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# 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 disproportionately 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<sup>1,2</sup>, declines of subjective well-being<sup>3</sup>, harm on cognitive competence<sup>4,5</sup>, disturbance on ecosystem health<sup>6</sup>, diminished value of local environmental amenities and properties<sup>7</sup>, rises in

39 household medical expenditure, etc. Accurate assessment of such externalities is crucial to  
40 estimating the social cost of pollution for the design and evaluation of policies such as a  
41 Pigouvian tax that imposes the polluters for such external cost for pollution control, or a cap-and-  
42 trade program that establishes a market issuing allowances to internalize such cost<sup>8</sup>. While direct  
43 pollution damages are often measured in existing studies, there are not many discussions in the  
44 literature about the magnitude of the co-damages. A key challenge to quantify these co-damages,  
45 however, is to understand the feedback and interactions among pollution, human behaviors<sup>9</sup>, and  
46 technologies. People can mitigate exposure to environmental risks by taking various avoidance  
47 behaviors, such as adjusting outdoor activities<sup>10,11</sup> and purchasing facemasks and air purification  
48 systems in the short term<sup>9,12</sup>, and migrating to new living locations in the longer term<sup>13</sup>.  
49 Avoidance behaviors alleviate the negative health impact by pollution<sup>14</sup> but come at a cost, for  
50 example spending less time for outdoor activities<sup>10,15</sup>, and may lead to further impacts such as  
51 increased energy consumption due to a shift from natural to mechanical ventilation<sup>16</sup>, increased  
52 needs for heating or air-conditioning or other activities such as watching TV<sup>17,18</sup> in residential  
53 buildings. The commercial buildings may also be affected via further complexities if individuals  
54 choose to work remotely due to air pollution to avoid exposure during commuting<sup>19</sup>. However,  
55 on the other hand commercial buildings might have better indoor air quality due to better  
56 ventilation<sup>20</sup> so that people can stay in commercial buildings for longer period of time. These  
57 two effects can cancel out, and thus we hypothesize that air pollution does not have a statistically  
58 significant impact on commercial buildings as a whole. Such effects and the consequential extra  
59 environmental damage are, however, hardly addressed explicitly and quantitatively in the current  
60 studies, and thus lead to biases in the damage evaluation. Our paper fills in this gap in literature.

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

77 As pollution co-damages are closely related to both demand-side human behaviors and supply-  
78 side solar power generation, the distribution of these co-damages would raise environmental  
79 justice concerns. Lower-income households or minority ethnic groups can be more vulnerable to  
80 the impact of air pollutions. Individuals from these groups usually reside in locations with higher  
81 air pollution levels<sup>24</sup>. Moreover, they may live in affordable houses and buildings that are aged,  
82 not insulated well, equipped with fewer energy-efficient appliances, and thus lead to higher  
83 energy-related expenditures<sup>25,26</sup>. The increased electricity bills due to more indoor hours,  
84 therefore, translate into a larger proportion of the household income compared to their higher-

85 income or non-minority counterparts. This constraints other essential expenditures on medical  
86 services by lower-income and minority households, thus leading to further adverse health  
87 impacts <sup>27</sup>. Our analyses incorporate the equity aspects of pollution co-damages to provide  
88 necessary implications for policy design towards environmental justice.

89 This article demonstrates how the interactions among air pollution, human defensive behavior,  
90 and energy supply system can influence the estimates of negative externalities caused by air  
91 pollution. Using consumer-level daily and hourly electricity consumption data and solar panel  
92 generation records in Phoenix metropolitan, Arizona during 2013-2018, we testify how  
93 particulate air pollution, indicated by concentrations of both PM<sub>10</sub> and PM<sub>2.5</sub> (particulate matter  
94 10 micrometers or less in diameter, and 2.5 micrometers or less, respectively), triggers consumer  
95 avoidance behaviors as well as lowers the generation of solar energy. Our sample covers 4,313  
96 residential buildings and 17,422 commercial buildings. A variety of demographic and socio-  
97 economic characteristics are associated with the consumer data set, based on which we further  
98 explore the heterogeneity of the co-damages associated with income and ethnicity. Estimates can  
99 be biased by endogeneity issues due to reverse causality (i.e. air pollution induces changes in  
100 energy consumption as well as solar electricity generation, which in turn also affects the air  
101 quality) and missing variables (e.g. unobservable characteristics of the local economy and  
102 physical environment can affect the air quality and energy consumption simultaneously). To  
103 address the endogenous biases, we use wind direction as an instrumental variable (IV) for the  
104 pollution concentration. This IV has a direct impact on concentrations of pollutants but not on  
105 energy consumption, which creates variation in air quality that is exogenous to consumption,  
106 thus leading to non-biased estimation of the pollutant coefficient. Our main results are based on  
107 daily average data. We also analyze hourly data to examine the intra-day heterogeneity in the  
108 impact on electricity usage. The study area of our analysis is the fifth most populated city in the  
109 United States<sup>28</sup> and ranks among the top five most polluted cities in the country<sup>29</sup>. This suggests  
110 that even though based on a developed country region, our results can provide valuable insights  
111 and benchmark statistics when compared with studies in the developing context with dense  
112 population and low-ranked air quality.

113

### **Effect of air pollution on the demand sectors**

114 Through an instrumental variable (IV) fixed effects panel regression, we regress the individual  
115 household's daily electricity consumption on air pollution level, while controlling for other  
116 confounding variables. Detailed modeling can be found in the *Methods* section. The validity of  
117 IV estimation is also supported by the first-stage regression which shows a strong positive  
118 correlation between the daily average cosine of the prevailing-hourly wind direction angle and  
119 the concentration of air pollution, meaning that wind in the upwind direction of pollution sources  
120 would bring higher particulate concentration (Column 1 and 3 in Table 1). The considerable F  
121 statistics far more than 10 indicates a strong IV in both the regressions for PM<sub>10</sub> and PM<sub>2.5</sub>. We  
122 find that a higher concentration of particulate pollutant results in a statistically significant  
123 increase in residential electricity consumption. An increase of 1 $\mu\text{g}/\text{m}^3$  in PM<sub>10</sub> concentration  
124 raises the daily residential electricity consumption by 0.020 kWh (Column 2 in Table 1).  
125 Residents turn out to be more sensitive to the change of PM 2.5 concentration as 1 $\mu\text{g}/\text{m}^3$  rise in  
126 PM<sub>2.5</sub> concentration causes 0.145 kWh (Column 4 in Table 1) increase in daily electricity  
127 consumption. In this way, one more standard deviation of PM<sub>10</sub> and PM<sub>2.5</sub> would increase the

128 daily residential electricity consumption by 0.85% and 1.74% from the mean based on the  
129 descriptive statistics in Supplementary Table 1, respectively. Such effects are also seasonally  
130 heterogeneous (Supplementary Table 12) as the increased electricity consumption is of larger  
131 magnitude in summer peak (July and August), while the significance diminishes during the  
132 winter (November to April).

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

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

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

169 The results show that lower-income and Hispanic consumers have a larger increase in electricity  
170 consumption in response to a unit increase in PM pollution. The IV estimates in Figure 2  
171 illustrate that the marginal effect of pollution on electricity demand is the highest for the low-  
172 income group. For ethnic groups, Hispanic consumers increase their electricity consumption

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

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

205 Such an insignificant effect on commercial buildings overall is likely a result of mixed-effects by  
206 air pollution that cancel each other out. On one hand, when estimating the micro-environment  
207 exposure, incorporating work activities will induce higher exposure to air pollution compared to  
208 home-only activities, partially due to higher pollution exposure during transit or commute<sup>19</sup>. This  
209 implies that workers have the incentives to stay at home or work from home to avoid higher  
210 average pollution exposure, which lowers the energy consumption of the commercial buildings.  
211 We further test this hypothesis by our analysis of the effect of air pollution on personal trips.  
212 With a daily county-level dataset of mobility nationwide in the United States, we test whether  
213 individuals tend to reduce outdoor trips (details are included in *Methods*). As shown in  
214 Supplementary Table 13, the number of trips per person reduces as the concentration of air  
215 pollution rises. The same conclusion holds for both work trips (Supplementary Table 14) and  
216 non-work trips (Supplementary Table 15). On the other hand, commercial buildings on average  
217 might have different building envelope or better building management system <sup>20</sup> that can lead to  
218 better indoor environment <sup>33</sup> compared to residential buildings, so that when ambient air

219 pollution increases some people might want to stay inside commercial buildings for a longer  
220 period time, potentially increasing electricity in these buildings. Building occupants may also  
221 utilize less natural ventilation in polluted weather, and thus can increase the energy consumption  
222 of buildings due to increased mechanical ventilation <sup>16</sup>. These effects may cancel out so that we  
223 are not observing a statistically significant effect of air pollution on average for all commercial  
224 buildings in our sample.

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

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

## Effect of air pollution on the supply sector

261 We then use a similar panel IV regression to regress individual consumer's daily solar electricity  
262 generation on air pollution level, while controlling for confounding variables (See details in  
263 *Methods*). The IV of wind direction again turns to be powerful in explaining the variation of  
264 PM10 and PM2.5 with its positive significance in Column 1 and 3 in both Table 3 and Table 4,  
265 while the F statistics continue to verify it as strong. We find that particulate pollution also  
266 reduces the electricity generation of distributed solar panels in both residential and commercial  
267 buildings. IV estimation shows that  $1\mu\text{g}/\text{m}^3$  increase in PM10 concentration significantly reduces  
268 the electricity generated by solar panels by 0.435 kWh in residential buildings (Column 2 in  
269 Table 3) and by 0.022 kWh in commercial buildings (Column 2 in Table 4). PM2.5 demonstrates  
270 an even larger effect -- 1.888 kWh reduction per  $\mu\text{g}/\text{m}^3$  increase for residential buildings  
271 (Column 2 in Table 3) and 0.093 kWh reduction per  $\mu\text{g}/\text{m}^3$  increase for commercial buildings  
272 (Column 4 in Table 4). In terms of percentage change, one standard deviation increase of PM10  
273 and PM2.5 would result in 25.01% and 30.64% reduction of solar electricity generation for  
274 residential buildings with solar panels from the mean solar electricity generation, and 0.13% and  
275 0.15% reduction for commercial buildings, respectively. The comparison also indicates that  
276 commercial buildings are much less affected if considering that the power of solar panels is  
277 averagely larger in the commercial buildings referring to the descriptive statistics in  
278 Supplementary Table 1 and Supplementary Table 3. A possible reason is that the solar panels in  
279 commercial buildings are better maintained with dust cleaned timely.

## Discussion

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

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

301 Several critical policy implications stem from the findings of this research. First, when  
302 calculating the marginal damage factors from air pollution, policymakers need to explicitly



303 consider these co-damages generated from the feedbacks among consumer behaviors and clean  
304 technology performance, which is insufficiently discussed in the current literature as well as  
305 policy analysis and evaluation. Lack of consideration of these pollution co-damages will lead to  
306 under-estimation of welfare gains from pollution control policies. Our results also stress the  
307 necessity to investigate comprehensively the consequences of air quality alerting systems, e.g.  
308 alleviated health risks <sup>36</sup>, changed automobile traffic flows as individuals endeavor to escape  
309 from pollution as a response <sup>37</sup>, decreased outdoor recreation <sup>10,38</sup>, etc. Second, the fact that air  
310 pollution disproportionately affects low socio-economic status threatens energy and environmental  
311 justice, and again stresses that air pollution control can not only result in health benefit as a  
312 whole, but also contribute to equitable distribution of such benefit. The disproportional impact  
313 also highlights the importance of energy policies that can improve the home energy-efficiency of  
314 lower-income and ethnic minority groups to accelerate the achievement of fairness and equity.  
315 Third, our findings provide one more justification for the need to clean the electricity grid and  
316 improve the efficiency of renewable energy generation techniques. In addition, the expansions of  
317 solar power should take into consideration the effect of air pollution when setting reasonable  
318 development targets. The results comparing the impacts on commercial PV and residential PV  
319 suggest that there should be clear messages or incentives to communicate the importance of  
320 cleaning and maintenance of PV to the residential consumers.

321

322

323

## Methods

### 324 Data

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

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

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

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

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

### 375 **Empirical strategies**

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

$$378 \quad Elec\_Con_{it} = \beta_1 Pollution_{it} + \mathbf{X}_{it} + \alpha_i + \tau_y + \delta_m + Weekend_t + Holiday_t + \varepsilon_{it} \quad (1)$$

379 where  $i$  indexes individual residential or commercial consumer and  $t$  indexes day of the sample.  
380  $Elec\_Con_{it}$  refers to the daily electricity consumption of consumer  $i$  on day  $t$ .  $Pollution_{it}$  is the  
381 daily average concentration of either PM10 or PM2.5.  $\mathbf{X}_{it}$  is a vector of control variables,  
382 including cooling degree days (CDD) and heating degree days (HDD) (estimated using daily  
383 average temperature), daily total precipitation, wind speed, and electricity price (average daily  
384 electricity price for the residential consumers, and demand charge and energy charge for the  
385 commercial units). We also control for the concentration of ozone as another major pollutant that  
386 affects the air quality and thus the outdoor activities of consumers.  $\alpha_i$  is customer fixed effects

387 and it controls for the time-invariant attributes of the consumer such as square footage and the  
 388 number of stories as well as environmental awareness of building occupants. The time fixed  
 389 effects  $\tau_y$  and  $\delta_m$  include the year fixed effect and the month-of-year fixed effect. The time  
 390 fixed effects capture the time-varying factors across years and seasons such as economic  
 391 development and change in local energy policies. *Weekend* and *Holiday* are dummy variables  
 392 for holidays and weekends, respectively. Holiday dummy is equal to 1 if the day belongs to the  
 393 following federal holidays: New Year’s Day, Martin Luther King Day, Presidents’ Day,  
 394 Memorial Day, Independent Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving Day,  
 395 and Christmas Day.  $\varepsilon_{i,d}$  is the error term. Standard errors are clustered at the building level. We  
 396 are interested in  $\beta_1$  which indicates the electricity use raised by per  $\mu\text{g}/\text{m}^3$  increase of particulate  
 397 concentration ceteris paribus.

398 We analyze how the impact of air pollution differs by different income groups. Using the  
 399 available data on household characteristics, the sample is divided into three levels of per capita  
 400 income: low, medium, and high. The division is provided by Pew research center based on the  
 401 minimum household income level of different household size varying from 1-5  
 402 (\$24,042/34,000/41,641/48,083/53,759 for middle income, and  
 403 \$72,126/102,001/124,925/144,251/161,277 for upper income in 2014<sup>46</sup>). Since the household  
 404 size is recorded as 1.5, 3.5, and 5, we take an average of the two adjacent minimum household  
 405 income levels for 1.5- and 3.5-people households.

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

$$408 \quad Elec\_Solar_{it} = \beta_1 Pollution_{it} + \mathbf{X}_{it} + \alpha_i + \tau_y + \delta_m + Weekend_t + Holiday_t + \varepsilon_{it} \quad (2)$$

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

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

426 To address these issues, we resort to wind direction for an instrumental variable estimation. Its  
 427 validity has been verified by multiple existing air pollution studies<sup>47,49,50</sup>. The idea is that wind  
 428 direction affects regional air quality as it transports pollutants in specific directions. As the wind  
 429 direction fluctuates on a daily or even hourly basis, it can convert the study area between the

430 upwind or downwind of the pollution. Other than this pathway, wind direction (while controlling  
431 for wind speed) can hardly affect electricity consumption or solar electricity generation, and thus  
432 can meet the exclusive restriction for a valid instrumental variable.

433 We use the daily average cosine of the angle between the prevailing wind direction and the  
434 hourly wind direction as our instrumental variable following the previous studies<sup>47,51</sup> with  
435 modification in adapting to our daily-level data. We first plot the distribution of the hourly wind  
436 direction of all the climate stations to obtain the prevailing wind direction which turns out to be  
437 180°. We then calculate the cosine of the angle between each hourly wind direction observation  
438 and this prevailing direction, and finally obtain the daily average for each climate station that  
439 matches with different zip code zones. In this way, we can conduct the first stage regression  
440 before running equation (1) or (2) as

$$441 \quad \text{Pollution}_{it} = \gamma_1 \text{Wind\_dir}_{it} + \mathbf{X}_{it} + \alpha_i + \tau_y + \delta_m + \text{Weekend}_t + \text{Holiday}_t + e_{it} \quad (3)$$

442 where  $\text{Wind\_dir}_{it}$  indicates the daily wind direction variable,  $e_{it}$  is the error term, and other  
443 terms are the same as in equation (1) or (2). The coefficient  $\gamma_1$  after we run the first stage model  
444 is statistically significant with an F-value larger than 10, implying that the instrumental variable  
445 is relevant and strong. We then use the predicted values of pollution from equation (3) in the  
446 second stage model when we run equation (1) or (2).

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

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

472 study by Clements et al.<sup>52</sup> As a result, the hourly change in building energy consumption will not  
473 alter local PM pollution in Phoenix metropolitan area immediately.

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

$$476 \quad Trip_{jt} = \beta_1 Pollution_{jt} + X_{jt} + \pi_j + \delta_m + dow_t + \varepsilon_{jt} \quad (4)$$

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

$$482 \quad Pollution_{jt} = \gamma_1 Wind\_dir_{jt} + X_{jt} + \pi_j + \delta_m + dow_t + e_{jt} \quad (5)$$

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

488

489

## 490 **Data availability**

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

501

## 502 **Code availability**

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

506

507

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624

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632

## 633 **Author contributions**

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

637

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640

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## 642 **Competing interests**

643 The authors declare no competing interests.

644

645

646 *Figure 1 Change in residential hourly electricity consumption due to 1 unit increase in air pollution concentration.* The colored  
647 dots show the changes in hourly electricity consumption, obtained from panel regression at hourly level. The colored vertical



648 lines show the 95% confidence intervals. As the information on hourly electricity price is available only for a small part of the  
 649 residential and commercial samples, we conduct the analysis both with and without the regressor of price as a control variable.  
 650 Source data

651

652 *Figure 2 Change in daily residential electricity consumption due to 1 unit increase in air pollution concentration.* Results are  
 653 based on instrumental variable methods. The solid dots represent the values of the coefficients that measure the change in  
 654 daily electricity consumption in response to a 1  $\mu\text{g}/\text{m}^3$  increase in PM concentration. The vertical lines represent 95%  
 655 confidence intervals. Source data

656

657 *Figure 3 Change in commercial hourly electricity consumption due to 1 unit increase in air pollution.* The colored dots show the  
 658 changes in hourly electricity consumption, obtained from panel regression at hourly level. The colored vertical lines show the  
 659 95% confidence intervals. Source data

660

661 *Figure 4 Change in daily commercial electricity consumption due to 1 unit increase in air pollution.* Results are based on  
 662 instrumental variable methods. The solid dots represent the values of the coefficients that measure the change in daily  
 663 electricity consumption in response to a 1  $\mu\text{g}/\text{m}^3$  increase in PM concentration. The vertical lines represent 95% confidence  
 664 intervals. Source data

665

666

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

	(1) IV-first stage	(2) IV-second stage	(3) IV-first stage	(4) IV-second stage
Wind direction (cosine)	13.740*** (0.016)		1.852*** (0.008)	
PM10 concentration		0.020*** (0.004)		
PM2.5 concentration				0.145*** (0.032)
Ozone concentration	-8.223*** (0.766)	58.849*** (1.643)	-2.587*** (0.204)	58.606*** (1.618)
Heating degree days	-0.383*** (0.001)	0.779*** (0.012)	0.134*** (0.001)	0.751*** (0.012)
Cooling degree days	0.145*** (0.001)	1.103*** (0.009)	0.002*** (0.000)	1.106*** (0.009)
Precipitation accumulation	-3.503*** (0.067)	-0.142** (0.068)	-1.771*** (0.038)	0.048 (0.086)
Wind speed	1.094*** (0.007)	-0.119*** (0.014)	-1.264*** (0.003)	0.087** (0.044)
Relative humidity	-0.430*** (0.001)	0.044*** (0.002)	-0.020*** (0.000)	0.038*** (0.001)
Daily electricity price (log)	-0.507*** (0.119)	-8.003*** (0.819)	0.631*** (0.027)	-8.078*** (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 <sup>2</sup>		0.507		0.507
F statistics	7.7*10 <sup>5</sup>		49475.29	

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

668

669

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

	(1)	(2)	(3)	(4)
	IV-first stage	IV-second stage	IV-first stage	IV-second stage
Wind cosine	13.749*** (0.008)		2.149*** (0.004)	
PM10 concentration		-0.007 (0.011)		
PM2.5 concentration				-0.045 (0.074)
Ozone concentration	-9.828*** (0.490)	9.241** (3.598)	-5.344*** (0.124)	8.917** (3.558)
Heating degree days	-0.554*** (0.001)	0.093*** (0.018)	0.080*** (0.000)	0.100*** (0.026)
Cooling degree days	0.213*** (0.001)	0.649*** (0.023)	0.006*** (0.000)	0.648*** (0.022)
Precipitation accumulation	-3.833*** (0.025)	-0.899*** (0.107)	-1.685*** (0.013)	-0.948*** (0.143)
Wind speed	1.011*** (0.004)	0.647*** (0.038)	-1.315*** (0.001)	0.581*** (0.089)
Relative humidity	-0.455*** (0.000)	0.033*** (0.003)	-0.027*** (0.000)	0.035*** (0.003)
Demand charge (log)	0.470*** (0.117)	68.257*** (22.572)	0.095*** (0.027)	68.404*** (22.614)
Energy charge (log)	0.277*** (0.043)	15.871*** (3.603)	0.112*** (0.007)	15.896*** (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 <sup>2</sup>		0.011		0.011
F statistics	3.0*10 <sup>6</sup>		2.3*10 <sup>5</sup>	

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

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

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

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

678

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*** (0.014)		1.551*** (0.006)	
PM10 concentration		-0.022*** (0.005)		
PM2.5 concentration				-0.093*** (0.020)
Heating degree days	-0.422*** (0.001)	-0.028*** (0.005)	0.287*** (0.001)	0.008 (0.006)
Cooling degree days	0.149*** (0.001)	0.021*** (0.003)	-0.022*** (0.000)	0.015*** (0.003)
Precipitation accumulation	-20.052*** (0.115)	-0.737*** (0.133)	-3.273*** (0.021)	-0.590*** (0.104)
Wind speed	0.037*** (0.005)	0.084*** (0.013)	-1.417*** (0.001)	-0.048** (0.025)
Demand charge (log)	-10.492*** (0.075)	0.792 (0.593)	-0.414*** (0.009)	0.991 (0.613)
Energy charge (log)	-8.105*** (0.113)	-0.986*** (0.260)	-1.143*** (0.017)	-0.911*** (0.249)
Surface albedo	213.255*** (0.655)	41.617*** (5.044)	-8.850*** (0.121)	35.990*** (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 <sup>2</sup>		0.001		0.001
F statistics	2.1*10 <sup>5</sup>		73964.88	

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