable (IV) for the pollution concentration. This IV has a direct impact on concentrations of pollutants but not on energy consumption, which creates variation in air quality that is exogenous to consumption, thus leading to non-biased estimation of the pollutant coefficient. Our main results are based on daily average data. We also analyze hourly data to examine the intra-day heterogeneity in the impact on electricity usage. The study area of our analysis is the fifth most populated city in the United States[28] and ranks among the top five most polluted cities in the country[29]. This suggests that even though based on a developed country region, our results can provide valuable insights and benchmark statistics when compared with studies in the developing context with dense population and low-ranked air quality.

Effect of air pollution on the demand sectors

Through an instrumental variable (IV) fixed effects panel regression, we regress the individual household's daily electricity consumption on air pollution level, while controlling for other confounding variables. Detailed modeling can be found in the *Methods* section. The validity of IV estimation is also supported by the first-stage regression which shows a strong positive correlation between the daily average cosine of the prevailing-hourly wind direction angle and the concentration of air pollution, meaning that wind in the upwind direction of pollution sources would bring higher particulate concentration (Column 1 and 3 in Table 1). The considerable F statistics far more than 10 indicates a strong IV in both the regressions for PM10 and PM2.5. We find that a higher concentration of particulate pollutant results in a statistically significant increase in residential electricity consumption. An increase of 1μg/m^3 in PM10 concentration raises the daily residential electricity consumption by 0.020 kWh (Column 2 in Table 1). Residents turn out to be more sensitive to the change of PM 2.5 concentration as 1μg/m^3 rise in PM2.5 concentration causes 0.145 kWh (Column 4 in Table 1) increase in daily electricity consumption. In this way, one more standard deviation of PM10 and PM2.5 would increase the daily residential electricity consumption by 0.85% and 1.74% from the mean based on the descriptive statistics in Supplementary Table 1, respectively. Such effects are also seasonally heterogeneous (Supplementary Table 12) as the increased electricity consumption is of larger magnitude in summer peak (July and August), while the significance diminishes during the winter (November to April).

To validate our hypothesis that the increased electricity consumption is caused by averting behaviors that shift outdoor activities indoor, we next examine the pollution-kWh relationship on an hourly basis. Results using hourly data confirm that air pollution increases residential electricity consumption and imply a possible reallocation of time due to air pollution. As shown in Figure 1, residential electricity consumption increases considerably during the daytime but decreases slightly during evenings when affected by air pollution. While both are statistically significant, the summed change (the area above the horizontal line of 0 minus the area below) still shows an overall increase of daily electricity consumption aligning with the findings based on Table 1. This possibly indicates a change of activities during a day: as air quality deteriorates, residents tend to participate in indoor energy-dependent activities such as watching TV and turning on the heating/cooling system. They may also move activities usually conducted in the evenings, e.g. laundries, ahead to the daytime so that the electricity consumption during the nights drops. The drop in consumption during the evening can also be due to the pre-cooling or pre-heating effects from turning on the HVAC system during the daytime.

To further support our finding, we test whether individuals tend to reduce outdoor trips using a daily county-level dataset of mobility nationwide in the United States (details are included in *Methods*). As shown in Supplementary Table 13, the number of trips per person reduces as the concentration of air pollution rises, implying that people are staying home for more hours due to air pollution.

We next discern the effects of air pollution among residential consumers with different socio-economic characteristics. The potential heterogeneous effects can be caused by environmental injustice in different aspects. On the one hand, as consumers of disadvantaged socio-economic status can be exposed to higher pollution [8] and live in houses that are less energy-efficient[25,26], their pollution-induced increase in electricity demand could be larger than their advantaged counterparts. On the other hand, their abilities to self-protect against air pollution are likely to be restricted by their limited disposable income or they are simply less attentive to air pollution. If the effect of these constraints dominates their behavioral responses to pollution, then we may observe a smaller change in electricity demand for disadvantaged households. As a result, whether and how the effect of air pollution on electricity consumption differs across socio-economic status becomes an empirical question. Our summary statistics show that lower-income and non-white consumers are associated with higher PM concentrations and lower baseline electricity consumption (Supplementary Table 2), implying a possible heterogeneous effect. Thus, we test such heterogeneity for different income and racial-ethnic groups. Using the available data on household characteristics, the sample is divided into three levels of per capita income: low, medium, and high (see *Methods* for details). The sample is also divided into four ethnic groups (White, Asian, Hispanic, and Other) to conduct the regression analysis separately.

The results show that lower-income and Hispanic consumers have a larger increase in electricity consumption in response to a unit increase in PM pollution. The IV estimates in Figure 2 illustrate that the marginal effect of pollution on electricity demand is the highest for the low-income group. For ethnic groups, Hispanic consumers increase their electricity consumption more than white consumers. The empirical estimates for heterogeneous groups imply that the effect of low energy-efficiency and high exposure possibly overrides the constraint of disposable income. In contrast, a previous study found that higher-income consumers need to use more energy in response to changing weather conditions in China [30]. Existing studies have found that lower-income tend to live in homes that are not energy-efficient [25,26] which can lead to a higher increase in electricity consumption due to air pollution. Two studies [31,32]find that Hispanic households have higher energy use intensity due to residing in less energy-efficient homes. These findings of Hispanic households help justify our results because when air pollution increases and people need to spend more time indoors, inefficient homes (such as Hispanic homes) will increase more electricity consumption compared to an efficient home. The Medium-income group shows less electricity increase compared to both low-income and high-income groups, which can be a result of low-income households having inefficient homes [25,26] and high-income households needing more energy in response to changing weather conditions [30]. The socio-economic heterogeneity embedded in air pollution issues requires more subtle investigations and tests given the multiple mechanisms that can balance the effects of each other. We also rerun the model separately for each residential building to get the unique estimated impact for the individual consumer. The results show similar heterogeneity. As shown in Supplementary Figure 1, air pollution demonstrates a different marginal effect for each building, and the summary statistics in Supplementary Table 5 shows a similar pattern as observed in Figure 2.

Our results show that contrary to the findings in the residential sector, electricity usage in the commercial buildings as a whole sample is not significantly affected by air pollution in general, although the usage in individual industries shows statistically significant changes. As presented in Table 2, despite that the instrument variable is still valid and strong (the coefficients of Wind cosine are positively significant in the first stage results in Column 1 and 3 and the F statistics are considerable), IV estimates indicate no statistically significant effects (Column 2 and 4 in Table 2). In this way, the hypothesis that particulate pollution has no effect on energy use in commercial buildings as a whole cannot be rejected. We then examine if the hourly estimates could imply any indoor-outdoor activity shifts. There is not sufficient evidence to show that air pollution affects electricity usage in commercial buildings (Figure 3). Although the results show a similar pattern of electricity consumption in the commercial buildings as in the residential buildings, the coefficients of hourly pollution concentrations are barely statistically significant.

Such an insignificant effect on commercial buildings overall is likely a result of mixed-effects by air pollution that cancel each other out. On one hand, when estimating the micro-environment exposure, incorporating work activities will induce higher exposure to air pollution compared to home-only activities, partially due to higher pollution exposure during transit or commute[19]. This implies that workers have the incentives to stay at home or work from home to avoid higher average pollution exposure, which lowers the energy consumption of the commercial buildings. We further test this hypothesis by our analysis of the effect of air pollution on personal trips. With a daily county-level dataset of mobility nationwide in the United States, we test whether individuals tend to reduce outdoor trips (details are included in *Methods*). As shown in Supplementary Table 13, the number of trips per person reduces as the concentration of air pollution rises. The same conclusion holds for both work trips (Supplementary Table 14) and non-work trips (Supplementary Table 15). On the other hand, commercial buildings on average might have different building envelope or better building management system [20] that can lead to better indoor environment [33] compared to residential buildings, so that when ambient air pollution increases some people might want to stay inside commercial buildings for a longer period time, potentially increasing electricity in these buildings. Building occupants may also utilize less natural ventilation in polluted weather, and thus can increase the energy consumption of buildings due to increased mechanical ventilation [16]. These effects may cancel out so that we are not observing a statistically significant effect of air pollution on average for all commercial buildings in our sample.

The insignificant effect of air pollution on commercial buildings as a whole actually validates our residential electricity consumption result. There could be possibly a concern that our regression model can still fail to capture some physical relationship between electricity consumption and other unmeasured meteorological variables which can be correlated with air pollution. Or there could be a concern about misspecified functional form (incorrect description of the relationship between our independent and dependent variables). As a result, the positive impact of air pollution on residential electricity consumption could be purely due to these physical relationships, and not due to consumer behavioral change. The insignificant result in the commercial sector actually implies that our regression model can capture those physical relationships well, so that our estimated increase in residential electricity consumption is indeed due to consumers' behavior change.

Such statistically insignificant results of commercial buildings can, however, conceal the sectoral heterogeneity as air pollution can significantly affect the commercial sectors that are closely related to indoor activities. Due to the nature of different industries, each commercial building serves with a specific purpose, with some sectors more likely to be affected by air pollution. Sectors such as retail trade, recreation, and service can have increased electricity consumption where more of their customers spend more time inside the buildings to avoid being exposed to outdoor pollution. Thus, we separate the effect by sectors as shown in Figure 4. With a similar averaged pollution concentration across all sectors (Supplementary Table 4), the retail sectors respond most intensely to the increase of air pollution concentration (0.086 kWh rise in electricity consumption per $\mu g/m^3$ increase of PM10 concentration, and 0.560 kWh rise per $\mu g/m^3$ increase of PM2.5 concentration), followed by the recreation and service sectors (0.026 kWh per $\mu g/m^3$ and 0.167 kWh per $\mu g/m^3$, respectively). In contrast, the other sectors reduce their electricity consumption also as expected (0.028 kWh per $\mu g/m^3$ and 0.178 kWh per $\mu g/m^3$ for PM10 and PM2.5, respectively, both significant at 90% confidence level). As a result, one standard deviation increase of PM10 and PM2.5 would lead to 1.82% and 3.34% rise in retail trading sector, 1.13% and 2.00% rise in recreation and service sector, as well as 0.79% and 1.39% reduction of electricity consumption in the other sectors, respectively. These effects with opposite directions in different sectors balance out each other when being summed up, and thus lead to an insignificant change of energy consumption for the whole sample. Taken together with our analysis above, these results show that individuals are more likely to reduce outdoor trips in general and particularly related to work. However, the final destinations for the remaining trips may shift at least partially from open spaces to sheltered areas, and thus lead to more energy consumption in malls, recreation centers, etc. This distributional result stresses the importance of looking into sectoral nuance based on understandings of how consumer behaviors differ by industries as a response to the varying air quality.

Effect of air pollution on the supply sector

We then use a similar panel IV regression to regress individual consumer's daily solar electricity generation on air pollution level, while controlling for confounding variables (See details in *Methods*). The IV of wind direction again turns to be powerful in explaining the variation of PM10 and PM2.5 with its positive significance in Column 1 and 3 in both Table 3 and Table 4, while the F statistics continue to verify it as strong. We find that particulate pollution also reduces the electricity generation of distributed solar panels in both residential and commercial buildings. IV estimation shows that 1μg/m^3 increase in PM10 concentration significantly reduces the electricity generated by solar panels by 0.435 kWh in residential buildings (Column 2 in Table 3) and by 0.022 kWh in commercial buildings (Column 2 in Table 4). PM2.5 demonstrates an even larger effect -- 1.888 kWh reduction per μg/m^3 increase for residential buildings (Column 2 in Table 3) and 0.093 kWh reduction per μg/m^3 increase for commercial buildings (Column 4 in Table 4). In terms of percentage change, one standard deviation increase of PM10 and PM2.5 would result in 25.01% and 30.64% reduction of solar electricity generation for residential buildings with solar panels from the mean solar electricity generation, and 0.13% and 0.15% reduction for commercial buildings, respectively. The comparison also indicates that commercial buildings are much less affected if considering that the power of solar panels is averagely larger in the commercial buildings referring to the descriptive statistics in Supplementary Table 1 and Supplementary Table 3. A possible reason is that the solar panels in commercial buildings are better maintained with dust cleaned timely.

Discussion

This study explores the co-damage of air quality degradation via human defensive behavior and the performance of clean energy techniques on the demand and supply sides, respectively. Our results show that particulate pollution, while exposing individuals to health risks with direct emissions, can further add to the loss with regenerative feedback which boosts energy consumption due to longer indoor time-spending and downgrades the performance of solar panels. While previous studies predominantly focus on the positive consequences of the defensive behaviors in alleviating the health impacts [10,12], this research shows the possible pathways in which air pollution generates extra damage by interacting with such defensive behaviors [9]. Our analysis also shows that residents from low-income or Hispanic groups are more heavily affected, highlighting the vulnerability of specific socio-economic status in responding to environmental change and the potential environmental justice issues that should be addressed by policy design[24,27].

Several limitations should be noted. First, our analysis addresses the situation in Phoenix metropolitan, Arizona. In spite of its top ranking in the air pollution levels of U.S. cities, the concentration of particulate matter is still far less than in many developing countries such as Mexico or China [34,35]. Meanwhile, responsive levels can also differ due to cultural differences. Therefore, our results should be extrapolated with caution. In addition, our dataset lacks the information on specific household end-use activities (e.g. heating and cooling, air purification). Thus, we are not able to pinpoint exactly what appliance(s) are more intensively used against higher particulate concentration for further details on the mechanisms that we discuss. We leave these for future research that draws on high-resolution data in various geographical areas.

Several critical policy implications stem from the findings of this research. First, when calculating the marginal damage factors from air pollution, policymakers need to explicitly consider these co-damages generated from the feedbacks among consumer behaviors and clean technology performance, which is insufficiently discussed in the current literature as well as policy analysis and evaluation. Lack of consideration of these pollution co-damages will lead to under-estimation of welfare gains from pollution control policies. Our results also stress the necessity to investigate comprehensively the consequences of air quality alerting systems, e.g. alleviated health risks [36], changed automobile traffic flows as individuals endeavor to escape from pollution as a response [37], decreased outdoor recreation [10,38], etc. Second, the fact that air pollution disproportionally affects low socio-economic status threats energy and environmental justice, and again stresses that air pollution control can not only result in health benefit as a whole, but also contribute to equitable distribution of such benefit. The disproportional impact also highlights the importance of energy policies that can improve the home energy-efficiency of lower-income and ethnic minority groups to accelerate the achievement of fairness and equity. Third, our findings provide one more justification for the need to clean the electricity grid and improve the efficiency of renewable energy generation techniques. In addition, the expansions of solar power should take into consideration the effect of air pollution when setting reasonable development targets. The results comparing the impacts on commercial PV and residential PV suggest that there should be clear messages or incentives to communicate the importance of cleaning and maintenance of PV to the residential consumers.

Methods

Data

The data are provided by Salt River Project, one of the two largest utility companies in Arizona. Hourly electricity consumption in kWh is available for 4,313 residential units (spanning from May 2013 to April 2017) and 17,422 commercial units (spanning from May 2013 to April 2018). For the residential units in the sample, a Residential Equipment and Technology (RET) survey is also conducted in 2014 which asked about detailed sociodemographic information, building characteristics, appliance and other energy technology attributes, and energy consumption behaviors. For the commercial units, a 6-digit code in the North American Industry Classification System (NAICS) is available to identify the sector type of the building. We aggregate the electricity consumption to daily level for analysis. The daily electricity price is constructed by taking the average of the hourly prices. For commercial consumers, both electricity charge and demand charge are included as price variables. The zip code zone of each building is also available in the dataset that enables a spatial match with the air quality and meteorological variables.

Salt River Project also has distributed-solar consumers in its service territory. These solar panels can be installed on the rooftop of buildings or can be ground-mounted. For each distributed solar consumer, our dataset has the information on the hourly electricity generated by the consumer's solar panels, along with the installation dates of the solar panels. There are 260 residential distributed solar consumers (6.03% of the residential sample) and 330 commercial distributed solar consumers (1.89% of the commercial sample) in our dataset.

We combine meteorological observations from multiple sources. Records of air quality, including daily average concentrations of PM 2.5 and PM10, are retrieved from Pre-Generated Data Files of United States Environmental Protection Agency (US EPA)[39]. Climate factors including the daily average temperature, total precipitation, and average wind speed are obtained from Global Surface Summary of the Day[40]. The hourly wind direction data comes from EPA Pre-Generated Data Files. We obtain the solar irradiance data from the National Renewable Energy Laboratory (NREL)'s National Solar Radiation Data Base[41]. For missing solar irradiance data for a given location in a given time period, we use the simulated solar irradiance by NREL for a given day in that location in a typical meteorological year.

We adopt an inverse distance weighting interpolation that is commonly used in the previous literature [42,43] to match the air quality and meteorological records with the zip code zone of each building. First, the distance between each pair of air quality monitoring station and the geometric center of a zip code zone is calculated. Next, the daily records of all the stations less than 50 km away from the geometric center are averaged with a weight of their inversed distance to the center as the matched air quality record for all the buildings within the zip code zone. The climate records are matched in a similar way. The inverse distance weighting is conducted in Stata 14.0 using the wtmean command with 34 meteorological stations and 67 air pollution monitoring stations. To test whether our analysis is sensitive to the radius of the inverse distance weighting procedure, we change the caliper to 10km and 20km and rerun the analysis. As shown in Supplementary Tables 16-19 (for 10km) and Supplementary Tables 20-23 (for 20km). The coefficients change only slightly in magnitude but their signs and statistical significance remain, indicating the robustness of our results.

Since datasets address individual traveling behavior are rarely publicly available at the localized level for the study area, we resort to the COVID-19 Impact Analysis Platform by the University of Maryland[44,45] for a national-level exploration. Established for studies on COVID-19's impact, this dataset includes the daily number of trips per person at the county level starting from January 1st, 2020, which is further broken down to work and non-work trips. The information on trips comes from mobile device location data. Since the massive outbreak of COVID-19 in the United States took place no earlier than March, we adopt the records in January and February and match them with the air pollution and climate data from the above sources using a similar method.

Empirical strategies

We first estimate a Generalized Linear Squared model on the panel dataset of residential and commercial units separately with the equation

$$Elec\_Con_{it} = \beta_1 Pollution_{it} + \boldsymbol{X_{it}} + \alpha_i + \tau_y + \delta_m + Weekend_t + Holiday_t + \varepsilon_{it} \quad (1)$$

where *i* indexes individual residential or commercial consumer and *t* indexes day of the sample. $Elec\_Con_{it}$ refers to the daily electricity consumption of consumer *i* on day *t*. $Pollution_{it}$ is the daily average concentration of either PM10 or PM2.5. $\boldsymbol{X_{it}}$ is a vector of control variables, including cooling degree days (CDD) and heating degree days (HDD) (estimated using daily average temperature), daily total precipitation, wind speed, and electricity price (average daily electricity price for the residential consumers, and demand charge and energy charge for the commercial units). We also control for the concentration of ozone as another major pollutant that affects the air quality and thus the outdoor activities of consumers. α_i is customer fixed effects and it controls for the time-invariant attributes of the consumer such as square footage and the number of stories as well as environmental awareness of building occupants. The time fixed effects τ_y and δ_m include the year fixed effect and the month-of-year fixed effect. The time fixed effects capture the time-varying factors across years and seasons such as economic development and change in local energy policies. $Weekend$ and $Holiday$ are dummy variables for holidays and weekends, respectively. Holiday dummy is equal to 1 if the day belongs to the following federal holidays: New Year's Day, Martin Luther King Day, Presidents' Day, Memorial Day, Independent Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving Day, and Christmas Day. $\varepsilon_{i,d}$ is the error term. Standard errors are clustered at the building level. We are interested in β_1 which indicates the electricity use raised by per μg/m^3 increase of particulate concentration ceteris paribus.

We analyze how the impact of air pollution differs by different income groups. Using the available data on household characteristics, the sample is divided into three levels of per capita income: low, medium, and high. The division is provided by Pew research center based on the minimum household income level of different household size varying from 1-5 ($24,042/34,000/41,641/48,083/53,759 for middle income, and $72,126/102,001/124,925/144,251/161,277 for upper income in 2014[46]). Since the household size is recorded as 1.5, 3.5, and 5, we take an average of the two adjacent minimum household income levels for 1.5- and 3.5-people households.

We test whether and by how much the particulate pollution affects the solar energy generation with

$$Elec\_Solar_{it} = \beta_1 Pollution_{it} + \boldsymbol{X_{it}} + \alpha_i + \tau_y + \delta_m + Weekend_t + Holiday_t + \varepsilon_{it} \quad (2)$$

where $Elec\_Solar_{it}$ refers to the daily electricity generated by solar for consumer *i* on day *t*, and other terms are the same as in equation (1). $\boldsymbol{X_{it}}$ is modified to adapt to factors that can affect the power generation of solar panels, including climate factors which can also affect the performance of solar power (temperature, precipitation, wind speed, and surface albedo), and the electricity prices which can affect the motivation of consumers in actively maintaining a good condition of solar panel (consumers would be encouraged to do so if the price is higher). The distributed solar consumers in our sample were on the net-metering plan under which they could sell excessive solar electricity at retail electricity prices.

The naïve GLS estimation (results shown in Supplementary Tables 6-9) suffers from endogeneity issues due to reverse causality and missing variables [47,48]. As air pollution changes the behavior patterns and increases the energy consumption of consumers, the latter can result in more electricity generation and thus pollution emissions. Meanwhile, if consumers spend more time indoors, the demand for vehicle traveling may also decrease and lead to reduced emissions from transportation [48]. Omitting such pathways would lead to a biased estimation of the effect of air pollution. Besides, air quality and individual socio-economic activities can be jointly affected by the same factors such as the local economy and physical environment [47]. Since all such factors cannot be observed in our datasets, these missing variables could bias the estimation.

To address these issues, we resort to wind direction for an instrumental variable estimation. Its validity has been verified by multiple existing air pollution studies [47,49,50]. The idea is that wind direction affects regional air quality as it transports pollutants in specific directions. As the wind direction fluctuates on a daily or even hourly basis, it can convert the study area between the upwind or downwind of the pollution. Other than this pathway, wind direction (while controlling for wind speed) can hardly affect electricity consumption or solar electricity generation, and thus can meet the exclusive restriction for a valid instrumental variable.

We use the daily average cosine of the angle between the prevailing wind direction and the hourly wind direction as our instrumental variable following the previous studies[47,51] with modification in adapting to our daily-level data. We first plot the distribution of the hourly wind direction of all the climate stations to obtain the prevailing wind direction which turns out to be 180°. We then calculate the cosine of the angle between each hourly wind direction observation and this prevailing direction, and finally obtain the daily average for each climate station that matches with different zip code zones. In this way, we can conduct the first stage regression before running equation (1) or (2) as

$$Pollution_{it} = \gamma_1 Wind\_dir_{it} + \boldsymbol{X_{it}} + \alpha_i + \tau_y + \delta_m + Weekend_t + Holiday_t + e_{it} \quad (3)$$

where $Wind\_dir_{it}$ indicates the daily wind direction variable, e_{it} is the error term, and other terms are the same as in equation (1) or (2). The coefficient γ_1 after we run the first stage model is statistically significant with an F-value larger than 10, implying that the instrumental variable is relevant and strong. We then use the predicted values of pollution from equation (3) in the second stage model when we run equation (1) or (2).

It should be noted that the maximum value of electricity consumption of commercial buildings in our sample is extraordinarily large (Supplementary Table 3). However, there is no way for us to rule out the possibility that this value is reasonable given the decent variation of daily electricity consumption in the commercial building that this value belongs to. Therefore, we keep these potential outliers for the main analysis but also rerun the regressions dropping commercial buildings with maximum daily electricity consumption over 500kWh and 1000kWh, respectively. The results provided in Supplementary Tables 10-11 show that our key results remain robust after the change. Also, there are about 10% of buildings with constant daily electricity consumption of 0 in the raw data. We regard them as shutdown buildings and drop them from our sample.

We further test how air pollution affects residential and commercial electricity consumption at the hourly level. The identification is similar to equation (1) but using the matched hourly data of electricity use and air quality (lagged for one hour). The electricity consumption and solar electricity generation of one particular hour will not influence the air quality of the last hour, and thus there is no reverse causality issue. In addition, such immediate hourly reaction of building energy use will not lead to immediate change (within the same hour) in local PM pollution levels for the following reason. The hourly change in building electricity consumption leads to an hourly change in electricity generated at power plants. The coal-fired power plants surrounding the Phoenix metropolitan area are all located at least 100 miles away. This implies that the transmission of the PM pollution from these power plants to Phoenix metropolitan will take time (considering that the average wind speed in Arizona cities is less than 23 miles per hour and the average wind speed in our sample is 2.66 meters/second or 6 miles/hour), and thus will not influence the local PM pollution within an hour. The significant hourly variation in local PM pollution (such as in morning hours and late afternoon hours) in Arizona mostly comes from other sources such as motor vehicles and road dust, instead of from power plants, based on the study by Clements et al.[52] As a result, the hourly change in building energy consumption will not alter local PM pollution in Phoenix metropolitan area immediately.

To examine whether individuals stay at home instead of commuting to work in polluted days, we conduct a regression analysis on personal trips with

$$Trip_{jt} = \beta_1 Pollution_{jt} + \boldsymbol{X_{jt}} + \pi_j + \delta_m + dow_t + \varepsilon_{jt} \quad (4)$$

where $Trip_{jt}$ indicates the trips per person in county j on day t, π_j and dow_{jt} denotes the county and day-of-week fixed effect, and other terms are similar as in equation (1) or (2) but at the county level. On the basis of regressions using the total trips, we further test the effect of pollution concentration on the work and non-work trips. Due to a similar source of endogeneity, we are instrumenting the pollution using the wind direction with

$$Pollution_{jt} = \gamma_1 Wind\_dir_{jt} + \boldsymbol{X_{jt}} + \pi_j + \delta_m + dow_t + e_{jt} \quad (5)$$

where $Wind\_dir_{jt}$ indicates the daily wind direction variable for county j on day t, and other terms are the same as in equation (4). We calculate the daily average cosine of the angle between the prevailing wind direction and the hourly wind direction as our instrumental variable in a similar way as described above. The prevailing wind direction is retrieved from the median of the wind angle of each county during the study period.

Data availability

Records of air quality and hourly wind direction are retrieved from Pre-Generated Data Files of United States Environmental Protection Agency (US EPA) at https://aqs.epa.gov/aqsweb/airdata/download_files.html. Climate factors are obtained from Global Surface Summary of the Day at ftp://ftp.ncdc.noaa.gov/pub/data/gsod/. The solar irradiance data from National Renewable Energy Laboratory (NREL)'s National Solar Radiation Data Base at https://maps.nrel.gov/nsrdb-viewer. The high-frequency electricity data are from the SRP. As restricted by a non-disclosure agreement, they are available from the authors upon reasonable request and with permission from the SRP. The county level trip data is available upon request from the COVID-19 Impact Analysis Platform of University of Maryland at https://data.covid.umd.edu/about/index.html. Source data are provided with this paper.

Code availability

All data and models are processed in Stata 14.0. The figures are produced in R studio (based on R 3.6.1). All custom code is available on Github from https://github.com/hepannju/Increase-in-domestic-electricity-consumption-from-particulate-air-pollution.

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Author contributions

All the authors conceived the paper and designed the research. The co-first-authors, P.H., J.L. and Y.Q. designed the analysis methods, performed the analyses and wrote and revised the paper. B.X. processed the data. Q.L. reviewed several drafts and made revisions.

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Competing interests

The authors declare no competing interests.

Figure 1 Change in residential hourly electricity consumption due to 1 unit increase in air pollution concentration. The colored dots show the changes in hourly electricity consumption, obtained from panel regression at hourly level. The colored vertical lines show the 95% confidence intervals. As the information on hourly electricity price is available only for a small part of the residential and commercial samples, we conduct the analysis both with and without the regressor of price as a control variable. Source data

Figure 2 Change in daily residential electricity consumption due to 1 unit increase in air pollution concentration. Results are based on instrumental variable methods. The solid dots represent the values of the coefficients that measure the change in daily electricity consumption in response to a 1 μg/m3 increase in PM concentration. The vertical lines represent 95% confidence intervals. Source data

Figure 3 Change in commercial hourly electricity consumption due to 1 unit increase in air pollution. The colored dots show the changes in hourly electricity consumption, obtained from panel regression at hourly level. The colored vertical lines show the 95% confidence intervals. Source data

Figure 4 Change in daily commercial electricity consumption due to 1 unit increase in air pollution. Results are based on instrumental variable methods. The solid dots represent the values of the coefficients that measure the change in daily electricity consumption in response to a 1 μg/m3 increase in PM concentration. The vertical lines represent 95% confidence intervals. Source data

Table 1 Effect of air pollution on electricity consumption in residential buildings

	(1)	(2)	(3)	(4)
	IV-first stage	IV-second stage	IV-first stage	IV-second stage
Wind direction (cosine)	13.740***		1.852***	
	(0.016)		(0.008)	
PM10 concentration		0.020***		
		(0.004)		
PM2.5 concentration				0.145***
				(0.032)
Ozone concentration	-8.223***	58.849***	-2.587***	58.606***
	(0.766)	(1.643)	(0.204)	(1.618)
Heating degree days	-0.383***	0.779***	0.134***	0.751***
	(0.001)	(0.012)	(0.001)	(0.012)
Cooling degree days	0.145***	1.103***	0.002***	1.106***
	(0.001)	(0.009)	(0.000)	(0.009)
Precipitation accumulation	-3.503***	-0.142**	-1.771***	0.048
	(0.067)	(0.068)	(0.038)	(0.086)
Wind speed	1.094***	-0.119***	-1.264***	0.087**
	(0.007)	(0.014)	(0.003)	(0.044)
Relative humidity	-0.430***	0.044***	-0.020***	0.038***
	(0.001)	(0.002)	(0.000)	(0.001)
Daily electricity price (log)	-0.507***	-8.003***	0.631***	-8.078***
	(0.119)	(0.819)	(0.027)	(0.820)
Fixed effects				

Consumer	Y	Y	Y	Y
Weekend	Y	Y	Y	Y
Holiday	Y	Y	Y	Y
Month-of-year	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	5287985	5287985	5274599	5274599
R^2		0.507		0.507
F statistics	$7.7*10^5$		49475.29	

Notes: Standard errors in parentheses are clustered to building unit level. * p<0.1, ** p<0.05, *** p<0.01.

Table 2 Effect of air pollution on electricity consumption in commercial buildings

	(1) IV-first stage	(2) IV-second stage	(3) IV-first stage	(4) IV-second stage
Wind cosine	13.749***		2.149***	
	(0.008)		(0.004)	
PM10 concentration		-0.007		
		(0.011)		
PM2.5 concentration				-0.045
				(0.074)
Ozone concentration	-9.828***	9.241**	-5.344***	8.917**
	(0.490)	(3.598)	(0.124)	(3.558)
Heating degree days	-0.554***	0.093***	0.080***	0.100***
	(0.001)	(0.018)	(0.000)	(0.026)
Cooling degree days	0.213***	0.649***	0.006***	0.648***
	(0.001)	(0.023)	(0.000)	(0.022)
Precipitation accumulation	-3.833***	-0.899***	-1.685***	-0.948***
	(0.025)	(0.107)	(0.013)	(0.143)
Wind speed	1.011***	0.647***	-1.315***	0.581***
	(0.004)	(0.038)	(0.001)	(0.089)
Relative humidity	-0.455***	0.033***	-0.027***	0.035***
	(0.000)	(0.003)	(0.000)	(0.003)
Demand charge (log)	0.470***	68.257***	0.095***	68.404***
	(0.117)	(22.572)	(0.027)	(22.614)
Energy charge (log)	0.277***	15.871***	0.112***	15.896***
	(0.043)	(3.603)	(0.007)	(3.611)
Fixed effects				
Building	Y	Y	Y	Y
Weekend	Y	Y	Y	Y
Holiday	Y	Y	Y	Y
Month-of-year	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	23561924	23561924	23527526	23527526

R^2		0.011		0.011
F statistics	$3.0{*}10^6$		$2.3{*}10^5$	

Notes: Standard errors in parentheses are clustered to building unit level. * p<0.1, ** p<0.05, *** p<0.01. The demand charge and energy price are calculated by taking the average of the marginal prices of a price plan in a given month. Thus, the coefficients for the prices measure the differences in electricity consumption of consumers across different price plans across different months. Some large electricity-using consumers were on price plans that have lower prices.

Table 3 Effect of air pollution on solar energy generation in residential buildings

	(1) IV-first stage	(2) IV-second stage	(3) IV-first stage	(4) IV-second stage
Wind cosine	7.622***		1.751***	
	(0.129)		(0.046)	
PM10 concentration		-0.435***		
		(0.027)		
PM2.5 concentration				-1.888***
				(0.125)
Heating degree days	-0.608***	-0.142***	0.048***	0.214***
	(0.010)	(0.015)	(0.003)	(0.016)
Cooling degree days	0.619***	0.382***	0.021***	0.154***
	(0.015)	(0.024)	(0.002)	(0.011)
Precipitation accumulation	-9.181***	-5.659***	-1.346***	-4.197***
	(0.941)	(0.668)	(0.155)	(0.557)
Wind speed	0.551***	-0.450***	-1.243***	-3.038***
	(0.053)	(0.045)	(0.015)	(0.175)
Daily electricity price (log)	1.617***	0.104	1.413***	2.024**
	(0.536)	(0.794)	(0.117)	(0.858)
Surface albedo	777.950***	447.377***	60.592***	223.112***
	(13.426)	(28.414)	(2.118)	(18.319)
Constant				
Fixed effects				
Building	Y	Y	Y	Y
Weekend	Y	Y	Y	Y
Holiday	Y	Y	Y	Y
Month-of-year	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	199613	199613	198579	198579
R^2		0.032		0.135
F statistics	3488.99		1435.08	

Notes: Standard errors in parentheses are clustered to building unit level. * p<0.1, ** p<0.05, *** p<0.01.

Table 4 Effect of air pollution on solar energy generation in commercial buildings

	(1)	(2)	(3)	(4)
	IV-first stage	IV-second stage	IV-first stage	IV-second stage
Wind cosine	6.390***		1.551***	
	(0.014)		(0.006)	
PM10 concentration		-0.022***		
		(0.005)		
PM2.5 concentration				-0.093***
				(0.020)
Heating degree days	-0.422***	-0.028***	0.287***	0.008
	(0.001)	(0.005)	(0.001)	(0.006)
Cooling degree days	0.149***	0.021***	-0.022***	0.015***
	(0.001)	(0.003)	(0.000)	(0.003)
Precipitation accumulation	-20.052***	-0.737***	-3.273***	-0.590***
	(0.115)	(0.133)	(0.021)	(0.104)
Wind speed	0.037***	0.084***	-1.417***	-0.048**
	(0.005)	(0.013)	(0.001)	(0.025)
Demand charge (log)	-10.492***	0.792	-0.414***	0.991
	(0.075)	(0.593)	(0.009)	(0.613)
Energy charge (log)	-8.105***	-0.986***	-1.143***	-0.911***
	(0.113)	(0.260)	(0.017)	(0.249)
Surface albedo	213.255***	41.617***	-8.850***	35.990***
	(0.655)	(5.044)	(0.121)	(4.580)
Fixed effects				
Building	Y	Y	Y	Y
Weekend	Y	Y	Y	Y
Holiday	Y	Y	Y	Y
Month-of-year	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	22259565	22259565	22226277	22226277
R^2		0.001		0.001
F statistics	$2.1*10^5$		73964.88	

Notes: Standard errors in parentheses are clustered to building unit level. * p<0.1, ** p<0.05, *** p<0.01.