Global Gains from a Green Energy Transition: Evidence on Coal-Fired Power and Air Quality Dissatisfaction*

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Phasing out coal-fired power in favor of renewables is a central part of the green transition. As well as reducing carbon emissions, it should have an immediate and perceptible benefit for air quality. This paper uses geocoded survey data from 51 countries to show that people living within 40 km of coal-fired power plants are indeed more dissatisfied with ambient air quality. We then construct the equivalent variation for closing down coal-fired power plants and find that air quality benefits support the case for a green transition, with implications for policy action in this area. (*JEL* I31, Q42, Q53, Q58)

I Introduction

There is now widespread recognition that phasing out coal-fired power is a central plank of the green transition towards renewable energy. But there is also much concern that the pace of change is too slow, most often blamed on the failure of political will. Moreover, some countries continue to invest in coal-fired power plants and are even building new ones. Coal-fired power is not just bad for carbon emissions, it is detrimental to air quality with negative consequences for public health (see, for example,

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Lelieveld et al. (2015)). This is worse when plants are located near dense population centers.[1] But it also implies that some benefits from closing coal-fired power should be both rapid and local so that local political processes can play a role in spearheading the green transition.

However, even though individual citizens may suffer the consequences of air pollution, it has long been argued that without increasing the political salience of the issue, public action may not take place (e.g. Crenson (1971) for the US and Singh and Thachil (2023) for India). Moreover, one way to galvanize such action is to provide evidence of collective benefits from closing down coal-fired power plants. This links to the increased interest in measuring environmental damages alongside studying ways to adapt to and mitigate their consequences (see, for example, Stern (2007) and Aghion et al. (2019)). Research in environmental psychology tries to uncover relationships between individual characteristics and incentives, location attributes, and perceptions towards damages, and how these interact with governance and politics (Whitmarsh (2008); Egan and Mullin (2017); Poortinga et al. (2019)). Some of these studies have established correlations using variations in existing datasets at the state or the city level (Howe et al. (2015); Konisky, Hughes, and Kaylor (2016)) and others leverage more granular analysis using bespoke local surveys (Kaiser (2006); Bogner and Wiseman (1999)).

However, such issues are rarely studied in low- and middle-income countries where data availability is more limited. Yet, the damages due to air pollution and climate change are argued to be disproportionately higher in the Global South (Cruz and Rossi-Hansberg (2021)). Furthermore, the growth in coal-fired power in recent years has also predominantly been in the middle-income countries. This makes studying such contexts even more relevant.

This paper has two main aims. First, we study the link between air quality perceptions and coal-fired power to show that citizens do appear to notice the detrimental effects of this polluting technology. Second, we use data on life satisfaction to construct a measure of the benefits of closing down coal-fired power stations and replacing them with renewables. We show that air quality benefits alone can be used to make the case for a green transition.

The paper takes advantage of a unique dataset, which provides geocodes of the locations of survey respondents in 51 countries covered in the Gallup World Poll, most of which are low- and middle-income countries. Using the precise locations of interviews, we could construct a measure of proximity to coal-fired power stations. We find robust evidence that those respondents who live closer to an operational coal-fired

1. There are at least ten thermal power plants in states of Punjab, Haryana, and Uttar Pradesh that are located in the vicinity of New Delhi, which is the most densely populated city of India. *Source:* Economic Times - Energy News, 4 June, 2021.

power plant express greater air quality dissatisfaction compared to others in the same country/region who are farther away from an operational coal-fired power plant. The link between dissatisfaction and proximity to coal-fired power cannot be explained by a priming effect since respondents were not asked about coal-fired power prior to answering the air quality question.

To construct a measure of benefits for closing down coal-fired power stations, we leverage an equivalent variation (EV) measure. We make use of a life satisfaction question from the same survey, and compare the coefficient on air quality dissatisfaction (which impacts life satisfaction negatively) and income (which impacts life satisfaction positively). This allows us to construct a monetary value of the benefit of a switch to renewables for those who live within a 40 km radius of operational coal-fired power stations. Such renewable technologies are now sufficiently scalable to match the mainstream capacity generation that can be achieved through coal-fired power and many high-income countries have already ramped-up investments in renewables and pushed most of their existing coal-fired power plants either towards retirement or conversion into natural gas plants (Davis, Holladay, and Sims (2022)).[2] Moreover, since R&D investments in energy storage technologies promise finding a way of balancing out supply and demand,[3] the transition looks technologically feasible in the near future. We find that just looking at air quality benefits yields a strong case for replacing coal-fired power with clean energy.

We use these estimates to show that the air quality satisfaction benefits from closing the "top" 25 coal-fired power stations in our sample of countries are large enough to justify their closure, even without factoring in the carbon reduction benefits. We also use our estimated benefits "out of sample", i.e., for countries that are not in our survey data, projecting the valuations of air quality and finding a similarly strong case for closing coal-fired power stations elsewhere based solely on the air quality benefits.

These findings provide a new window on the case for phasing out coal-fired power since it stresses that this is coming from citizens' own perceptions rather than expert opinion. It therefore compliments approaches that estimate public health benefits from reducing reliance on coal-fired power, such as Lelieveld et al. (2019) which attributes 65% of excess global mortality to fossil fuel-related emissions, with significant heterogeneity across regions.

Those who focus on climate change imperatives often refer to air quality improvement as a co-benefit from low-carbon investments (see, for example, Stern (2016)) and

2. Coal will account for 85% of U.S. electricity generating capacity retirements in 2022. *Source:* US Energy Information Administration

3. In 2019, around 80% of all public energy R&D spending was on low-carbon technologies – energy efficiency, CCUS, renewables, nuclear, hydrogen, energy storage, and cross-cutting issues such as smart grids. *Source:* IEA World Energy Investment Report, 2020

that coal generation has a negative value added when accounting for the external social costs of the air pollution it produces (Muller, Mendelsohn, and Nordhaus (2011)). But, when it comes to politics, it can be first-order due to its visibility. However, individuals might be aware of poor ambient air quality without being able to attribute it to their proximity to a coal-fired power station and, even if they are aware of it, they need not know about collective benefits, which are obtained by aggregating across individuals, as we do here. Ultimately, domestic and international policies to reduce carbon emissions are likely to be encouraged if citizens, firms, and civil society demand change. As stressed in Besley and Persson (2023), facilitating a green transition requires citizens as voters and consumers to embrace green values. Citizens' perceptions of the need for change are likely to be the key drivers in increasing the salience of policy issues in this area where global debates about abstract notions, like climate change, may not readily cut through.

The remainder of the paper is organized as follows. In the next section, we discuss the data that we use. In Section III, we establish a robust empirical link between a survey respondent's proximity to a coal-fired station and their satisfaction with air quality. The policy implications of these findings are developed in Section IV. Section V contains some concluding comments.

II Data

II.A Geocoded Gallup World Poll

The outcomes data is taken from the Gallup World Poll, an annual, nationally-representative survey of citizens which began data collection in 2006 and represents around 99% of the world's adult population living in more than 160 countries. We only use the 2019 data in which we are given access to geocoded data for a sample of countries where face-to-face interviews were undertaken. This excludes the US and a majority of Western European countries with phone surveys as shown in the top panel of Figure B.1 in the Appendix. For the sample countries, we have exact latitudes and longitudes of the interview clusters and we use them to measure the distance of survey locations from the nearest coal-fired power plant. This gives a sample of 17,964 surveys from 51 countries listed in Table B.1 and mapped in the bottom panel of Figure B.1 in the Appendix. The main outcome variable is a binary indicator of the survey respondent's dissatisfaction with ambient air quality. The exact question (translated into English) is: *"In the city or area where you live, are you satisfied or dissatisfied with the quality of air?"*

We also use survey responses to a question on current life satisfaction as a proxy for overall wellbeing. It asks respondents to rate their present life on an eleven-point scale from 0 ("the worst possible life") to 10 ("the best possible life"). This measure of life satisfaction is popular among researchers and has been used extensively to make cross-country comparisons of wellbeing, particularly for less-developed countries (Deaton (2008); Kahneman and Deaton (2010)). Apart from these two "outcome" variables, we also use controls for education, age, income, gender, and whether or not they have children under 15 years of age (also from the Gallup World Poll). We also make use of a different, but related, attitudinal survey based on a subset of countries included in the Gallup World Poll: the Lloyd's Register Foundation World Risk Poll.[4] Here also, we restrict the sample to 51 countries from the main analysis.

II.B Global Energy Monitor Coal Plants Tracker

Data on coal-fired power plants come from the Global Coal Plant Tracker (GCPT) database released by the Global Energy Monitor (GEM).[5] This is freely-available data that tracks all coal-fired generating units, which are 30 MW or larger, in different stages of operation across the world and provides units' precise locations in terms of latitudes and longitudes and other characteristics, such as capacity, annual CO_2 emissions, etc. At present, it has detailed information on 13,412 coal units located in 108 countries. Of the total reported units, 6,613 units are operational, and these generate more than 2 million megawatts of power and produce 12 trillion kilograms of CO_2 each year. The database makes available rich data on other energy sources also, such as natural gas, wind, and solar and heavy industries, such as iron and steel. Figures B.2 and B.3 in the Appendix show the distribution of operational and planned units respectively for coal, solar, and wind energy generation across 51 countries that constitute our main analysis sample.

We also use remote-sensing data on vegetation cover and pollutant concentration from the NASA Earth Observations project for each survey location and a 1 km $\times$ 1 km grid population count from the Gridded Population of the World v4 (GPWv4) database for the year 2020 to compute the population estimates.

4. In this survey, 150,000 interviews were done by Gallup in 142 countries in 2019 to measure the risk perceptions around climate change, pollution, food, cyber security, etc. (LRF (2020))

5. GCPT provides information on coal-fired power units from around the world generating 30 megawatts and above. It catalogues every operating coal-fired generating unit, every new unit proposed since 2010, and every unit retired since 2000. *Source:* Global Coal Plant Tracker - Global Energy Monitor

III Air Quality Satisfaction and Coal-Fired Power

Our first step is to show that there is a robust link between air quality dissatisfaction and proximity to coal-fired power plants. This observation underpins the policy exercise that we turn to in the next section. We first lay out the empirical approach, and then develop some core results and explore their robustness.

III.A Approach

Suppose that air quality dissatisfaction, $AirDiss$, for an individual, i, located near a coal plant, c, surveyed in location, ℓ, can be explained as follows:

$$AirDiss_{i\ell} = \alpha\delta_{ic} + \tau_i + \varepsilon_{i\ell} \tag{1}$$

where δ_{ic} is i's distance to the nearest operating coal-fired power plant, c, and τ_i represents unobserved idiosyncratic distaste for air pollution. Obviously, we cannot estimate this exact relationship in practice because we observe each individual only once in the data, but it has value for the discussion to go forward.

If coal plants were randomly assigned to different locations, or equivalently, if individuals chose to locate randomly across different locations, then OLS would give us an unbiased estimate of α, i.e., how, on average, distance from the nearest coal-fired power plant is related to perceived ambient air quality.

If policy-makers may choose to locate coal-fired power stations where opposition is lowest, i.e., where people are less concerned about pollution or people who care strongly about pollution move away from locations where there is heavy air pollution then OLS could underestimate the negative impact of coal-fired power on the general population. So we think of our results as a lower bound on the effect.[6]

Our core results come from supposing that $\tau_i = \beta\mathbf{X}_{i\ell} + \eta_\ell$, where $\mathbf{X}$ contains the geocode (latitude×longitude)-level and individual-level controls, and where η_ℓ are region fixed effects, either at the country (admin 0) or state/province (admin 1) level.

6. More formally, note that

$$\widehat{\alpha}_{OLS} = \frac{cov\left(AirDiss_{i\ell}, \delta_{ic}\right)}{var\left(\delta_{ic}\right)} = \frac{cov\left(\alpha\delta_{ic} + \tau_i + \varepsilon_{i\ell}, \delta_{ic}\right)}{var\left(\delta_{ic}\right)} = \alpha + \frac{cov\left(\tau_i, \delta_{ic}\right)}{var\left(\delta_{ic}\right)}$$

If $cov(\varepsilon_{i\ell}, \delta_{ic}) = 0$, then any bias in OLS comes from the final term representing the correlation between unobserved tolerance for air pollution and the location of coal-fired power stations. The two sources of biases that we have mentioned would lead use to expect that $cov(\tau_i, \delta_{ic}) > 0$, implying that the estimate of α is, if anything, biased downwards as an estimate of the average relationship between being located close to a coal-fired power station and air quality dissatisfaction. In the Appendix Section A, we report results from an instrumental variables strategy which, consistent with this, finds much larger estimates of the relationship between coal-fired power and air pollution.

We then estimate the following core equation using OLS:

$$AirDiss_{i\ell} = \alpha\delta_{ic} + \beta\mathbf{X}_{i\ell} + \eta_{\ell} + \varepsilon_{i\ell} \tag{2}$$

Prior research on perceptions and actual impacts lead us to expect a larger effect on households, which are closer to coal-fired power stations (Zhang et al. (2022); Datt et al. (2023)). We therefore present our main findings for three distance bands: 0-40 km, 40-80 km, and 80-120 km, which are distances between a survey location and the nearest coal-fired power plant.[7]

III.B Core Findings

Table I reports the results.[8] In Columns 1, 2, and 3 we use country fixed effects while those in Columns 4, 5, and 6 use state/province fixed effects. Columns 1 and 4 are for distance band 0-40 km, 2 and 5 for 40-80 km, and 3 and 6 for 80-120 km. The results in Columns 1 and 4 confirm our hypothesis that α is negative, i.e., air quality dissatisfaction is negatively correlated with distance from the nearest coal plant for respondents located within 40 km of a coal-fired power plant.[9]

The core results are robust to changing the range of distance i.e., starting from 0 km and ending at 60 km as the upper limit of domain. However, there is no effect of distance on perception when using 40-80 km or 80-120 km distance bins, thereby suggesting that the "immediate" effect is local (Ha et al. (2015)).[10]

Table I also gives suggestive evidence that "elite" opinion is geared towards some form of climate action as evidenced in the gradient on education level; individuals with higher education levels tend to be significantly more dissatisfied compared to the

7. We look at the concentration of pollutants around the operational coal-fired power plants to check if people's perceptions are not totally off the actual level of air pollution. We rely on remote-sensing data on pollutant concentration from NASA Earth Observations and Donkelaar et al. (2021). Figure B.4 reports the mean $PM_{2.5}$ and NO_2 concentration in different distance bins relative to a coal power plant. The pollutant level goes down as one moves away from coal plant locations.

8. The OLS estimation uses a linear probability model, which might be a strong assumption given the binary nature of the dependent variable. We test the robustness of OLS results by estimating a logistic regression model with region fixed effects alongside the same controls as in the OLS specification. Results reported in Table B.2 suggest that the OLS estimates are robust to relaxing the linearity assumption.

9. We also run a specification using Equation (2) with a general measure of health problems as the dependent variable. The exact survey question is: *Do you have any health problems that prevent you from doing any of the things that people of your age normally can do?* This is a portmanteau health question, and as expected, we do not detect any significant effect of our main regressor, δ.

10. Throughout the paper, we report region-clustered heteroscedasticity-robust standard errors. However, following Conley (1999) and Conley (2008), which allow for spatial correlation in the errors across neighboring areas with distances less than a specified threshold, we report results in Table B.3 with spatial clusters defined at 5 km distance threshold. The results are essentially identical with slightly smaller standard errors.

less educated ones, *ceteris paribus*. This significant result, along with mixed patterns on age group and income, has been documented in other studies, which use different attitudes datasets (Dechezleprêtre et al. (2022)).

Taken together these results suggest that the mere existence of coal-fired power stations nearby do indeed affect perceptions of air quality negatively.[11] Also, to reiterate, we expect these to be lower bound estimates, so the actual effects could be much larger.

III.C Robustness and Additional Findings

We now present a range of additional results that explore the validity of our core findings. We first show that the granularity from using geocoded data is essential to our findings. We then ask whether the core results are reflected in individual climate risk perceptions rather than air quality satisfaction. As a "placebo" test, we check whether non-operational power stations have a similar effect on air quality perceptions to those that are operational. To ensure that this effect is coming from coal-fired power plants, we also check whether the location of other polluting industries, such as iron and steel production, have similar links to air quality dissatisfaction. We also look for heterogeneous effects based on whether survey respondents are located upwind or downwind from operational coal-fired power plants. Finally, we use a semi-parametric approach to examine the validity of the distance cutoff used in our core results.

III.C.1 Data aggregated at regional level

A unique feature of the analysis is being able to use spatially granular data. Most previous work has used much less granular data. To show that this is important, we contrast our core findings with results using data aggregated to the region level. While we have a less clear-cut way of measuring survey respondents' proximity to coal-fired power stations, it does permit a longer time period to be studied since we can now use the World Poll for all years rather than just 2019, the year for which we have geocoded data. However, to maintain comparability, we will use the same 51 countries as in our main analysis.

We experiment with different ways of defining exposure at a regional level. Our first measure is the number of operational coal-fired plants in a region in a given year divided by the total area of the region. This can be constructed without knowing

11. To see if there is a relationship between the level of emissions and air quality dissatisfaction conditional on distance, we estimate Equation (2) and include an interaction of the distance regressor and the nearest plant-level annual CO_2 emissions. We find that the interaction term is not statistically significant, as reported in Table B.4 in the Appendix. This highlights that, in our case, distance is a "sufficient statistic" to explain the effect of coal plants on people's perceptions.

specifically where a respondent lives. The second measure is closer to what we use in Equation (2), and is the logarithm of the average distance between all survey geocodes and the nearest operational coal-fired power plant at the region level for survey locations that are within 40 km of the plant in 2019.[12]

Results using aggregated data, which is reported in Table II, show no significant relationship between any of the two measures of exposure to coal-fired power defined at the regional level and the average air quality dissatisfaction in a region. Even though the coefficients are not statistically significant, it is interesting to note that the coefficient on the second exposure variable, which is our closest counterpart to the main results reported in Table I, is of the same order of magnitude as in the core results.[13]

These findings underline the value of using spatially granular data to assess the impact of coal-fired power on air quality dissatisfaction. Even our best estimate of exposure to coal-fired power based on aggregation to the region level is much less precisely estimated than what we find with precise locations.

III.C.2 Risk perceptions

Data from the World Risk Poll allow us to estimate a similar specification to Equation (2) but with the left hand side variable now being individual risk assessments on pollution and climate. Table III reports the results.

Whether we use admin-0 or admin-1 fixed effects, we find that, as before, a significant negative relationship exists between an individual's location relative to the nearest coal power plant and their pollution risk perception when they are located within the 0-40 km distance band. However, there is no such relationship when we look at perception of risk of climate change damages.[14] This suggests that air quality perception is more linked to a visible source of risk and not linked to climate change *per se*, something that we return to when think of possible political economy implications.

III.C.3 Placebo tests

We report two kinds of placebo test. First, we should not expect a relationship between perceptions of air quality and *retired* (closed) or *planned* (for the future) coal-fired power plants in new locations i.e., plants that are no longer operational[15] or have

12. For this to be an accurate exposure measure for all years, the locations of the sample collected in 2019 needs to be similar to that in other years.

13. The results in Table II also show that the magnitude of the coefficient on the exposure to coal-fired power is not sensitive to the inclusion of year fixed effects. This is also shown in Figure B.5 in the Appendix. It suggests stable air quality perceptions over time across sample countries, thereby allaying some concerns around using only a single cross-section for 2019 for our core results.

14. Results for 40-80 km and 80-120 km distance band are reported in Table B.5 in the Appendix.

15. Units that have been permanently decommissioned or converted to another fuel are classified as retired while units that have been deactivated or put into an inactive state but are not retired are called

been announced, at a pre-permit or permit stage of commissioning. Second, we do not expect proximity to coal-fired power plants to be associated with reduced perceptions of other environmental amenities such as water quality.

The results are in Table IV and, as expected, the coefficients on distance are not significantly different from zero. Similarly, the effect of distance from the nearest operational coal-fired power plant on water quality dissatisfaction is also insignificant, thereby confirming our placebo hypothesis.[16]

III.C.4 Other polluting industries

Iron and steel production plants tend to be located near coal-fired power plants and are also a major source of local air pollution. We now see whether they have similar effects on air quality dissatisfaction.

We use the GEM database as a source of geolocations for iron and steel plants around the world. To our core specification, we add the logarithm of the straight-line distance between an operational coal-fired power plant in the analysis and the nearest iron and steel plant, when estimating Equation (2). Table V reports the results. The point estimates for distance between the survey locations and coal plants remain same as from Table I. In addition, the coefficient estimates for the new control variable, though smaller in magnitude, are also negative, suggesting that iron and steel plants do affect air quality perceptions but with smaller magnitude compared to coal-fired power plants.

III.C.5 Wind direction

Wind transports air pollutants across space and previous work has found it to be a source of heterogeneity when looking at the effects of pollution (see, for example, Deryugina et al. (2019)). In the case of coal-fired power plants, we expect that areas lying downwind from the plants will receive more pollution.

We exploit cross-sectional variation in the wind direction to see whether this is a source of heterogeneity. To do so, we use the so-called u- and v-component of wind, which are wind velocities in two orthogonal directions, to derive the resultant wind direction vector at each coal-fired power plant location for all the survey geocodes located in its domain of influence.[17]

mothballed units.

16. Results for 40-80 km and 80-120 km distance band are reported in Table B.6 in the Appendix.

17. We use the monthly averaged u- and v-component of wind at 10 meter elevation from ground surface for single pressure level using the global version from ERA5 Climate Data Store. We do the further averaging over the monthly data for years 2015-19 to arrive at one u- and v-component for each coal plant location. To define the domain of influence i.e., wind buffer zones for each coal plant, we use the 0-40 km distance band, same as earlier, but also employ angular restrictions viz. 60°, 90° and 120°

We re-estimate the Equation (2) with the distance variable interacted with a downwind dummy that takes a value of 1 if a survey geocode is located in the domain of influence of a coal-fired power plant. Table VI reports the regression results. The estimates on the downwind dummy suggest that being in the downwind direction of an operational coal power plant does not have a significant effect on local air pollution perceptions. However, under strong restrictions on the domain of influence i.e., within a 0-40 km distance band and 60° angle, individuals located in downwind areas do show some tendency to express more dissatisfaction with ambient air quality, as Column 4 shows.[18] We have also looked at whether wind direction affects actual pollution measured using the $PM_{2.5}$ concentration at the geocode level. Here we also find no significant effect.[19]

III.C.6 Distance cutoff

Our core measure of distance focused on survey respondents residing in areas, which are less than 40 km from the nearest operational coal-fired power plant. Those who live further away do not appear to show higher levels of air quality dissatisfaction.

To explore the validity of the 40 km cutoff, Figure I shows the result of estimating a semi-parametric locally-smoothed polynomial to show how air quality dissatisfaction varies with distance. It demonstrates that air quality dissatisfaction decays, essentially to zero at around 20 km from coal power plants. Using this as our core distance measure would, however, give us a much smaller number of survey respondents, only 6% of the survey respondents live within 20 km of a coal-fired power plant compared to 13% living within 40 km. So, we are likely to get more statistical power at 40 km.[20]

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angular width with the wind direction vector defining the central azimuth. All the survey geocodes that fall in the buffer zone are classified as downwind points. Figure B.6 shows the buffer zones for 60° angular restriction and 40 km distance band for operational coal power plants located in some parts of the Indian subcontinent.

18. Note that we are using annual averages on wind direction, thereby removing seasonal and almost entire idiosyncratic variations that could be more important for shaping perceptions. Wind direction predictions at coal plant locations may also be measured with error due to intervening convection and radiation currents due to coal plants' operations itself (see, for example, Balboni, Burgess, and Olken (2021), which reports null effects on the propagation of forest fires).

19. See Table B.7 where we use actual pollution levels i.e. $PM_{2.5}$ concentration, and still find null effects.

20. As a further robustness check, we run our main regressions for the 0-20 km bandwidth to see whether our results continue to hold. Table B.8 shows that both the main and placebo results do continue to hold even though we lose some statistical significance on the main results due to the smaller number of observations from which we are trying to identify the effect.

IV Policy Implications

We have now established that perceptions of ambient air quality are indeed related to the proximity to coal-fired power plants. We use this observation to calibrate a measure of the air quality satisfaction benefits of closing down coal-fired power stations for the approximately 1.12 billion people living within 40 km of an operational coal-fired power plant in our sample of countries and the 2.18 billion (about one-third of the global population) in the world as a whole.

The policy analysis proceeds in three steps. First, we construct the equivalent variation (EV) of increasing air quality satisfaction from the survey data using the life satisfaction responses. Second, we aggregate this across the affected population. Third, we obtain a ballpark measure of the cost of replacing coal-fired power generation with a non-polluting source, such as solar or wind energy, and compare this to the benefits.

This approach builds on the large existing literature that links life satisfaction to the value of "amenities" (for example, Layard, Mayraz, and Nickell (2008); Kahneman and Deaton (2010)), a sub-strand of which has focused on valuing natural disasters (Luechinger and Raschky (2009)) and environmental amenities (Frey and Stutzer (2002); Frey, Luechinger, and Stutzer (2010); Welsch (2006)). Data limitations mean that the scope of these studies has been limited to the US and parts of Europe. The correlation between objective and perceived air quality is not always strong (Liu, Cranshaw, and Roseway (2020)), and, arguably, it is the latter that matters most for economic decision-making (Chasco and Gallo (2013)) and political activism.

To construct an EV measure, we demonstrate a negative correlation between a standard life-satisfaction measure from the Gallup survey data and air quality dissatisfaction. Since income and well-being are correlated, this can be used to calibrate the marginal rate of substitution between money and air quality dissatisfaction that can be used to create a benefit measure, which can be compared with the cost of clean energy transition. This method can be used to measure aggregate benefits but could also be deployed to gauge much more disaggregated, plant-level benefits, based on the affected local population.

IV.A Approach

We first estimate the determinants of life satisfaction by OLS using the following econometric specification:[21]

$$LifeSat_{i\ell} = \psi \log(AirDiss_{i\ell}) + \phi \log(Income_{i\ell}) + \beta \mathbf{X}_{i\ell} + \eta_\ell + \varepsilon_{i\ell} \tag{3}$$

where the dependent variable, $LifeSat_{i\ell}$, is the life satisfaction score on a 0-10 Cantril ladder for individual i in location ℓ, η_ℓ controls for region fixed effects, $Income$ stands for household income in 1000 USD, $AirDiss$ is air quality dissatisfaction that takes value 2 (1) if individual is dissatisfied (satisfied) with ambient air quality, and $\mathbf{X}$ is a vector of controls, which are the same as in our previous specifications.

We use the estimates of ϕ and ψ to quantify the relationship between income and air quality dissatisfaction with life satisfaction. Equation (3) is estimated for all 51 countries in our sample.[22] The results are reported in Table VII.[23] To be cautious, we consider upper and lower bound estimates, from a 95% confidence interval, rather than just point estimates.[24]

Our EV measure, denoted by e, uses a reference level of air quality based on a Cobb-Douglas utility function and is defined in a standard way, as the amount of money that an individual would need to obtain the reference air quality dissatisfaction level, $\widetilde{AirDiss} < AirDiss$. This is given by:

$$\psi \log(\widetilde{AirDiss}) + \phi \log(Income - e) = \psi \log(AirDiss) + \phi \log(Income)$$

which implies that the equivalent variation is:

$$e = Income \left[1 - \exp \left\{ \frac{\psi}{\phi} \log \left(\frac{AirDiss}{\widetilde{AirDiss}} \right) \right\} \right] \tag{4}$$

To estimate e in Equation (4), we use the parameter estimate for $\frac{\psi}{\phi}$ from Column 2 of

21. There is no consensus in the literature on the exact econometric equation that should be used here, but the majority of previous work in this vein has used a specification similar to ours. The coefficient on logarithm of income is precisely estimated and is around 0.5, which lies well-within the bounds estimated in the existing literature (Layard, Mayraz, and Nickell (2008)).

22. As in Section III, there is a potential concern about downward bias due to selection issues here also. Some studies using a life satisfaction approach for air pollution have used IV approaches and tend to find IV estimates that are significantly larger than those found using OLS (Luechinger (2010)).

23. We also estimate Equation (3) using actual pollution level i.e., $PM_{2.5}$ concentration at the geocode level to see whether respondents' perceptions appear "misguided". Results reported in Table B.9 suggest that they are not, as the coefficient on actual pollutant level is also negative.

24. Figure B.7 in the Appendix shows 95% confidence interval bounds on ϕ and ψ estimates for each of the 51 countries in our main sample. There appears to be a fair amount of heterogeneity in preferences across countries (Falk et al. (2018)). However, this is less true for air quality preferences than income preferences.

Table VII.[25] and the average level of dissatisfaction outside the 0-40 km distance band for the 51 countries in the core sample. The results are in Column 6 of Table VIII where we report results for both point estimates and at the upper and lower bounds of the 95% confidence interval from Column 2 of Table VII.

To obtain an Aggregate Equivalent Variation (AEV hereafter), we scale up the individual values using the measure of affected population i.e., those located within 40 km of operational coal-fired power plants. Our core results are for the world and use the population figures reported in Column 7 of Table VIII, adjusted for the household size to get to the total *residences* within 40 km of coal-fired plants. Multiplying this by e, we obtain our estimate of the global AEV which we report in Column 9 of Table VIII. We will also produce plant-level AEVs using the population that resides within 40 km of any given plant.

To represent a green transition, we consider a thought experiment where coal-fired power plants are replaced with either solar or wind farms of equivalent generation capacity over a period of time. To give a ballpark estimate of the costs involved, we use the total power generation capacity of coal plants and the source-specific average global Levelized Cost of Energy (LCOE).[26] We extract country-level LCOE estimates of coal, solar, and onshore wind energy from a variety of sources, which include the International Renewable Energy Agency, International Energy Agency, country reports, etc. All data references are in the Appendix. We assume a gradual "linear" transition over twenty-five years where 4% of coal-fired power production is replaced by solar or wind in each year.[27]

25. Since life satisfaction has no obvious cardinality, we follow Ferreri-Carbonell and Frijters (2004) and test the robustness of our results by estimating ordered logit models with region fixed effects alongside the same controls as in the OLS specification. The results from this exercise are in Table B.10. Our estimate of $\frac{\psi}{\phi}$ in this case is -1.047 which is close to the value of -0.989 that we get from the OLS estimation. We use the OLS estimates in the analysis that follows.

26. LCOE is a popular measure to estimate the costs associated with renewables technology projects. It measures lifetime costs divided by energy production and accounts for the present value of the total cost of building and operating a power plant over an assumed lifetime. This measure allows a comparison of different technologies of unequal life spans, project size, different capital cost, risk, return, capacity factor, and capacity for each of the respective sources. Figure B.8 in the Appendix shows the LCOE for all 51 countries in our sample; the per unit cost of energy generation is highest in the coal sector for most of the countries.

27. Fulfilling highly variable grid demand requires reliable sources of energy, such as coal and natural gas, which can supply just enough power to match both peak and off-peak demands without wasting energy whereas renewable sources suffer from uncertain fluctuations due to weather conditions. Advancement in energy storage technology is important and, apart from advancement in electrochemical storage technology, R&D investments are being made in less conventional ways to store energy, such as mechanical storage using liquid CO_2, thermal storage, and chemical storage using hydrogen. *Source:* The Economist, Technology Quarterly, June 25, 2022. In light of "excess" coal power capacity in many countries, including China (Lin, Kahrl, and Liu (2018)), making a transition could also pay dividends in other forms also i.e., by overcoming the sunk cost fallacy around investments in coal-fired power. Indonesia's path to green transition is getting blocked due to large sunk investments from Japan and China on coal-fired power plants in the country. *Source:* IEEFA.org

IV.B Findings

IV.B.1 Global benefits

In Figure II, we show the aggregate benefits over time for the twenty-five year time horizon for the entire world, discounted at a constant rate of 2% per annum.[28] As well as point estimates, we give a shaded area for the upper and lower bounds of the global AEV. It is striking that, even at the lower bound, and only considering air quality benefits, a green energy transition at the global scale is worthwhile. Moreover, these results are not particularly sensitive to the exact choice of discount factor.[29]

We have made no adjustment for the possibility that any additional fiscal burden could be costly if the transition were publicly financed. However, we do not view this as a major issue since the cost is of the order of only 1% of annual household income.[30] Hence, even as a tax-financed proposition, our proposed green transition looks feasible.

IV.B.2 Plant-specific benefits

In practice, the decisions that policy-makers will have to make to bring about a green transition will involve deciding whether to decommission specific coal-fired power plants (see, for example, Tong et al. (2021) for a discussion of the strategic importance of population density in scheduling plant retirements). Our approach allows us to construct plant-specific benefits using the AEV for those living within 40 km of any given plant. Hence, Table IX presents a "league table" of the "top" 25 coal-fired power plants based on the affected population for our sample of 51 countries ranked by the total population affected by poor air quality. It is noteworthy that most of the plants on this list are in India and China, the two most populous countries in the world.[31]

Table IX also presents the benefits and the costs of closing down each power station while replacing them with either wind or solar farms of equivalent generation capacities. In line with the country-level results, we find that for these highly polluting power stations, air quality benefits alone are in excess of the costs even at the lower bound estimates for gross benefits of closing them.

28. Following Stern (2007), there is also a debate about the correct discount rate; using 2% annual discount rate is in line with many existing studies such as (Hassler, Krusell, and Nycander (2016) and Nordhaus (2014)).

29. We have established the robustness to using alternative discount rates. See Figure B.9 in the Appendix.

30. Figure B.10 in the Appendix shows the values over the transition period of 25 years.

31. Table B.11 in the Appendix looks at the plants by affected population for the world as a whole. Most of the plants are again located in China and India, and 16 out of 25 plants repeat from the previous list. Moreover, all the new plants, which are now on the list, are located in China.

We can also look at the benefits from closing coal-fired power stations in countries, which are not in our sample of 51 countries by using our estimates of $\frac{\psi}{\phi}$ to estimate benefits for these countries. Specifically, we take operational coal power plants across the globe in 2019 outside of the 51 countries in our survey sample with Table X giving a list of the top 25 most polluting coal plants for this sample. It is notable that most of the plants in this sample are located in Germany and Japan. Although the plant-level gross benefits are somewhat smaller for these plants compared to those in Table IX, the air quality benefits at the lower bound estimates are still able to generate positive net benefits for all plants. Thus, our finding about ambient air quality provides a potentially compelling case to close these power stations too.

As a final step, Figure III gives the plant-level net benefits for *all* operational coal-fired power plants across the world in 2019. It gives a good sense of the distribution of benefits and makes it clear that replacing coal plants with solar and wind generation units would be beneficial in almost all cases, even if we use the lower bound estimates of the net benefits of air quality improvement.[32]

IV.C Lessons for Political Economy

Creating a green transition that moves away from coal-fired power requires a political process and whether having a high net benefit, as represented by our AEV measures, is sufficient to generate public action depends on the politics of decision-making. Our findings on aggregate benefits can be thought of as an input into policy-making via whatever process is in place.

To sharpen things further, we consider two countries, China and India, which. as we saw earlier, are home to most of the plants with large affected populations. For these two large countries, it makes sense to look at benefits using country-specific parameters.[33] We now find that the gains from a green transition based on air quality dissatisfaction are lower in India than China mainly due to differences in estimated preference parameters.[34] This finding could explain why even if they have a political

32. There is a growing evidence base in the engineering literature on estimating the costs of replacing fossil fuels with renewable energy generation. It suggests that the transition is unlikely to be one-to-one. Bolsona, Prieto, and Patzeka (2022) estimates that replacing 1W of fossil fuel is equivalent to installing 4W of solar capacity or 2W of wind power. We use these estimates to inflate our global LCOE values and re-plot Figure III. The new plot is in Figure B.11, which suggests that, though smaller, net benefits continue to be positive for the majority of coal plants around the world. Also, the net benefits for more plants are now negative.

33. See Table B.12 in the Appendix for country-specific parameters values.

34. See Table B.13 in the Appendix for country-specific AEV values. Figure B.12 in the Appendix gives the benefits and costs over time for each country. Note though that the air quality benefits tend to go up substantially in India when we re-compute benefits with global preference parameters as reported in Panel 2 of Table B.14 in the Appendix.

voice, Indian citizens may put less pressure on their government to reduce dependence on coal-fired power, while policy action by Chinese political elites could be justified to their citizens more easily given our finding. Either way, drawing conclusions on the potential for public action based on the findings depends critically on how such findings land in policy discussions, and the political salience of air pollution is an issue (see, for example, Crenson (1971); Singh and Thachil (2023)).

Heterogeneity by education level is also interesting since those who are politically active in all kinds of governance systems tend to be more educated. Our main findings assume that $\frac{AirDiss}{\widetilde{AirDiss}}$ is common across all education categories and set it to the global level. The differences in EV are mostly guided by differences in income level across education categories, with only small proportions of these differences explained by variation in preferences, i.e., $\frac{\psi}{\phi}$ ratio across the categories as reported in Table B.15 in the Appendix. Again, using Equation (4), we find that the EV for better air quality satisfaction among highly educated individuals is more than double that of those with only primary or intermediate-level education as reported in Table B.16 in the Appendix. This too may be relevant in political economy terms across a range of political systems given how important elite opinion is in policy-making.

IV.D Further Issues

Comparison to alternative approaches We now compare our estimates to those that are obtained using Contingent Valuation Methods (CVM) and Revealed Preference (RP) approaches. We find that our estimates lie somewhere in between these two.

CVM methods, relying on survey responses, are widely used in environmental impact assessment more generally (Arrow et al. (1993); Hanemann (1994)).[35] One well-known critique of such methods is that by asking directly about negative impacts of something like coal-fired power survey respondents are "primed" to think about something negative. Nevertheless, the Gallup World Poll surveys do not even mention coal-fired power in the survey instruments, let alone prime respondents about it. Due to this fact, our study do not suffer from various issues raised in Diamond and Hausman (1994). To benchmark our findings against CVM studies, we use a value of \$247.95 per tonne of CO_2 emissions, taken from a survey of CVM studies (Mitchell and Carson (1989)).[36] Using this, we find that the aggregate benefit from eliminating coal-fired power is about 1.828 trillion USD,[37] which is 42% (215%) higher than the

35. Such studies have also been used to study coal-fired power, e.g. Chikkatur, Chaudhary, and Sagar (2011); Wang and Mullahy (2006).

36. The average social cost of carbon is 200 EUR per 'ton' of CO_2 emitted, which when converted to USD per 'tonne' using the average 2020 EUR-USD exchange rate of 1.125 and the tonne-to-ton conversion factor of 1.102, comes out to be \$247.95 per tonne of CO_2 emissions.

37. The total annual emissions in 2019 from the operational coal-fired power plants located in the

upper (lower) bound of our global AEV estimates reported in Table VIII.

There is also a body of work that estimates the value of clean air using RP approach (Chay and Greenstone (2005); Ito and Zhang (2020)). To compare our AEV estimates to the those obtained using RP methods, we use the lower bound estimates valued at \$19.84 per tonne of CO_2 emissions from Rodemeier (2023).[38] Using this, we obtain the aggregate global benefits to be about 0.146 trillion USD,[39] which is about a quarter of the lower bound aggregate AEV estimates reported in Table VIII. Nonetheless, with the estimates of the social cost of carbon being revised upwards, more than quadrupling in the last 10 years (Tol (2022)), we expect estimates based on RP approaches to be larger in the future.

Adding carbon benefits Coal-fired power generation is one of the biggest sources of CO_2 emissions across the world, accounting for nearly 30% of total annual global emissions with the lion's share coming from Asia.[40] Therefore, shutting down coal-fired power plants has an additional dividend in terms of carbon reduction benefits that could help mitigate the climate change problem (Greenstone and Looney (2012)).

There is much debate about the appropriate Social Cost of Carbon (SCC) to use, with widely different numbers being available (Tol (2022)).[41] We therefore assume lower and upper bound values of \$20 and \$100 per ton of CO_2 for our estimated benefits. Recent work estimates that the carbon benefits from a global closure of coal-fired plants is of the order of 80 trillion USD (Adrian, Bolton, and Kleinnijenhuis (2022)) using a SCC value of \$75 per ton of CO_2 (Parry, Black, and Vernon (2021)).

Figure IV adds in the carbon reduction benefits for a twenty-five year horizon using a 2% annual discount rate. The area covered by the upper and lower bounds on the air quality benefits are shaded, but we have not shown the upper bound of carbon reduction benefits since this, combined with air quality benefits, dwarfs other estimates. Not surprisingly, this further strengthens the case for a green energy transition.[42]

sample of 51 countries was 7.371 billion tonnes. We take the product of these total emissions and \$247.95 to get to the aggregate monetary benefit.

38. The lower bound of the social cost of carbon emissions is 16 EUR per 'ton' of CO_2 emitted, which when converted to USD per 'tonne' using the average 2020 EUR-USD exchange rate of 1.125 and the tonne-to-ton conversion factor of 1.102, comes out to be \$19.84 per tonne of CO_2 emissions.

39. The total annual emissions in 2019 from the operational coal-fired power plants located in the sample of 51 countries was 7.371 billion tonnes. We take the product of this these emissions and \$19.84 to get to the monetary equivalent of RP-based aggregate benefits.

40. Global energy-related emissions was around 33.1 Gt CO_2 in 2018; the power sector accounted for nearly two-thirds of emissions growth. Coal use in power alone surpassed 10 Gt CO_2. China, India, and the US accounted for 85% of the net increase in emissions, while emissions declined for Germany, Japan, Mexico, France and the UK. *Source:* Global Energy & CO_2 Status Report 2019

41. Although there has been more recent work on estimating these costs for specific cases, such as on human mortality and labor productivity, we do not use them as they are only partial SCC estimates (Carleton et al. (2022)).

42. We can also look at plant-level net benefits after adding the carbon reduction benefits; see Figure

The cost of air quality deterioration, using our measure of benefits, may be lower in the future if governments move coal-fired plants away from densely populated areas to please voters. There is some evidence that this is happening: planned (future) coal plants are, on average, located farther away from large population centers, when compared to the existing ones.[43]

Other effects Those who depend on the coal economy, directly or indirectly, tend to express lower dissatisfaction with its existence (Eyer and Kahn (2020)). Employment concerns could be important for shaping citizens' debates and policy design around a green energy transition. However, as Table B.17 shows, it is unclear that clean energy would lead to aggregate job losses, which would depend, in part, on whether the cost of energy is higher or lower in an age of renewables as new firms tend to locate in areas with lower energy prices and where labor is available (Kahn and Mansur (2013)). Nonetheless, the employment effects could still be distortionary at the local level, especially when low-skilled individuals are dependent on coal sector and allied activities. There is also a potential threat from intensive mining of aluminium, silicon, lithium, and cobalt, which are used in many forms of renewable energy generation. One also cannot discount the adverse health effects of some renewables, such as noise pollution generated by wind turbines (Zou (2017)).

V Conclusion

Some, but not all, countries are phasing out coal-fired electricity generation. This is, in part, motivated by concerns about climate change, but air pollution concerns are also important. As well as showing a direct link to air quality dissatisfaction, we find that citizens are more attentive to risk being framed as "pollution risk" rather than "climate risk" when they live in proximity to coal-fired power plants. Together these findings suggest that downgrading air quality to the status of a "secondary" benefit may be an error when analyzing drivers of the political economy of climate change, since air quality and local pollution may be more tangible issues.

To reinforce this message, we have used survey data to construct measures of benefits from improving air quality. By using geocoded perceptions data that we match to the location of coal-fired power stations, we have computed estimates of the benefit from phasing out coal-fired power plants based on air quality dissatisfaction. Being

B.13 in the Appendix. The net benefits from closing almost every coal-fired power plant on the Earth is positive now.

43. On average, an existing operational coal plant affects 3,457,731 individuals, while a typical planned plant, which was non-existent in 2019, is expected to affect 1,328,480 individuals.

able to do this for countries in the Global South, where expanding generation capacity is likely to be greatest in the years to come, is particularly important. These findings are particularly relevant to countries like China and India, which are home to many of the largest coal-fired power systems. The analysis suggests that air quality benefits alone (without factoring in carbon-reduction benefits) can make a credible case for phasing out coal-fired power in such places.

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Main Tables and Figures

Table I: **Results for air quality dissatisfaction and operational plants location**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.044***	-0.056	-0.094	-0.039***	-0.020	-0.111
	(0.0106)	(0.0407)	(0.0617)	(0.0106)	(0.0372)	(0.0837)
Geocode's vegetation index	-0.097**	-0.097*	-0.084	-0.063*	-0.104**	-0.139*
	(0.0327)	(0.0455)	(0.0473)	(0.0297)	(0.0395)	(0.0580)
Geocode area is urban	0.106***	0.144***	0.142***	0.089***	0.120***	0.125***
	(0.0215)	(0.0248)	(0.0359)	(0.0203)	(0.0172)	(0.0261)
Respondent's age is 26-60 years	0.020	0.016	0.027**	0.015	0.022*	0.030**
	(0.0104)	(0.0101)	(0.0082)	(0.0099)	(0.0090)	(0.0099)
Respondent's age is more than 60 years	-0.022	0.011	0.018	-0.020	0.017	0.027*
	(0.0150)	(0.0123)	(0.0125)	(0.0128)	(0.0119)	(0.0132)
Respondent's gender is male	-0.018*	-0.020*	-0.016*	-0.015*	-0.015*	-0.012
	(0.0089)	(0.0081)	(0.0064)	(0.0072)	(0.0068)	(0.0071)
Respondent's education is intermediate	0.057***	0.039*	0.037**	0.059***	0.036***	0.035***
	(0.0102)	(0.0150)	(0.0131)	(0.0100)	(0.0103)	(0.0100)
Respondent's education is high	0.089***	0.066***	0.059**	0.089***	0.059***	0.062***
	(0.0151)	(0.0173)	(0.0217)	(0.0142)	(0.0169)	(0.0159)
Log annual hh income in '000 USD	-0.006	-0.003	-0.009	-0.004	-0.006	-0.010*
	(0.0054)	(0.0052)	(0.0049)	(0.0050)	(0.0042)	(0.0047)
Respondent has children under 15 yrs	0.004	0.000	0.010	0.001	0.001	0.008
	(0.0077)	(0.0093)	(0.0111)	(0.0077)	(0.0078)	(0.0091)
Number of observations	17,964	16,461	13,137	17,964	16,461	13,137
Adj R-squared	0.128	0.092	0.110	0.179	0.167	0.162
Mean of dependent variable	0.327	0.249	0.240	0.327	0.249	0.240
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Distance band	0-40 km	40-80 km	80-120 km	0-40 km	40-80 km	80-120 km

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational coal-fired power plants. The sample used in each column is defined by the distance band i.e., how far the survey location is relative to the nearest coal power plant. Table B.1 provides the list of countries that are used in the main specification i.e., 0-40 km distance band and results are reported in Columns 1 and 4. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for first three columns and state/province/admin-1 level for last three columns. Columns 1-3 and Columns 4-6 control for admin-0 and admin-1 fixed effects respectively. The dependent variable, *Air Diss*, is a short-hand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. The main variable of interest is geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Vegetation index measures green cover for survey location and urban is a dummy variable for urban area classification. The regression also controls for the respondent's age group (young/middle-aged/old), gender (male/female), education level (primary/intermediate/high), logarithm of household income in 1000 USD, and whether the respondent has children under 15 years of age.

Table II: **Results for regional exposure to operational plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss
#Coal plants over total area of region	-2.337	-1.870		
	(1.7254)	(1.4962)		
Log avg. region-level distance from coal plant			-0.015	-0.015
			(0.0112)	(0.0111)
Regional vegetation index	-0.299*	-0.046	-0.124	-0.101
	(0.1247)	(0.1219)	(0.0752)	(0.0770)
Area is urban	0.150***	0.149***	0.180***	0.180***
	(0.0103)	(0.0103)	(0.0206)	(0.0204)
Respondent's age is 26-60 years	0.003	0.003	0.003	0.003
	(0.0025)	(0.0025)	(0.0033)	(0.0034)
Respondent's age is more than 60 years	-0.033***	-0.032***	-0.032***	-0.031***
	(0.0041)	(0.0040)	(0.0059)	(0.0057)
Respondent's gender is male	-0.016***	-0.016***	-0.018***	-0.018***
	(0.0027)	(0.0027)	(0.0047)	(0.0046)
Respondent's education is intermediate	0.032***	0.033***	0.034**	0.036**
	(0.0040)	(0.0041)	(0.0101)	(0.0105)
Respondent's education is high	0.072***	0.074***	0.076***	0.079***
	(0.0055)	(0.0055)	(0.0123)	(0.0129)
Log annual hh income in '000 USD	-0.001	-0.000	0.002	0.003
	(0.0018)	(0.0018)	(0.0043)	(0.0047)
Respondent has children under 15 yrs	-0.001	-0.001	-0.001	-0.002
	(0.0024)	(0.0024)	(0.0028)	(0.0027)
Number of observations	340,657	340,657	340,657	340,657
Adj R-squared	0.141	0.142	0.118	0.119
Mean of dependent variable	0.288	0.288	0.288	0.288
Region fixed effects	Admin-1	Admin-1	Admin-0	Admin-0
Time fixed effects	-	Year	-	Year
Years included	2009-20	2009-20	2009-20	2009-20

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational coal-fired power plants where δ is replaced by an "exposure" variable, which is either (i) the number of coal plants per square kilometers of area of region or (ii) logarithm of average distance of survey geocodes from the nearest operational coal-fired power plant at the region level in 2019. Columns 1-2 and 3-4 use exposure variable (i) and (ii) respectively. All the regressions use the sample of 51 countries in the main analysis, as given in Table B.1. Standard errors, which are reported in parentheses, are clustered at admin-1 level for Columns 1-2 and at admin-0 level for the remaining ones. Columns 2 and 4 control for year fixed effects. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. Please refer to Table I notes for details on other variables.

Table III: **Risk assessment results for operational plants**

	(1) Poll Risk	(2) Poll Risk	(3) Clim Risk	(4) Clim Risk
Geocode's log dist from nearest plant	-0.005**	-0.006*	0.005	0.006
	(0.0018)	(0.0027)	(0.0044)	(0.0054)
Geocode's vegetation index	0.004	0.010*	0.023	0.021
	(0.0036)	(0.0050)	(0.0183)	(0.0181)
Geocode area is urban	-0.002	-0.004	-0.021*	-0.016*
	(0.0032)	(0.0043)	(0.0098)	(0.0080)
Respondent's age is 26-60 years	0.000	-0.001	0.008	0.006
	(0.0029)	(0.0029)	(0.0068)	(0.0049)
Respondent's age is more than 60 years	-0.004	-0.004	0.012	0.014*
	(0.0044)	(0.0037)	(0.0083)	(0.0067)
Respondent's gender is male	-0.003	-0.003	-0.003	-0.004
	(0.0020)	(0.0022)	(0.0057)	(0.0046)
Respondent's education is intermediate	0.003	0.003	-0.003	-0.004
	(0.0023)	(0.0025)	(0.0082)	(0.0062)
Respondent's education is high	0.008*	0.008*	0.009	0.006
	(0.0042)	(0.0040)	(0.0070)	(0.0081)
Log annual hh income in '000 USD	-0.000	-0.000	0.002	0.004
	(0.0016)	(0.0016)	(0.0031)	(0.0023)
Respondent has children under 15 yrs	0.001	0.002	-0.001	-0.001
	(0.0022)	(0.0025)	(0.0043)	(0.0047)
Number of observations	15,117	15,117	15,117	15,117
Adj R-squared	0.031	0.030	0.036	0.061
Mean of dependent variable	0.016	0.016	0.062	0.062
Region fixed effects	Admin-0	Admin-1	Admin-0	Admin-1
Distance band	0-40 km	0-40 km	0-40 km	0-40 km

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2). The sample used in each column is defined by the distance band i.e., how far the survey location is relative to the nearest coal power plant. Table B.1 provides the list of countries that are used in the main specification i.e., 0-40 km distance band. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1 and 3 and state/province/admin-1 level for remaining columns. Columns 1 and 3 and Columns 2 and 4 control for admin-0 and admin-1 fixed effects respectively. The dependent variables, *Poll Risk* and *Clim Risk*, are shorthands for Pollution Risk and Climate Risk respectively. Poll Risk/Clim Risk take value 1 (0) if the surveyed individual does (does not) considers pollution/climate as one of the two major sources of risks to their safety in daily life. The main variable of interest is the geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

Table IV: **Placebo results for non-operational plants and water quality perception**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Water Diss
Geocode's log dist from nearest plant	0.004	-0.001	-0.045	-0.015	-0.012
	(0.0162)	(0.0199)	(0.0344)	(0.0290)	(0.0099)
Geocode's vegetation index	-0.141*	-0.039	-0.479**	-0.420	-0.023
	(0.0612)	(0.0774)	(0.1178)	(0.2328)	(0.0450)
Geocode area is urban	0.108*	0.117**	0.046	0.070	0.011
	(0.0401)	(0.0390)	(0.0320)	(0.0645)	(0.0160)
Respondent's age is 26-60 years	0.026	0.011	-0.006	0.009	0.036***
	(0.0244)	(0.0261)	(0.0194)	(0.0324)	(0.0094)
Respondent's age is more than 60 years	0.021	0.010	-0.047	-0.026	0.001
	(0.0240)	(0.0347)	(0.0275)	(0.0322)	(0.0117)
Respondent's gender is male	-0.022	-0.019	-0.027*	-0.029	-0.019**
	(0.0183)	(0.0241)	(0.0090)	(0.0200)	(0.0071)
Respondent's education is intermediate	0.023	0.015	0.068*	0.073**	0.036***
	(0.0274)	(0.0231)	(0.0295)	(0.0224)	(0.0100)
Respondent's education is high	-0.002	-0.015	0.077*	0.066	0.057***
	(0.0378)	(0.0323)	(0.0253)	(0.0351)	(0.0134)
Log annual hh income in '000 USD	-0.022	-0.015	-0.015	-0.015	-0.006
	(0.0132)	(0.0124)	(0.0081)	(0.0097)	(0.0050)
Respondent has children under 15 yrs	-0.000	0.009	-0.016	-0.041	-0.005
	(0.0236)	(0.0190)	(0.0231)	(0.0303)	(0.0079)
Number of observations	2,948	2,948	2,317	2,317	18,027
Adj R-squared	0.059	0.114	0.125	0.192	0.106
Mean of dependent variable	0.284	0.284	0.291	0.291	0.280
Region fixed effects	Admin-0	Admin-1	Admin-0	Admin-1	Admin-1
Distance band	0-40 km	0-40 km	0-40 km	0-40 km	0-40 km
Status of plant operation	Planned	Planned	Retired	Retired	Operational

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) separately for planned and retired and mothballed coal-fired power plants and for water quality dissatisfaction. The sample used in each column is defined by the distance band i.e., how far the survey location is relative to the nearest coal power plant. Table B.1 provides the list of countries that are used in the main specification i.e., 0-40 km distance band. Columns 1-2 and Columns 3-4 report results for planned and retired plants respectively and Column 5 reports results for water quality instead of air quality dissatisfaction. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1 and 3 and at state/province/admin-1 level for remaining columns. Columns 1 and 3 control for admin-0 fixed effects and remaining columns control for admin-1 fixed effects. The dependent variable, *Air (Water) Diss*, is a shorthand for Air (Water) Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air(water) quality. The main variable of interest is geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

Table V: **Results for operational plants with iron and steel plants' distance control**

	(1) Air Diss	(2) Air Diss
Geocode's log dist from nearest plant	-0.045***	-0.038***
	(0.0122)	(0.0107)
Coal plant's log dist from nearest steel plant	-0.023***	-0.018*
	(0.0081)	(0.0108)
Geocode's vegetation index	-0.094***	-0.062**
	(0.0313)	(0.0295)
Geocode area is urban	0.100***	0.084***
	(0.0211)	(0.0207)
Respondent's age is 26-60 years	0.019*	0.016
	(0.0102)	(0.0099)
Respondent's age is more than 60 years	-0.021	-0.020
	(0.0149)	(0.0128)
Respondent's gender is male	-0.017*	-0.016**
	(0.0090)	(0.0072)
Respondent's education is intermediate	0.055***	0.059***
	(0.0099)	(0.0100)
Respondent's education is high	0.089***	0.090***
	(0.0147)	(0.0141)
Log annual hh income in '000 USD	-0.008	-0.004
	(0.0055)	(0.0050)
Respondent has children under 15 yrs	0.005	0.001
	(0.0076)	(0.0077)
Number of observations	17,964	17,964
Adj R-squared	0.131	0.179
Mean of dependent variable	0.327	0.327
Region fixed effects	Admin-0	Admin-1
Distance band	0-40 km	0-40 km

Region-clustered robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents OLS estimates using the specification in Equation (2) but including an additional control variable for logarithm of distance between coal plants and iron and steel plant i.e., how far an operational coal power plant is from the nearest iron and steel production unit, for the distance band 0-40 km. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1 and at state/province/admin-1 level for Column 2. Columns 1 control for admin-0 fixed effects and Column 2 for admin-1 fixed effects. The dependent variable, *Air(Water) Diss*, is a shorthand for Air(Water) Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air(water) quality. The main variable of interest is geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

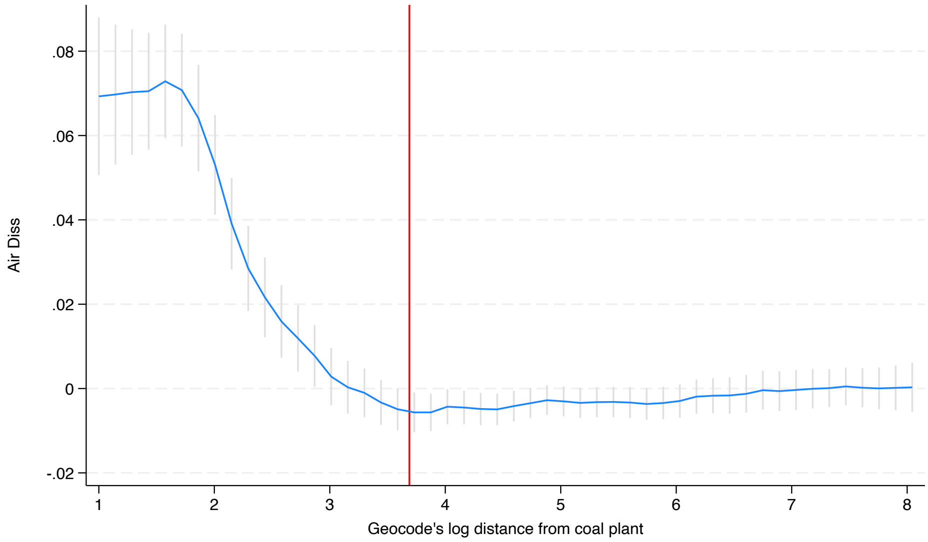
Table VI: **Results for operational plants with wind direction interaction**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.050***	-0.047***	-0.051***	-0.049***	-0.047***	-0.051***
	(0.0124)	(0.0124)	(0.0124)	(0.0123)	(0.0127)	(0.0130)
Downwind of plant	-0.046	-0.009	-0.029	-0.097	-0.064	-0.073
	(0.0645)	(0.0630)	(0.0585)	(0.0523)	(0.0521)	(0.0469)
Downwind of plant × Geocode's log dist from nearest plant	0.026	0.014	0.017	0.040*	0.027	0.025
	(0.0225)	(0.0221)	(0.0207)	(0.0188)	(0.0185)	(0.0163)
Geocode's vegetation index	-0.096**	-0.098**	-0.097**	-0.060*	-0.061*	-0.063*
	(0.0319)	(0.0322)	(0.0330)	(0.0294)	(0.0295)	(0.0299)
Geocode area is urban	0.107***	0.106***	0.107***	0.089***	0.089***	0.089***
	(0.0216)	(0.0215)	(0.0215)	(0.0204)	(0.0203)	(0.0204)
Respondent's age is 26-60 years	0.020	0.020	0.019	0.016	0.016	0.015
	(0.0104)	(0.0105)	(0.0104)	(0.0099)	(0.0099)	(0.0099)
Respondent's age is more than 60 years	-0.021	-0.021	-0.022	-0.020	-0.020	-0.020
	(0.0152)	(0.0152)	(0.0151)	(0.0128)	(0.0128)	(0.0128)
Respondent's gender is male	-0.018*	-0.018*	-0.018*	-0.016*	-0.016*	-0.016*
	(0.0088)	(0.0088)	(0.0088)	(0.0072)	(0.0072)	(0.0072)
Respondent's education is intermediate	0.057***	0.057***	0.057***	0.059***	0.059***	0.059***
	(0.0101)	(0.0100)	(0.0102)	(0.0100)	(0.0100)	(0.0100)
Respondent's education is high	0.088***	0.089***	0.089***	0.089***	0.089***	0.089***
	(0.0150)	(0.0149)	(0.0149)	(0.0142)	(0.0142)	(0.0142)
Log annual hh income in '000 USD	-0.006	-0.006	-0.006	-0.004	-0.004	-0.004
	(0.0054)	(0.0054)	(0.0054)	(0.0050)	(0.0050)	(0.0050)
Respondent has children under 15 yrs	0.003	0.003	0.003	0.001	0.001	0.001
	(0.0076)	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Number of observations	17,964	17,964	17,964	17,964	17,964	17,964
Adj R-squared	0.129	0.129	0.128	0.179	0.179	0.179
Mean of dependent variable	0.327	0.327	0.327	0.327	0.327	0.327
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Distance band	0-40 km	0-40 km	0-40 km	0-40 km	0-40 km	0-40 km
Wind direction angular buffer	60°	90°	120°	60°	90°	120°

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational coal-fired power plants but interacting δ with a dummy for downwind direction of coal-fired power plant. The sample used in each column is defined by the distance band 0-40 km and the angular buffer around the coal-fired power plant i.e., all survey locations that are located within 40 km and falling in the angular buffer of either 60°, 90° or 120° of an operational coal power plant. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1-3 and state/province/admin-1 level for remaining columns. Columns 1-3 control for admin-0 fixed effects and remaining columns control for admin-1 fixed effects. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. Geocode's logarithm of distance from the nearest plant is a measure of straight-line distance between the survey location and nearest coal plant location. Wind direction is a dummy, which takes value of 1 if the survey geocode falls in the downwind buffer region of a coal-fired power plant, and that varies based on the angular threshold used. Please refer to Table I notes for details on other variables.

Figure I: **Effect of distance from operational plants on air quality dissatisfaction**



Notes: The graph above shows local polynomial regression results with 90% confidence intervals spikes for the effect of logarithm of distance of geocode from an operational coal plant on the residualized value of air quality dissatisfaction that is obtained after running an OLS similar to Equation (2) but without the distance regressor. The red line shows our chosen distance threshold of 40 km. We censor the distance values, which are less than "e" i.e., 2.718 km to avoid issues due to small sample in the left tail of the distance distribution. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. The main regressor, geocode's logarithm of distance from the nearest plant, is the straight-line distance between the survey and nearest coal plant location.

Table VII: **Life satisfaction regression results for operational plants**

	(1) Life Sat	(2) Life Sat
Log air quality dissatisfaction	-0.482***	-0.469***
	[-0.643,-0.321]	[-0.611,-0.326]
Geocode's vegetation index	-0.041	0.010
	[-0.310,0.227]	[-0.226,0.247]
Geocode area is urban	0.097	0.107
	[-0.037,0.232]	[-0.041,0.255]
Respondent's age is 26-60 years	-0.331***	-0.377***
	[-0.454,-0.209]	[-0.481,-0.272]
Respondent's age is more than 60 years	-0.431**	-0.467***
	[-0.746,-0.115]	[-0.623,-0.311]
Respondent's gender is male	-0.166*	-0.159***
	[-0.317,-0.016]	[-0.252,-0.067]
Respondent's education is intermediate	0.313***	0.328***
	[0.158,0.468]	[0.203,0.452]
Respondent's education is high	0.669***	0.703***
	[0.523,0.815]	[0.543,0.863]
Log annual hh income in '000 USD	0.489***	0.474***
	[0.357,0.620]	[0.404,0.543]
Respondent has children under 15 yrs	-0.023	0.031
	[-0.161,0.115]	[-0.062,0.124]
Number of observations	17,701	17,701
Adj R-squared	0.203	0.238
Mean of dependent variable	5.411	5.411
Mean household income in USD	14855	14855
Region fixed effects	Admin-0	Admin-1
Countries included	Global	Global

95% confidence interval in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

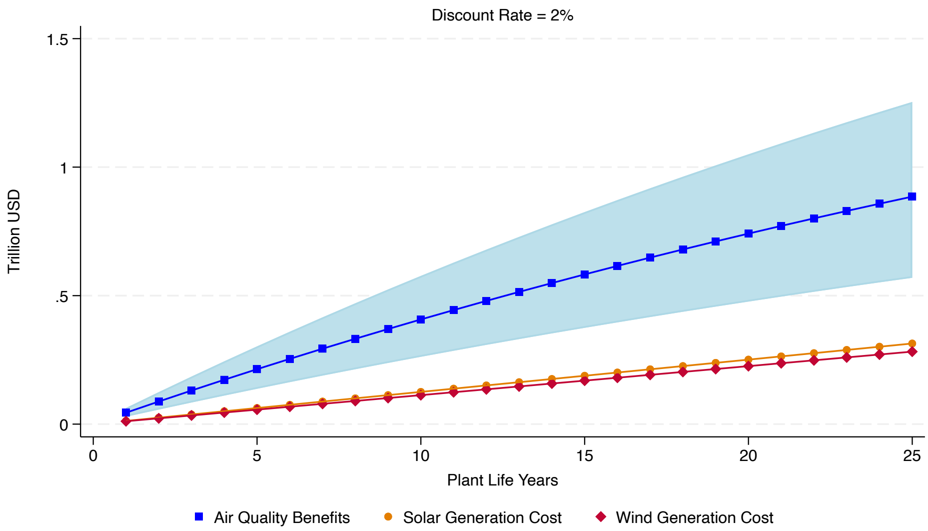
Notes: This table presents estimates using the specification in Equation (3) for operational coal-fired power plants. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within 40 km distance from the nearest coal power plant. Table B.1 provide the list of countries from which sample surveys are used in this specification. 95% confidence interval bounds are reported in square brackets. Column 1 controls for admin-0 fixed effects while Column 2 controls for admin-1 fixed effects. The dependent variable, *Life Sat*, is a shorthand for life satisfaction, which takes values between 0 ("the worst possible life") and 10 ("the best possible life") based on what surveyed individuals report as their current life satisfaction. The main variables of interest are logarithm of air quality dissatisfaction and logarithm of annual household income. The first variable takes value 2 (1) if an individual is dissatisfied (satisfied) with ambient air quality and the second variable is logarithm of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table VIII: **Aggregate equivalent variation results**

(1) Estimate Type	(2) ψ	(3) ϕ	(4) y (in $)	(5) $AirDiss/\widetilde{AirDiss}$	(6) e (in $)	(7) Affected Population	(8) HH Size (# persons)	(9) AEV (in tril. $)
Point estimate	-0.469	0.474	14855	1.37	3948	1,120,626,356	4.9	0.903
Lower bound	-0.326	0.543	14855	1.37	2539	1,120,626,356	4.9	0.581
Upper bound	-0.611	0.404	14855	1.37	5591	1,120,626,356	4.9	1.279

Notes: The three rows correspond to point estimates and lower and upper bounds of 95% confidence intervals of ψ and ϕ parameters respectively. Estimates on logarithm of annual household income, ϕ, logarithm of air quality dissatisfaction, ψ, and average income, y, are taken from Table VII. $\frac{AirDiss}{\widetilde{AirDiss}}$ is the ratio of air quality dissatisfaction level in the 0-40 km distance band and that outside of the band. e is the equivalent variation computed using Equation (4). The population data comes from the Gridded Population of the World, v4 (GPWv4) database for year 2020. AEV is generated by multiplying e with the population estimate downscaled by the number of persons living in a typical household, which is taken from the Area Database v4.1 of the Global Data Lab.

Figure II: **Aggregate air quality benefits and costs of closing operational plants**



Notes: Chart shows the cost-benefit analysis results for all 51 countries combined as listed in Table B.1. The policy experiment entails phasing out coal-fired power at a constant rate of 4% per year and replacing that freed capacity with solar or wind generation over a period of 25 years. The blue line represents point estimates of air quality benefits with the shaded area showing upper and lower bounds on the estimates. The costs of solar and wind energy generation are calculated by multiplying their respective source-specific average global LCOE values in USD/kWh with the total excess energy demand because of closing of coal plants. All the costs and benefits are expressed in present-discounted value terms with the annual discount rate set at 2% per year.

Table IX: **In-sample top-25 coal power stations based on affected population**

(1) Country	(2) State/Province	(3) Name of Plant	(4) Population	(5) Ann. Emission (in mil. tons)	(6) Capacity (in MW)	(7) Plant Life (in years)	(8) Solar Cost (in mil. $)	(9) Wind Cost (in mil. $)	(10) Gross Benefits (in mil. $)	(11) Gross Benefits LB (in mil. $)
India	Delhi	Rajghat Delhi	30871582	0.8	135	2	78.64	70.72	24874.62	15998.17
China	Shanghai	Wujing	29394098	2.8	600	14	349.52	314.31	23684.15	15232.51
China	Shanghai	Shanghai Gaoqiao	26608464	0.9	150	9	87.38	78.58	21439.64	13788.95
China	Shanghai	Baoshan Works	24979817	5.9	1050	11	611.67	550.04	20127.36	12944.96
India	West Bengal	Budge Budge	23684622	4.1	750	23	436.91	392.89	19083.77	12273.77
India	West Bengal	Southern CESC	23486539	0.8	135	11	78.64	70.72	18924.16	12171.12
India	West Bengal	Titagarh	23426320	1.2	240	5	139.81	125.72	18875.64	12139.91
India	Haryana	Faridabad	22755274	0.9	165	2	96.12	86.43	18334.95	11792.16
China	Guangdong	Guangzhou Refinery	22396021	1.0	200	28	116.51	104.77	18045.48	11605.99
Indonesia	West Java	Cikarang Babelan	21297338	1.4	280	38	163.11	146.68	17160.23	11036.64
India	Maharashtra	Trombay	21296044	4.0	810	16	471.86	424.32	17159.18	11035.97
China	Guangdong	Guangzhou Lixin	20995940	2.8	660	33	384.48	345.74	16917.37	10880.45
China	Guangdong	Mawan	20927798	9.4	1940	19	1130.13	1016.27	16862.47	10845.13
China	Guangdong	Lee & Man Paper	20536522	1.3	216	28	125.83	113.15	16547.20	10642.37
India	Uttar Pradesh	National Capital Dadri	19695645	9.0	1820	14	1060.22	953.40	15869.67	10206.61
Thailand	Bangkok	Bangkok HSFC Plant	18440092	0.2	36	29	20.97	18.86	14858.01	9555.96
Russia	Moscow Oblast	Moscow CHP-22	15602338	6.0	1160	7	675.75	607.66	12571.51	8085.39
Vietnam	Dong Nai	Nhon Trach Formosa	13878848	2.2	450	32	262.14	235.73	11182.81	7192.25
Indonesia	Banten	Banten Lontar	13412602	4.3	945	35	550.50	495.04	10807.14	6950.63
Pakistan	Sindh	Port Qasim EPC	12929133	5.2	1320	39	768.95	691.48	10417.58	6700.09
China	Guangdong	Sanshui Hengyi	12899233	5.0	1200	32	699.05	628.62	10393.49	6684.60
China	Guangdong	Dongguan Jianhui	12595530	0.3	50	29	29.13	26.19	10148.79	6527.21
China	Hebei	Sanhe Yanjiao	12573655	6.4	1300	30	757.30	681.00	10131.16	6515.88
China	Tianjin	Junliangcheng	12239822	4.6	1050	13	611.67	550.04	9862.18	6342.88
China	Tianjin	Tianjin Northeast	12096624	3.0	660	36	384.48	345.74	9746.79	6268.67

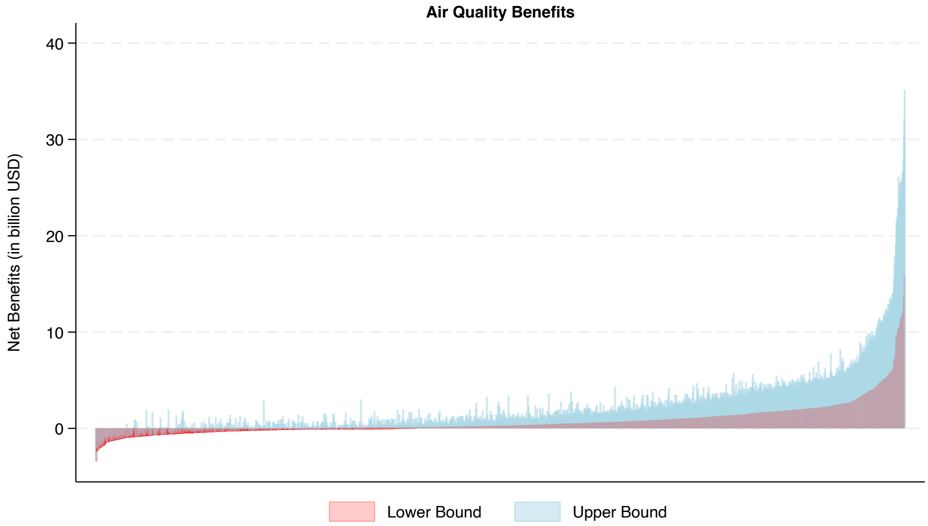
Notes: The table lists 25 coal power stations in our sample in decreasing order of total population affected, which is reported in Column 4. The population figures are the total number of individuals located within 40 km of respective plants. Solar and wind costs report the cost of green transition through solar and wind technology respectively. These costs are calculated by using source-specific average global LCOE values and respective capacities of coal plants as reported in Column 6. Air quality benefits in Column 10 are computed by multiplying EV values, which are computed by using Equation (4), with the total number of residences in the 0-40 km distance band. For EV calculations, global parameter values for ψ, ϕ, $\frac{AirDiss}{\widetilde{AirDiss}}$, and y are used. Column 11 reports the lower bound on the gross air quality benefits from shutting down each of the listed plants.

Table X: **Out-of-sample top-25 coal power stations based on affected population**

(1) Country	(2) State/Province	(3) Name of Plant	(4) Population	(5) Ann. Emission (in mil. tons)	(6) Capacity (in MW)	(7) Plant Life (in years)	(8) Solar Cost (in mil. $)	(9) Wind Cost (in mil. $)	(10) Gross Benefits (in mil. $)	(11) Gross Benefits LB (in mil. $)
Japan	Kanto	Isogo	19357188	5.0	1200	27	699.05	628.62	15596.96	10031.22
Hong Kong	Hong Kong	Castle Peak	18885140	20.4	4110	7	2394.24	2153.02	15216.61	9786.59
Japan	Kansai	Kobe	11970257	5.8	1400	24	815.56	733.39	9644.97	6203.19
Japan	Kansai	Nadahama Works	11295782	0.4	67	23	39.03	35.10	9101.52	5853.66
China	Tianjin	Dagang Oilfield	10829386	10.4	2000	10	1165.08	1047.70	8725.72	5611.97
Taiwan	Taipei	Shu-Lin	10181423	0.3	52	15	30.29	27.24	8203.63	5276.18
Taiwan	Taipei	Linkou Plant TP	10168361	0.2	36	11	20.97	18.86	8193.11	5269.41
Taiwan	Taoyuan	Jinshin	10098233	0.6	114	21	66.41	59.72	8136.60	5233.07
Taiwan	Taoyuan	Hwa Ya Cogen	10096528	1.6	300	25	174.76	157.15	8135.23	5232.19
Taiwan	Taipei	Linkou Power	9582077	9.0	2400	38	1398.10	1257.24	7720.71	4965.59
Japan	Chubu	Tokai Kyodo	7561710	0.9	149	11	86.80	78.05	6092.81	3918.60
Japan	Chubu	Meinan Kyodo Energy	7162755	0.1	31	39	18.06	16.24	5771.35	3711.86
Japan	Chubu	Nagoya	6499765	1.3	259	30	150.88	135.68	5237.15	3368.29
Germany	North Rhine-Westphalia	Krefeld-Uerdingen	5408234	0.7	120	7	69.90	62.86	4357.66	2802.64
Germany	North Rhine-Westphalia	Herne	5312472	2.3	500	10	291.27	261.92	4280.50	2753.01
United Kingdom	England	Fiddler's Ferry	5294138	10.4	2132	2	1241.98	1116.84	4265.73	2743.51
Germany	North Rhine-Westphalia	Cologne-Merkenich	5090692	0.5	85	31	49.52	44.53	4101.80	2638.08
Germany	North Rhine-Westphalia	Chempark Leverkusen	5088491	0.6	112	7	65.24	58.67	4100.03	2636.94
Germany	North Rhine-Westphalia	Scholven	4996383	3.8	740	4	431.08	387.65	4025.81	2589.21
Germany	North Rhine-Westphalia	Buer	4975825	0.4	76	6	44.27	39.81	4009.25	2578.56
Japan	Chubu	Hekinan	4964135	18.0	4100	17	2388.41	2147.78	3999.83	2572.50
Japan	Chubu	MC Shiohama Energy	4962023	0.2	34	29	19.81	17.81	3998.12	2571.40
Germany	North Rhine-Westphalia	Neurath	4879265	18.6	4112	14	2395.40	2154.06	3931.44	2528.52
Germany	North Rhine-Westphalia	Duisburg-Walsum	4848081	2.9	790	34	460.21	413.84	3906.32	2512.36
Germany	North Rhine-Westphalia	Niederaussem	4775255	14.7	2933	10	1708.59	1536.45	3847.64	2474.62

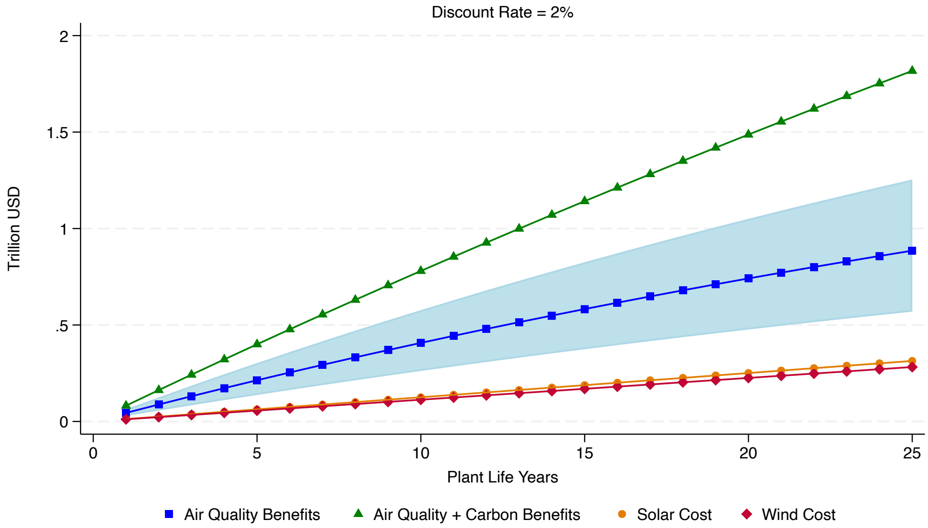
Notes: The table lists 25 coal power stations in the rest of the world i.e., countries outside our 51 country sample in the decreasing order of total population affected, which is reported in Column 4. The population figures are total number of individuals located within 40 km of respective plants. Solar and wind costs report the cost of green transition through solar and wind technology respectively. These costs are calculated by using source-specific average global LCOE values and respective capacity of coal plants as reported in Column 6. Air quality benefits in Column 10 are computed by multiplying EV values, which are computed by using Equation (4), with the total number of residences in the 0-40 km distance band. For EV calculation, global parameter values for ψ, ϕ, $\frac{AirDiss}{\widetilde{AirDiss}}$, and y are used. Column 11 reports the lower bound on the gross air quality benefits from shutting down each of the listed plants.

Figure III: **Plant-level net air quality benefits from closing operational plants**



Notes: Chart shows the net benefits from closing all the operational coal-fired power in 2019 located across the whole world. The parameter values for ψ, ϕ, $\frac{\hat{AirDiss}}{\widetilde{AirDiss}}$, and y are taken from the global estimates using all 51 countries combined. The policy experiment entails phasing out coal-fired power and replacing that freed capacity with 50% solar and 50% wind generation. The costs of solar and wind energy generation are calculated by multiplying respective source-specific global average LCOE values in USD/kWh with the total energy demand.

Figure IV: **Aggregate benefits and costs of closing operational plants**



Notes: Chart shows the cost-benefit analysis results after accounting for carbon reduction benefits. The green line shows the lower bound of carbon benefits added to the air quality benefits. Refer to Figure II for more details.

Appendix

A Instrumental Variables

We discuss how an IV approach may address the concerns about the selection of power-plant locations and/or migration patterns of citizens based on air quality preferences. We propose two instruments for coal-fired power station locations based on the need to supply such power stations with coal. They are (i) the logarithm of distance of survey locations from the nearest railroad and (ii) the logarithm of distance of survey locations from the nearest body of water, such as a lake, river, or sea. The first instrument picks up an important transportation linkage since the majority of coal worldwide is transported using railways. A small but significant fraction of coal transportation uses coal barges and other sea vessels (National Research Council (2007)). This is picked up in our second instrument. Proximity to water may also increase the reliability of water supply and eases waste treatment. We show below that these variables are strongly predictive of coal-fired power station locations.

To construct these instruments, we use global georeferenced data on railways and locations of water-bodies. The source of the railways network shapefile is the World Food Program-Logistics Cluster[44], which brings together various sources such as OpenStreetMap, American Digital Cartography, Global Discovery, etc. To get the location of water-bodies, we combine data from multiple sources[45] to create an "amalgam" water-bodies shapefile.

We also need a plausible exclusion restriction, i.e., that these two instrumental variables predict perceptions of pollution, conditional on covariates, only through the first-stage channel. Given that we have two instruments, we can use a formal test of over-identification. However, beyond this formal approach, we believe that it is plausible *a priori* to think that the exclusion restriction holds as there is no obvious reason to expect proximity to railroads or water-bodies to affect air quality perceptions. Railways that run on diesel are much less polluting than coal-fired power, and nearly 30% of the global railways network has now been electrified. So, it is highly unlikely that there is a direct effect of railway locations on air quality.[46]

More formally, we write the selection equation for δ as follows:

$$\delta_{ic} = \lambda\tau_i + \gamma_i z_\ell + \nu_{ic} \tag{5}$$

where z are factors, which affect distance other than taste for pollution, i.e., "instruments" for δ_{ic}. We allow γ, the relationship between z_ℓ and δ_{ic}, to be heterogeneous.

44. This program works to ensure effective and efficient humanitarian response by optimising logistics during times of disasters and other emergencies. It also acts as a provider of last resort for shared logistics services across the world.

45. Three data layers: (i) linear water showing lines of rivers, streams, and canals from ESRI, (ii) a shapefile for major rivers from UNESCO World-wide Hydrogeological Mapping and Assessment Program, and (iii) an ocean coastline shapefile from the North American Cartographic Information Society are merged using the spatial join tool in ArcGIS software.

46. Railways emit less than 1% of all transport NO_2 emissions and less than 0.5% of transport PM_{10} emissions. *Source:* European Environment Agency

We cannot estimate this relationship in practice because we only observe an individual once.

Now consider an IV estimator of α where we put in $\widehat{\delta}_{ic}$, as in the first-stage prediction of δ, under the 2SLS routine. Then, using Equations (1) and (5)

$$\widehat{\alpha}_{IV} = \frac{cov\left(z_\ell, AirDiss_{i\ell}\right)}{cov\left(z_\ell, \delta_{ic}\right)} = \frac{cov\left(z_\ell, \alpha\left[\lambda\tau_i + \gamma_i z_\ell + \nu_{ic}\right] + \tau_i + \varepsilon_{i\ell}\right)}{cov\left(z_\ell, \lambda\tau_i + \gamma_i z_\ell + \nu_{ic}\right)} = \alpha \tag{6}$$

as long as $cov(\tau_i, z_\ell) = 0$. Then the difference between OLS and IV is

$$\widehat{\alpha}_{OLS} - \widehat{\alpha}_{IV} = \frac{cov\left(\tau_i, \delta_{ic}\right)}{var\left(\delta_{ic}\right)} \tag{7}$$

Given $\alpha < 0$, a larger magnitude IV coefficient (relative to OLS) is plausible if $cov(\tau_i, \delta_{ic}) > 0$, i.e., those with more distaste for air pollution are less likely to locate to areas with high pollution – the selection issue at hand.

Having explained how an IV strategy could remove the OLS bias towards finding null effects, we estimate the following specification for households located in distance band 0-40 km from an operational coal-fired power plant:

$$AirDiss_{i\ell} = \alpha_{IV}\widehat{\delta}_{ic} + \beta\mathbf{X}_{i\ell} + \eta_\ell + \varepsilon_{i\ell} \tag{8}$$

where $\mathbf{X}$ contains geocode (latitude$\times$longitude)-level and individual-level controls and $\widehat{\delta}_{i\ell}$ is predicted from the first-stage using the vector of instruments, Ω:

$$\delta_{ic} = \theta\Omega_{i\ell} + \xi\mathbf{X}_{i\ell} + \zeta_\ell + \nu_{i\ell}. \tag{9}$$

In this case, we expect α_{IV} to be negative and larger in magnitude compared to α.

The results are reported in Table B.18. Columns 1 and 2 use country fixed effects and Columns 3 and 4 use state fixed effects. Columns 1 and 3 employ only the survey location's logarithm of distance from nearest railroad as an instrument, while Columns 2 and 4 use both nearest railroad and body of water distances as instruments. As hypothesised, α_{IV} is negative in all four specifications and has a magnitude nearly eight times that of α, which is reported in Table I and obtained by estimating Equation (2) using OLS.

Large values of first-stage Kleibergen-Paap F-statistics and Kleibergen-Paap LM statistics suggest that these are strong instruments. Moreover, for over-identified cases with two instruments, the over-identifying restrictions are valid as evidenced from low Hansen J-test statistics.[47] As a robustness test on the railroad instrument, we also check whether it predicts pre-determined variables, such as gender and age, thereby violating the exclusion restriction.[48] We do not find any evidence of correlations that might lead us to question the IV strategy. As another robustness test, we do the same IV estimation for retired plants. First-stage and reduced-form results are reported in Table B.21 in the Appendix. As expected, the first-stage results are significant i.e., railroads and water-bodies predict retired coal plants locations, but reduced-form results

47. The first-stage and reduced-form results are presented in Table B.19 in the Appendix.
48. Table B.20 in the Appendix reports the results.

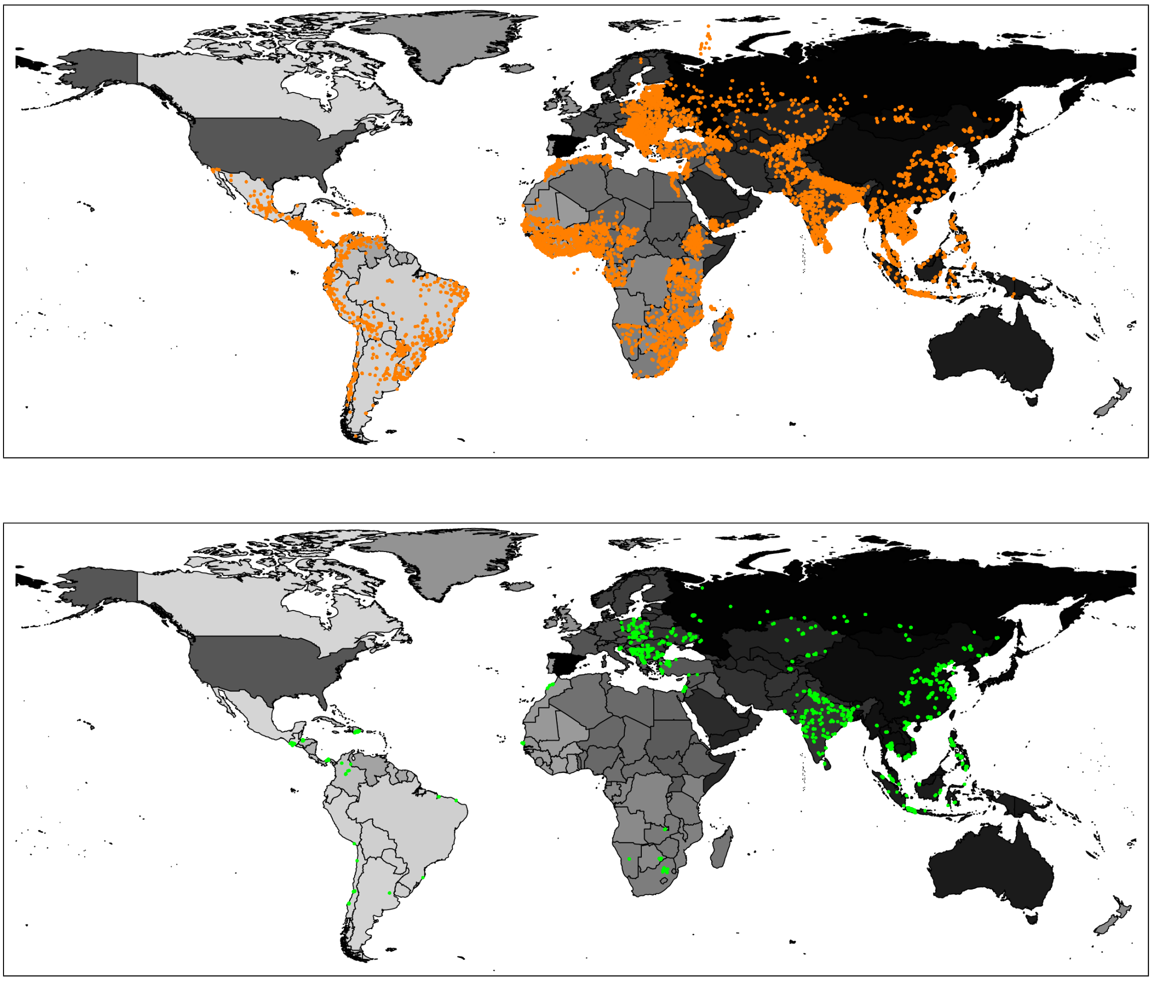
are insignificant, meaning that distance from railroads and water-bodies does not impact air quality perceptions.

These findings give credence to a causal interpretation of a link between air quality perception and proximity to coal-fired power plants. The difference in magnitude between OLS and IV estimates also highlights the potential importance of selection-bias if citizens who value air quality choose to locate further away from coal plants even though these areas are likely to be richer neighbourhoods with higher overall life satisfaction.[49] This is plausible since, once a government sets up a coal plant in an area, it could bring other socio-economic and cultural activities into the area.

49. See Figures B.14 and B.15 in the Appendix.

B Additional Tables and Figures

Figure B.1: **2019 Gallup World Poll survey geocodes**



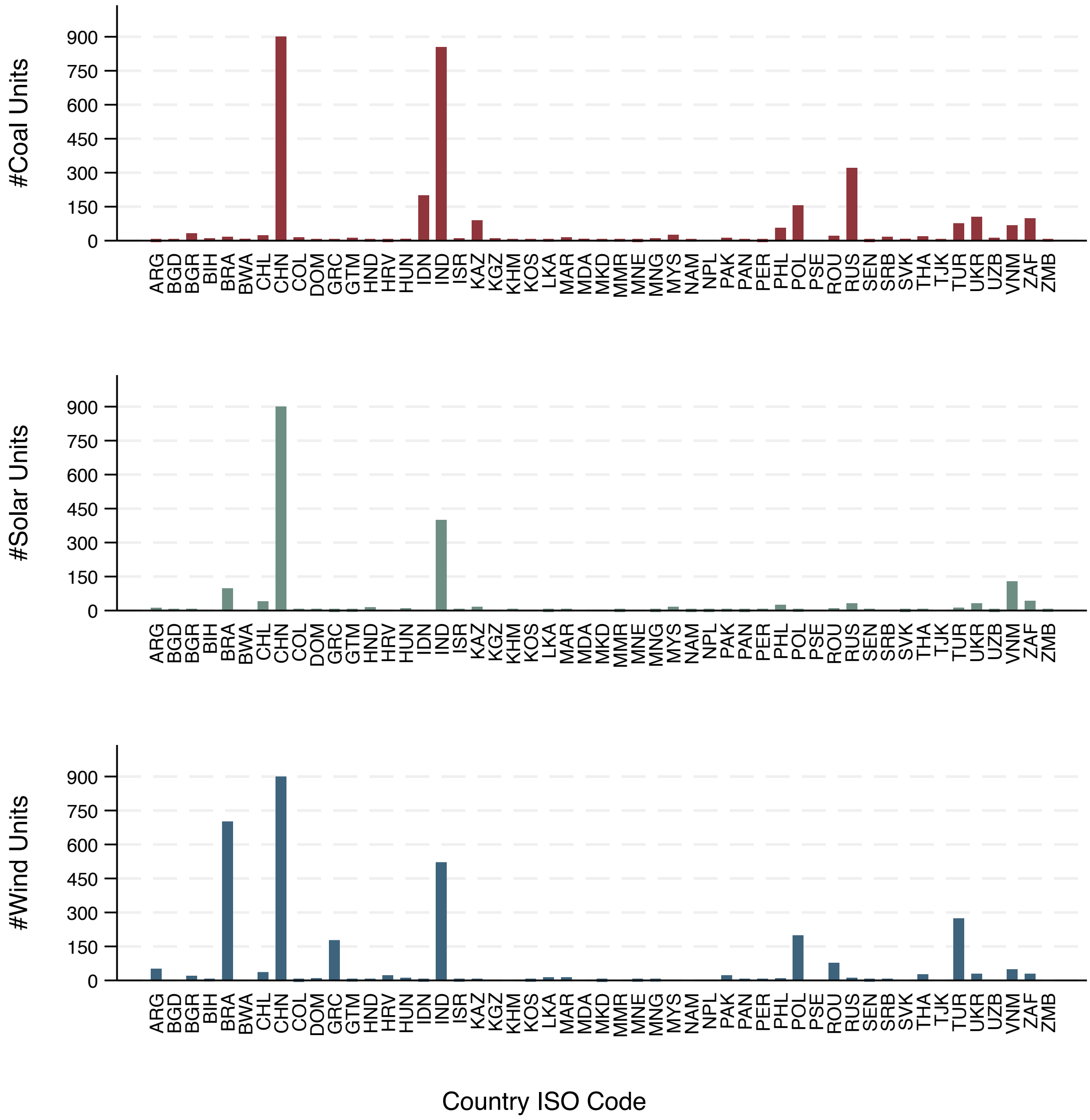
Notes: Top map shows all the surveys (in orange dots) where precise GPS coordinates were recorded in the 2019 round of the Gallup World Poll – a total of 138,242 surveys spread across 140+ countries worldwide. Bottom map shows the subset of surveys (in green dots) that are located in the 0-40 km distance band from an operational coal-fired power plant and this subset has been used in the main analysis – a total of 17,964 surveys, covering 51 countries listed in Table B.1.

Table B.1: **List of countries in the main analysis**

No.	ISO	Country
1	ARG	Argentina
2	BGD	Bangladesh
3	BIH	Bosnia and Herzegovina
4	BWA	Botswana
5	BRA	Brazil
6	BGR	Bulgaria
7	KHM	Cambodia
8	CHL	Chile
9	CHN	China
10	COL	Colombia
11	HRV	Croatia
12	DOM	Dominican Republic
13	GRC	Greece
14	GTM	Guatemala
15	HND	Honduras
16	HUN	Hungary
17	IND	India
18	IDN	Indonesia
19	ISR	Israel
20	KAZ	Kazakhstan
21	KOS	Kosovo
22	KGZ	Kyrgyzstan
23	MYS	Malaysia
24	MDA	Moldova
25	MNG	Mongolia
26	MNE	Montenegro
27	MAR	Morocco
28	MMR	Myanmar
29	NAM	Namibia
30	NPL	Nepal
31	MKD	North Macedonia
32	PAK	Pakistan
33	PSE	Palestine
34	PAN	Panama
35	PER	Peru
36	PHL	Philippines
37	POL	Poland
38	ROU	Romania
39	RUS	Russia
40	SEN	Senegal
41	SRB	Serbia
42	SVK	Slovakia
43	ZAF	South Africa
44	LKA	Sri Lanka
45	TJK	Tajikistan
46	THA	Thailand
47	TUR	Turkey
48	UKR	Ukraine
49	UZB	Uzbekistan
50	VNM	Vietnam
51	ZMB	Zambia

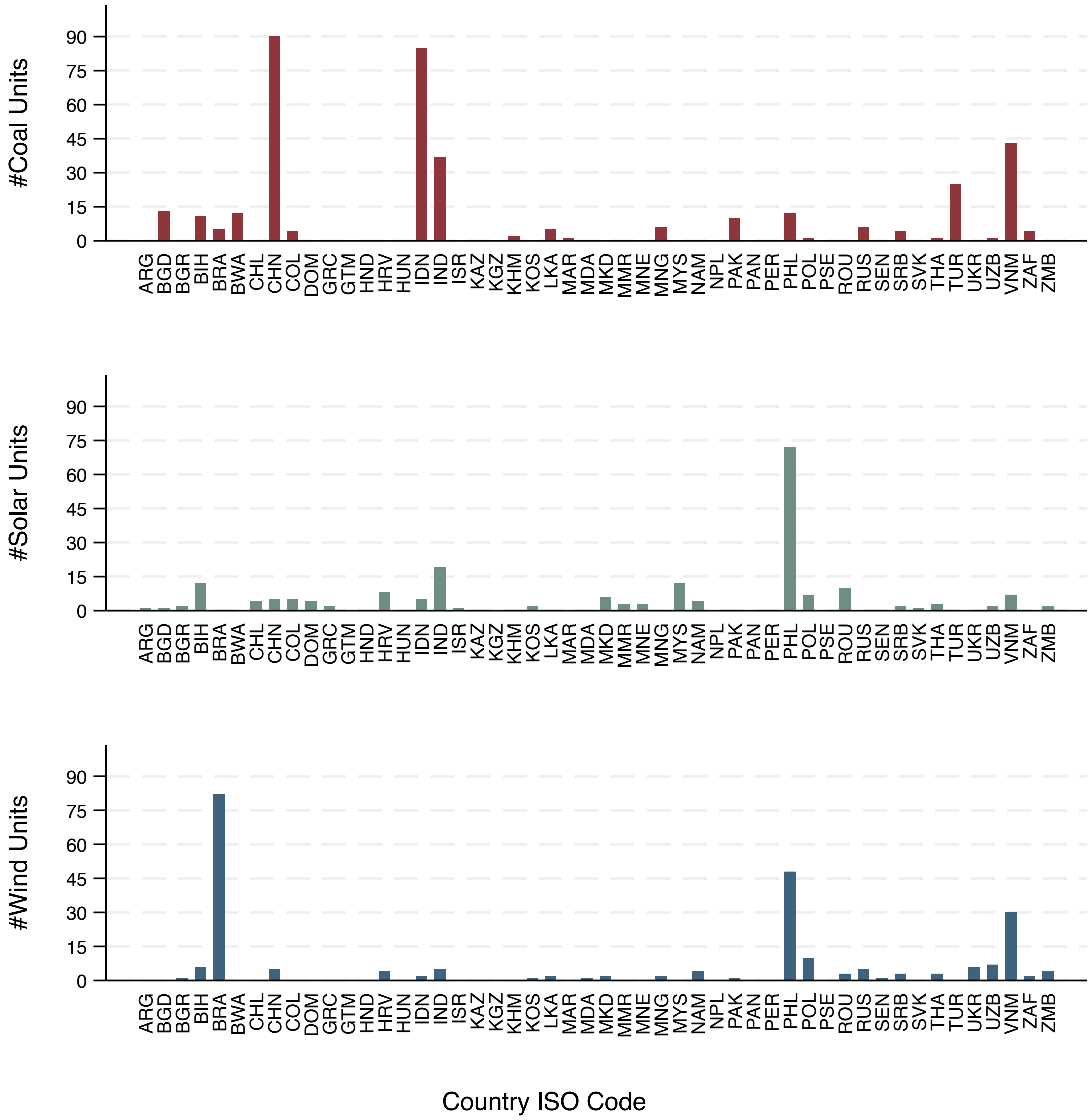
Notes: These countries contain the sample of surveys that are used in the main analysis. Some of the survey locations within these countries qualify under the distance band 0-40 km i.e., survey locations that are located within 40 km of the nearest operational coal-fired power plants. Bottom panel of Figure B.1 maps the geocodes of these survey locations.

Figure B.2: **Distribution of operational energy sources in sample countries**



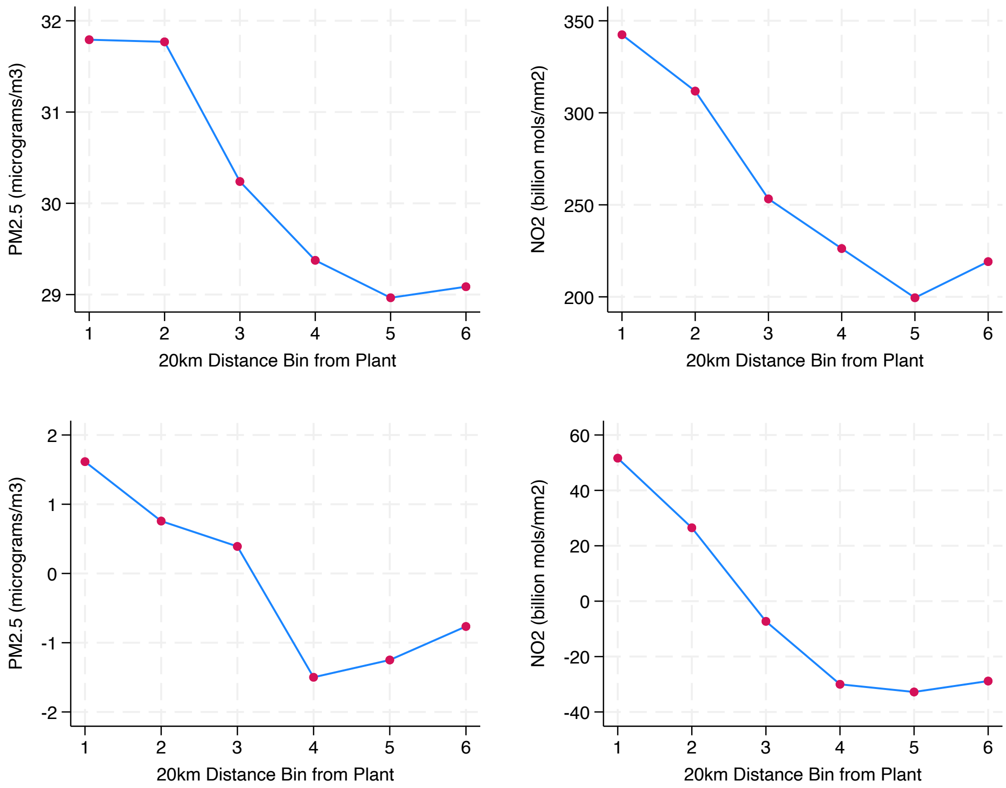
Notes: The graph shows the count of operational coal plants (top), solar farms (middle), and wind farms (bottom) for 51 countries in the main sample as listed in Table B.1. The number of units have been capped at 900 for display purpose, thereby censoring all units counts for China (CHN). The actual count of operational coal, solar, and wind units for CHN are 2990, 3782, and 2663 respectively.

Figure B.3: **Distribution of planned energy sources in sample countries**



Notes: The graph shows the count of planned coal plants (top), solar farms (middle), and wind farms (bottom) for 51 countries in the main sample as listed in Table B.1. The planned category includes plants/farms which are in the "announced", "pre-permit", or "permitted" stage of commissioning. The number of units have been capped at 90 for display purpose, thereby censoring coal units count for China (CHN). The actual count of planned coal units for CHN is 292.

Figure B.4: **Air pollution level indicators around operational plants**



Notes: The label on x-axis should be multiplied by 20 to get the distance bin of the survey location from the nearest coal plant. Top panel charts present raw means from the data using the pollutant concentration at each geocode in the respective distance bin and the bottom panel demeans all those observations of the country fixed effects.

Table B.2: **Conditional logit estimation results for operational plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.230***	-0.349	-0.621	-0.225***	-0.137	-0.827
	(0.0493)	(0.2423)	(0.3918)	(0.0594)	(0.2426)	(0.5689)
Geocode's vegetation index	-0.493**	-0.514*	-0.531*	-0.349*	-0.635**	-0.955**
	(0.1677)	(0.2375)	(0.2636)	(0.1623)	(0.2320)	(0.3363)
Geocode area is urban	0.536***	0.765***	0.768***	0.473***	0.691***	0.724***
	(0.1008)	(0.1163)	(0.1885)	(0.1037)	(0.0935)	(0.1480)
Respondent's age is 26-60 years	0.097	0.093	0.170***	0.079	0.140*	0.199**
	(0.0548)	(0.0621)	(0.0493)	(0.0547)	(0.0582)	(0.0663)
Respondent's age is more than 60 years	-0.112	0.066	0.114	-0.119	0.105	0.174*
	(0.0806)	(0.0730)	(0.0769)	(0.0715)	(0.0769)	(0.0885)
Respondent's gender is male	-0.095*	-0.118*	-0.096*	-0.088*	-0.093*	-0.076
	(0.0439)	(0.0458)	(0.0405)	(0.0398)	(0.0439)	(0.0466)
Respondent's education is intermediate	0.312***	0.246**	0.231**	0.335***	0.236***	0.237***
	(0.0560)	(0.0874)	(0.0758)	(0.0575)	(0.0676)	(0.0644)
Respondent's education is high	0.453***	0.374***	0.342**	0.484***	0.361***	0.391***
	(0.0724)	(0.0934)	(0.1210)	(0.0749)	(0.1009)	(0.0943)
Log annual hh income in '000 USD	-0.025	-0.013	-0.053	-0.018	-0.038	-0.063*
	(0.0283)	(0.0316)	(0.0305)	(0.0273)	(0.0267)	(0.0295)
Respondent has children under 15 yrs	0.017	-0.001	0.059	0.007	0.009	0.050
	(0.0396)	(0.0546)	(0.0685)	(0.0430)	(0.0498)	(0.0593)
Number of observations	17,964	16,452	13,108	17,729	16,033	12,567
Pseudo R-squared	0.028	0.027	0.024	0.018	0.017	0.020
Log likelihood	-9,994	-8,310	-6,353	-8,969	-7,206	-5,527
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Distance band	0-40 km	40-80 km	80-120 km	0-40 km	40-80 km	80-120 km

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table above reports results for conditional logistical model estimation with fixed effects corresponding to OLS estimation results reported in Table I. We implement a robust estimation for fixed effects conditional logit models using the estimator proposed by Baetschmann et al. (2020).

Table B.3: **Results with spatial clustering for operational plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.044***	-0.056	-0.094	-0.039***	-0.020	-0.111
	(0.0095)	(0.0325)	(0.0621)	(0.0090)	(0.0317)	(0.0648)
Geocode's vegetation index	-0.097**	-0.097**	-0.084*	-0.063*	-0.104**	-0.139**
	(0.0327)	(0.0373)	(0.0402)	(0.0287)	(0.0342)	(0.0491)
Geocode area is urban	0.106***	0.144***	0.142***	0.089***	0.120***	0.125***
	(0.0152)	(0.0157)	(0.0200)	(0.0166)	(0.0147)	(0.0194)
Respondent's age is 26-60 years	0.020*	0.016	0.027**	0.015	0.022**	0.030**
	(0.0091)	(0.0088)	(0.0095)	(0.0090)	(0.0082)	(0.0094)
Respondent's age is more than 60 years	-0.022	0.011	0.018	-0.020	0.017	0.027*
	(0.0122)	(0.0122)	(0.0130)	(0.0117)	(0.0119)	(0.0126)
Respondent's gender is male	-0.018*	-0.020**	-0.016*	-0.015*	-0.015*	-0.012
	(0.0071)	(0.0073)	(0.0070)	(0.0069)	(0.0068)	(0.0070)
Respondent's education is intermediate	0.057***	0.039***	0.037***	0.059***	0.036***	0.035***
	(0.0092)	(0.0092)	(0.0098)	(0.0089)	(0.0087)	(0.0091)
Respondent's education is high	0.089***	0.066***	0.059***	0.089***	0.059***	0.062***
	(0.0132)	(0.0155)	(0.0150)	(0.0129)	(0.0139)	(0.0135)
Log annual hh income in '000 USD	-0.006	-0.003	-0.009	-0.004	-0.006	-0.010*
	(0.0047)	(0.0046)	(0.0049)	(0.0045)	(0.0043)	(0.0048)
Respondent has children under 15 yrs	0.004	0.000	0.010	0.001	0.001	0.008
	(0.0077)	(0.0083)	(0.0087)	(0.0074)	(0.0079)	(0.0088)
Number of observations	17,964	16,461	13,137	17,964	16,461	13,137
Adj R-squared	0.032	0.030	0.025	0.018	0.016	0.018
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Distance band	0-40 km	40-80 km	80-120 km	0-40 km	40-80 km	80-120 km

Heteroskedasticity- and Autocorrelation-Consistent standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational coal-fired power plants. The sample used in each column is defined by the distance band i.e., how far the survey location is relative to the nearest coal power plant. Table B.1 provides the list of countries that are used in the main specification i.e., 0-40 km distance band and results are reported in Columns 1 and 4. Standard errors, which are reported in parentheses, are clustered spatially using the distance threshold of 5 km, following Conley (1999) and Conley (2008). Columns 1-3 and Columns 4-6 control for admin-0 and admin-1 fixed effects respectively. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. The main variable of interest is geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

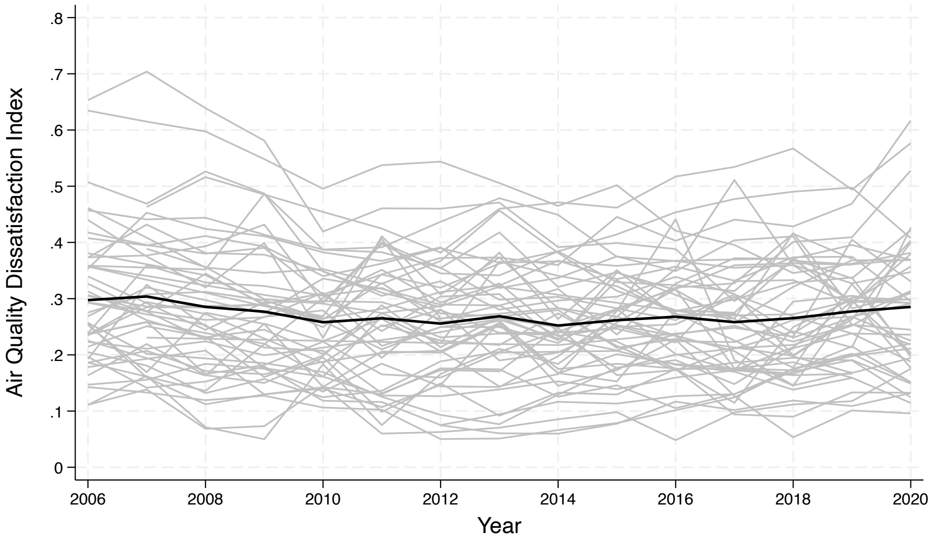
Table B.4: **Results with CO_2 interaction for operational plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss
Geocode's log dist from nearest plant	-0.042**	-0.046***	-0.036*	-0.039**
	(0.0128)	(0.0136)	(0.0143)	(0.0148)
Annual CO2 emission	0.005	-0.008		
	(0.0102)	(0.0087)		
Geocode's log dist from nearest plant × Annual CO2 emission	-0.001	0.003		
	(0.0030)	(0.0027)		
High CO2 emission			0.070	0.021
			(0.0745)	(0.0676)
High CO2 emission × Geocode's log dist from nearest plant			-0.017	0.001
			(0.0234)	(0.0221)
Geocode's vegetation index	-0.097**	-0.064*	-0.097**	-0.063*
	(0.0330)	(0.0300)	(0.0324)	(0.0299)
Geocode area is urban	0.107***	0.088***	0.107***	0.089***
	(0.0219)	(0.0205)	(0.0216)	(0.0204)
Respondent's age is 26-60 years	0.020	0.015	0.019	0.015
	(0.0103)	(0.0099)	(0.0103)	(0.0098)
Respondent's age is more than 60 years	-0.021	-0.021	-0.021	-0.020
	(0.0149)	(0.0128)	(0.0149)	(0.0127)
Respondent's gender is male	-0.018	-0.015*	-0.018*	-0.016*
	(0.0090)	(0.0073)	(0.0091)	(0.0073)
Respondent's education is intermediate	0.057***	0.058***	0.057***	0.058***
	(0.0102)	(0.0100)	(0.0102)	(0.0100)
Respondent's education is high	0.089***	0.089***	0.090***	0.089***
	(0.0152)	(0.0142)	(0.0149)	(0.0142)
Log annual hh income in '000 USD	-0.006	-0.004	-0.006	-0.004
	(0.0054)	(0.0050)	(0.0054)	(0.0050)
Respondent has children under 15 yrs	0.004	0.001	0.004	0.001
	(0.0076)	(0.0077)	(0.0077)	(0.0077)
Number of observations	17,964	17,964	17,964	17,964
Adj R-squared	0.128	0.179	0.128	0.179
Mean of dependent variable	0.327	0.327	0.327	0.327
Region fixed effects	Admin-0	Admin-1	Admin-0	Admin-1

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational coal-fired power plants but interacting δ with either a discrete or continuous measure of annual CO_2 emission from all the units of the nearest coal power plant. The sample used in each column is defined by the distance band 0-40 km i.e., all survey locations that are located within 40 km of an operational coal power plant. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1 and 3 and state/province/admin-1 level for remaining columns. Columns 1 and 3 control for admin-0 fixed effects and remaining columns control for admin-1 fixed effects. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. Geocode's logarithm of distance from the nearest plant is a measure of straight-line distance between the survey location and nearest coal plant location. Annual CO_2 emission is measured in million tonnes per annum and high (low) CO_2 emission correspond to above (below) median plant-level emissions. Please refer to Table I notes for details on other variables.

Figure B.5: **Air quality dissatisfaction trends across sample countries**



Notes: Each grey line represents one country from the list of countries in Table B.1. Each point on the line is generated by taking the average of all individuals in a country-year. The black line represents the average across all the 51 countries for each year.

Table B.5: **Risk assessments for 40-80 km and 80-120 km distance bands**

	(1) Poll Risk	(2) Poll Risk	(3) Poll Risk	(4) Poll Risk	(5) Clim Risk	(6) Clim Risk	(7) Clim Risk	(8) Clim Risk
Geocode's log dist from nearest plant	0.002	-0.006	0.006	-0.021	0.022	-0.042	0.007	-0.022
	(0.0039)	(0.0102)	(0.0054)	(0.0112)	(0.0171)	(0.0288)	(0.0184)	(0.0358)
Geocode's vegetation index	0.001	-0.006	0.007	0.007	-0.045*	-0.000	-0.026	0.003
	(0.0048)	(0.0054)	(0.0067)	(0.0047)	(0.0224)	(0.0181)	(0.0270)	(0.0232)
Geocode area is urban	0.000	-0.005	0.002	-0.004	-0.020*	-0.011	-0.018*	-0.010
	(0.0031)	(0.0039)	(0.0035)	(0.0030)	(0.0074)	(0.0099)	(0.0075)	(0.0103)
Respondent's age is 26-60 years	-0.001	0.001	-0.001	0.001	0.008	0.008	0.008	0.007
	(0.0022)	(0.0028)	(0.0024)	(0.0026)	(0.0059)	(0.0059)	(0.0057)	(0.0059)
Respondent's age is more than 60 years	-0.003	-0.004	-0.002	-0.003	0.013	0.010	0.015	0.012
	(0.0029)	(0.0031)	(0.0028)	(0.0026)	(0.0104)	(0.0087)	(0.0082)	(0.0074)
Respondent's gender is male	-0.000	0.001	-0.000	0.001	-0.011*	0.001	-0.012**	0.002
	(0.0019)	(0.0017)	(0.0018)	(0.0018)	(0.0046)	(0.0041)	(0.0044)	(0.0044)
Respondent's education is intermediate	0.002	0.003	0.002	0.003	0.007	-0.003	0.009	-0.002
	(0.0023)	(0.0015)	(0.0023)	(0.0019)	(0.0076)	(0.0052)	(0.0067)	(0.0056)
Respondent's education is high	0.003	0.003	0.004	0.003	0.010	-0.004	0.011	-0.003
	(0.0031)	(0.0038)	(0.0035)	(0.0035)	(0.0116)	(0.0083)	(0.0094)	(0.0079)
Log annual hh income in '000 USD	0.001	0.002*	0.001	0.001	0.001	0.006	0.003	0.005
	(0.0012)	(0.0007)	(0.0012)	(0.0008)	(0.0031)	(0.0035)	(0.0028)	(0.0029)
Respondent has children under 15 yrs	-0.001	-0.000	-0.001	0.000	-0.004	-0.005	-0.005	-0.005
	(0.0021)	(0.0023)	(0.0019)	(0.0021)	(0.0049)	(0.0041)	(0.0052)	(0.0053)
Number of observations	14,128	11,307	14,128	11,307	14,128	11,307	14,128	11,307
Adj R-squared	0.008	0.009	0.014	0.026	0.033	0.034	0.062	0.062
Mean of dependent variable	0.011	0.009	0.011	0.009	0.061	0.050	0.061	0.050
Region fixed effects	Admin-0	Admin-0	Admin-1	Admin-1	Admin-0	Admin-0	Admin-1	Admin-1
Distance band	40-80 km	80-120 km	40-80 km	80-120 km	40-80 km	80-120 km	40-80 km	80-120 km

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2). The sample used in each column is defined by the distance band i.e., how far the survey location is relative to the nearest coal power plant. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1-2 and 5-6 and state/province/admin-1 level for remaining columns. Columns 1-2 and 5-6 control for admin-0 fixed effects and remaining control for admin-1 fixed effects. Please refer to Table III notes for more details.

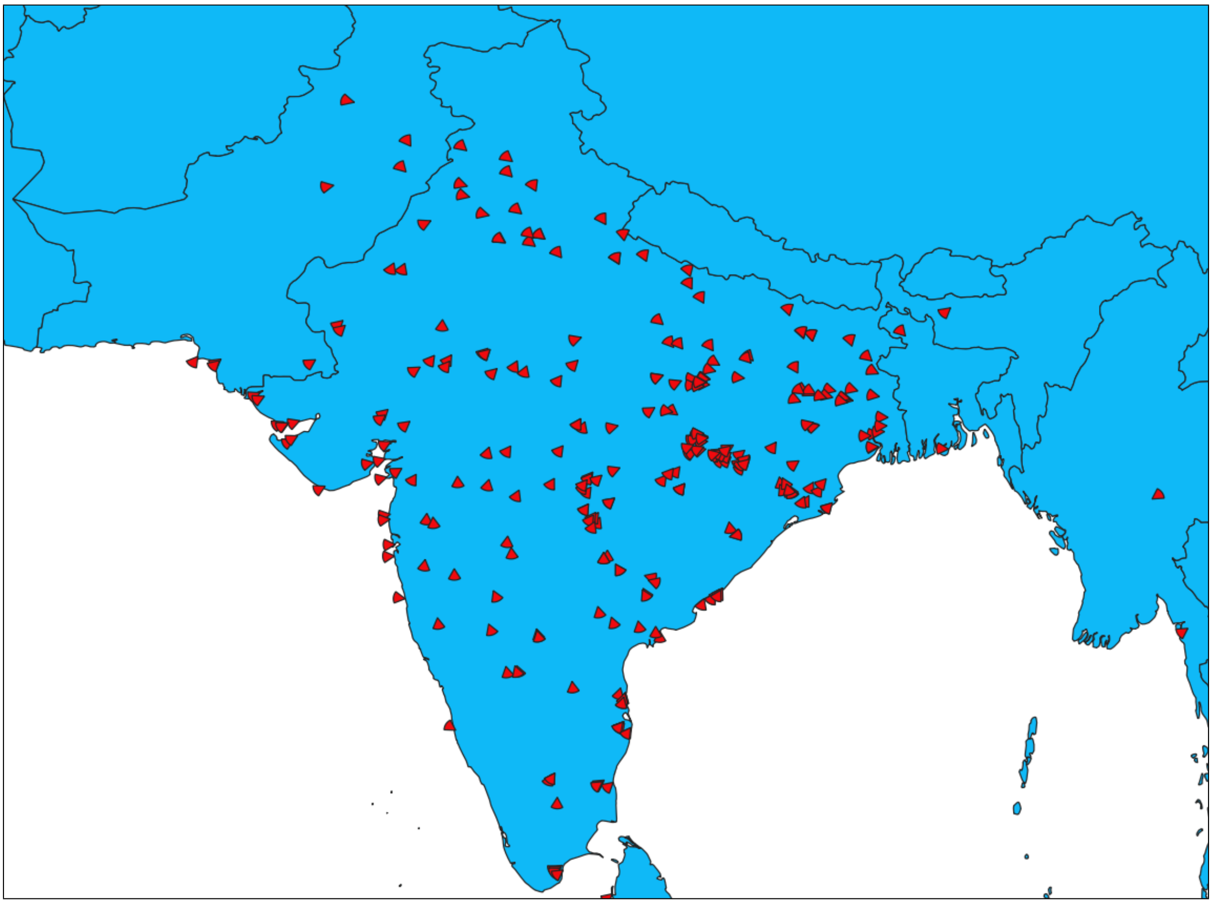
Table B.6: **Placebo results for 40-80 km and 80-120 km distance bands**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss	(7) Air Diss	(8) Air Diss	(9) Water Diss	(10) Water Diss
Geocode's log dist from nearest plant	-0.065	0.020	-0.077	0.142	-0.115	0.193*	-0.144	0.301*	-0.050	-0.117
	(0.0576)	(0.1206)	(0.0596)	(0.1150)	(0.0998)	(0.0925)	(0.0895)	(0.1225)	(0.0393)	(0.0849)
Geocode's vegetation index	-0.078	0.030	-0.100*	-0.136	-0.171	-0.111	0.009	-0.276***	-0.080	-0.106
	(0.0544)	(0.1053)	(0.0457)	(0.0722)	(0.0878)	(0.1594)	(0.0887)	(0.0674)	(0.0603)	(0.0546)
Geocode area is urban	0.114**	0.128*	0.085**	0.174***	0.161	0.074	0.132*	0.110**	0.029	0.022
	(0.0400)	(0.0494)	(0.0265)	(0.0482)	(0.0823)	(0.0523)	(0.0556)	(0.0374)	(0.0171)	(0.0208)
Respondent's age is 26-60 years	0.047*	0.036*	0.037*	0.036**	0.015	0.017	0.019	0.020	0.019	0.026*
	(0.0196)	(0.0145)	(0.0150)	(0.0135)	(0.0207)	(0.0167)	(0.0284)	(0.0163)	(0.0105)	(0.0120)
Respondent's age is more than 60 years	0.031	0.027	0.017	0.034	-0.054	-0.003	-0.019	0.007	0.001	0.020
	(0.0339)	(0.0314)	(0.0285)	(0.0250)	(0.0344)	(0.0157)	(0.0384)	(0.0191)	(0.0135)	(0.0157)
Respondent's gender is male	-0.015	0.002	-0.016	0.002	-0.008	-0.004	0.002	-0.005	0.002	-0.009
	(0.0138)	(0.0119)	(0.0146)	(0.0127)	(0.0131)	(0.0093)	(0.0155)	(0.0115)	(0.0068)	(0.0080)
Respondent's education is intermediate	0.046*	0.020	0.033*	0.006	0.020	0.057*	0.022	0.051**	0.032**	0.024
	(0.0197)	(0.0134)	(0.0166)	(0.0141)	(0.0217)	(0.0272)	(0.0200)	(0.0181)	(0.0098)	(0.0121)
Respondent's education is high	0.030	0.022	0.013	0.034	0.052	0.026	0.038	0.029	0.056***	0.041*
	(0.0397)	(0.0423)	(0.0339)	(0.0291)	(0.0431)	(0.0266)	(0.0262)	(0.0217)	(0.0142)	(0.0179)
Log annual hh income in '000 USD	-0.007	0.000	-0.007	-0.008	-0.019*	-0.018*	-0.014	-0.023**	-0.017***	-0.020***
	(0.0061)	(0.0091)	(0.0052)	(0.0088)	(0.0073)	(0.0080)	(0.0098)	(0.0085)	(0.0047)	(0.0055)
Respondent has children under 15 yrs	0.002	0.023	-0.002	0.009	0.012	0.023	0.021	0.028	0.009	0.020*
	(0.0126)	(0.0147)	(0.0119)	(0.0127)	(0.0172)	(0.0227)	(0.0164)	(0.0144)	(0.0091)	(0.0086)
Number of observations	5,903	6,361	5,903	6,361	3,608	4,162	3,608	4,162	16,549	13,241
Adj R-squared	0.067	0.041	0.116	0.120	0.113	0.061	0.190	0.180	0.123	0.133
Mean of dependent variable	0.280	0.234	0.280	0.234	0.260	0.230	0.260	0.230	0.271	0.303
Region fixed effects	Admin-0	Admin-0	Admin-1	Admin-1	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1	Admin-1
Distance band	40-80 km	80-120 km	40-80 km	80-120 km	40-80 km	80-120 km	40-80 km	80-120 km	40-80 km	80-120 km
Status of plant operation	Planned	Planned	Planned	Planned	Retired	Retired	Retired	Retired	Operational	Operational

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) separately for planned and retired and mothballed coal-fired power plants. The sample used in each column is defined by the distance band i.e., how far the survey location is from the nearest coal power plant. Columns 1-4 and Columns 5-8 report the results for planned and retired plants respectively. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1-2 and 5-6 and at state/province/admin-1 level for remaining columns. Columns 1-2 and 5-6 control for admin-0 fixed effects and remaining control for admin-1 fixed effects. Refer to Table IV notes for more details.

Figure B.6: **Wind buffer zones for operational plants**



Notes: The figure shows buffer zones for influence of wind using an angular restriction of 60° and a distance restriction of 40 km. The direction of the central azimuth through red sectors indicates the annual wind direction for the plants located at specific geo-locations on the map.

Table B.7: **Results for wind direction using $PM_{2.5}$ concentration**

	(1) PM2.5 Conc.	(2) PM2.5 Conc.	(3) PM2.5 Conc.	(4) PM2.5 Conc.	(5) PM2.5 Conc.	(6) PM2.5 Conc.
Downwind of plant	2.793	2.712	2.698	0.158	0.514	1.186
	(1.6611)	(1.5273)	(1.4113)	(0.6451)	(0.5481)	(0.6112)
Geocode's vegetation index	-1.235	-1.265	-1.096	-0.897	-0.893	-0.800
	(1.6470)	(1.6092)	(1.6285)	(0.9519)	(0.9533)	(0.9271)
Geocode area is urban	-0.251	-0.230	-0.149	0.631*	0.622*	0.628*
	(0.8499)	(0.8325)	(0.8057)	(0.3115)	(0.3107)	(0.3102)
Respondent's age is 26-60 years	-0.360	-0.377	-0.413	0.131	0.132	0.127
	(0.6591)	(0.6723)	(0.6888)	(0.1228)	(0.1224)	(0.1192)
Respondent's age is more than 60 years	-0.006	0.017	-0.042	0.171	0.171	0.151
	(0.2807)	(0.2670)	(0.2889)	(0.1692)	(0.1690)	(0.1625)
Respondent's gender is male	0.180	0.163	0.175	-0.078	-0.080	-0.079
	(0.2972)	(0.2961)	(0.2915)	(0.0772)	(0.0766)	(0.0770)
Respondent's education is intermediate	0.330	0.332	0.353	0.185*	0.186*	0.195*
	(0.2521)	(0.2400)	(0.2456)	(0.0917)	(0.0921)	(0.0928)
Respondent's education is high	0.142	0.162	0.161	0.007	0.008	0.005
	(0.1899)	(0.1916)	(0.1900)	(0.1192)	(0.1180)	(0.1182)
Log annual hh income in '000 USD	-0.335	-0.322	-0.332	0.113	0.113	0.109
	(0.2466)	(0.2452)	(0.2453)	(0.0933)	(0.0932)	(0.0910)
Respondent has children under 15 yrs	1.161	1.166	1.169	-0.065	-0.067	-0.072
	(0.9607)	(0.9749)	(0.9771)	(0.0956)	(0.0948)	(0.0940)
Number of observations	18,147	18,147	18,147	18,147	18,147	18,147
Adj R-squared	0.703	0.704	0.704	0.949	0.949	0.949
Mean of dependent variable	32.026	32.026	32.026	32.026	32.026	32.026
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Distance band	0-40 km	0-40 km	0-40 km	0-40 km	0-40 km	0-40 km
Wind direction angular buffer	60°	90°	120°	60°	90°	120°

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates by regressing $PM_{2.5}$ concentration at geocode level on the downwind dummy for operational coal-fired power plants. The sample used in each column is defined by the distance band 0-40 km and the angular buffer around the coal-fired power plant i.e., all survey locations that are located within 40 km and falling in the angular buffer of either 60°, 90° or 120° of an operational coal power plant. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1-3 and state/province/admin-1 level for remaining columns. Columns 1-3 control for admin-0 fixed effects and remaining columns control for admin-1 fixed effects. "Downwind of plant" is a dummy, which takes value of 1 if the survey geocode falls in the downwind buffer region of a coal-fired power plant, and that varies based on the angular threshold used. Please refer to Table I notes for details on other variables.

Table B.8: **Results for 0-20 km distance band**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.037*	-0.038*	-0.001	-0.035	-0.066	-0.034
	(0.0147)	(0.0150)	(0.0233)	(0.0283)	(0.0534)	(0.0401)
Geocode's vegetation index	-0.019	-0.009	-0.115	0.081	-0.492**	-0.503
	(0.0289)	(0.0376)	(0.0833)	(0.0807)	(0.1190)	(0.2773)
Geocode area is urban	0.092**	0.074*	0.071	0.035	0.077	0.115
	(0.0318)	(0.0322)	(0.0402)	(0.0599)	(0.0459)	(0.1048)
Respondent's age is 26-60 years	0.031*	0.023	0.032	0.030	-0.015	0.023
	(0.0122)	(0.0153)	(0.0326)	(0.0377)	(0.0237)	(0.0382)
Respondent's age is more than 60 years	-0.003	-0.003	0.082	0.084	-0.053	0.006
	(0.0147)	(0.0188)	(0.0474)	(0.0517)	(0.0289)	(0.0400)
Respondent's gender is male	-0.025	-0.021*	-0.028	-0.024	-0.015	-0.019
	(0.0128)	(0.0099)	(0.0297)	(0.0314)	(0.0206)	(0.0308)
Respondent's education is intermediate	0.064***	0.069***	0.052	0.045	0.068	0.081*
	(0.0131)	(0.0144)	(0.0447)	(0.0367)	(0.0459)	(0.0322)
Respondent's education is high	0.090***	0.094***	0.037	0.032	0.079	0.075
	(0.0166)	(0.0155)	(0.0736)	(0.0563)	(0.0452)	(0.0417)
Log annual hh income in '000 USD	-0.012	-0.011	-0.020	-0.011	-0.001	0.003
	(0.0062)	(0.0070)	(0.0245)	(0.0255)	(0.0027)	(0.0126)
Respondent has children under 15 yrs	0.008	0.008	-0.001	0.011	-0.019	-0.061
	(0.0094)	(0.0110)	(0.0220)	(0.0345)	(0.0348)	(0.0420)
Number of observations	8,356	8,356	1,032	1,032	1,352	1,352
Adj R-squared	0.169	0.230	0.066	0.115	0.172	0.253
Mean of dependent variable	0.383	0.383	0.249	0.249	0.352	0.352
Region fixed effects	Admin-0	Admin-1	Admin-0	Admin-1	Admin-0	Admin-1
Distance band	0-20 km	0-20 km	0-20 km	0-20 km	0-20 km	0-20 km
Status of plant operation	Operational	Operational	Planned	Planned	Retired	Retired

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents OLS estimates using the specification in Equation (2) for operational, planned, and retired and mothballed coal-fired power plants. The sample used in each column is defined by the distance band 0-20 km. Columns 1-2, Columns 3-4, and Columns 5-6 report the results for operational, planned, and retired plants respectively. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1, 3 and 5 and at state/province/admin-1 level for remaining columns. Columns 1, 3 and 5 control for admin-0 fixed effects and remaining control for admin-1 fixed effects. Refer to Table IV notes for more details.

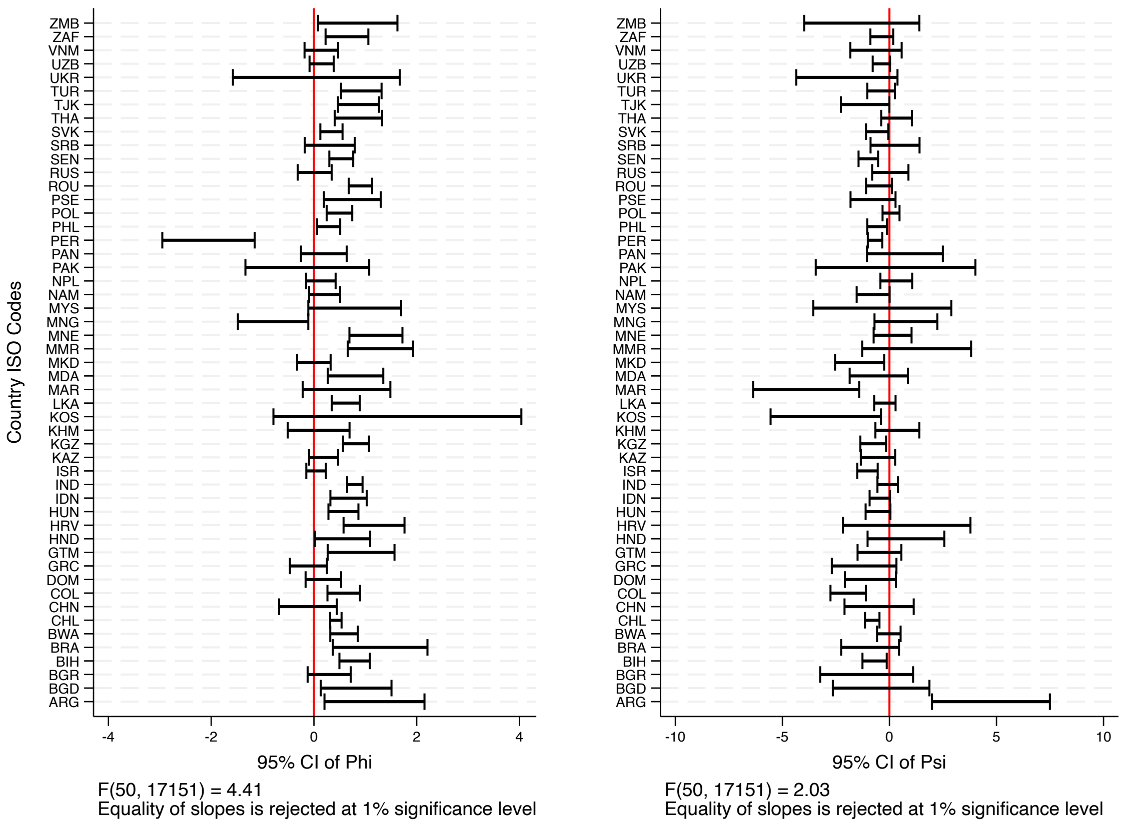
Table B.9: **Life satisfaction results using $PM_{2.5}$ concentration**

	(1) Life Sat	(2) Life Sat
Geocode's PM2.5 concentration in $\mu g/m^3$	-0.007	-0.015**
	[-0.018,0.003]	[-0.027,-0.004]
Geocode's vegetation index	-0.014	0.044
	[-0.293,0.265]	[-0.196,0.284]
Geocode area is urban	0.061	0.087
	[-0.076,0.198]	[-0.063,0.237]
Respondent's age is 26-60 years	-0.334***	-0.372***
	[-0.453,-0.214]	[-0.477,-0.268]
Respondent's age is more than 60 years	-0.429**	-0.464***
	[-0.744,-0.114]	[-0.621,-0.307]
Respondent's gender is male	-0.154*	-0.152**
	[-0.303,-0.006]	[-0.243,-0.060]
Respondent's education is intermediate	0.300***	0.316***
	[0.135,0.465]	[0.191,0.441]
Respondent's education is high	0.644***	0.676***
	[0.492,0.795]	[0.518,0.835]
Log annual hh income in '000 USD	0.487***	0.477***
	[0.358,0.615]	[0.408,0.546]
Respondent has children under 15 yrs	-0.020	0.022
	[-0.145,0.105]	[-0.071,0.115]
Number of observations	17,869	17,869
Adj R-squared	0.199	0.234
Mean of dependent variable	5.405	5.405
Mean household income in USD	14810	14810
Region fixed effects	Admin-0	Admin-1
Countries included	Global	Global

95% confidence interval in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents estimates using the specification in Equation (3) for operational coal-fired power plants. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within 40 km distance from the nearest coal power plant. Table B.1 provide the list of countries from which sample surveys are used in this specification. 95% confidence interval bounds are reported in square brackets. Column 1 controls for admin-0 fixed effects while Column 2 controls for admin-1 fixed effects. The dependent variable, *Life Sat*, is a shorthand for life satisfaction, which takes values between 0 ("the worst possible life") and 10 ("the best possible life") based on what surveyed individuals report as their current life satisfaction. The main variables of interest are $PM_{2.5}$ concentration at the geocode level and logarithm of annual household income. The first variable takes value 2 (1) if an individual is dissatisfied (satisfied) with ambient air quality and the second variable is logarithm of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Figure B.7: **Estimates of ϕ and ψ parameters for sample countries**



Notes: The chart shows 95% confidence interval for ϕ and ψ estimates for each of the 51 countries in the main sample by running a pooled regression with country interactions corresponding to Equation (3). Equality of slopes across countries for both ϕ and ψ is rejected at 1% significance level, thereby highlighting the heterogeneous effect of both income and air quality satisfaction on overall life satisfaction across countries.

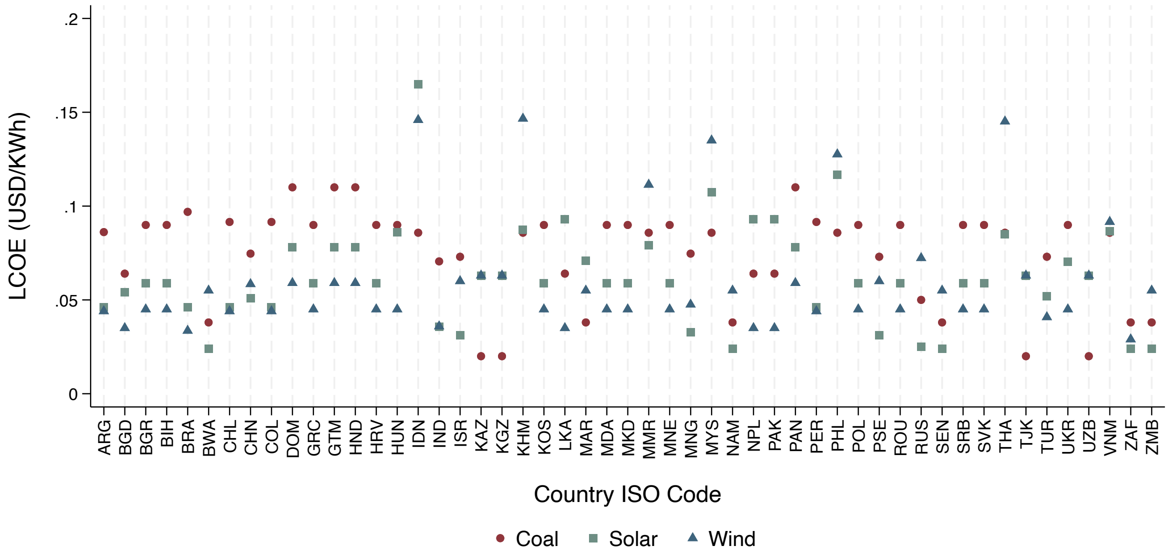
Table B.10: **Ordered logit estimation results for life satisfaction**

	(1) Life Sat
Log air quality dissatisfaction	-0.395***
	[-0.511,-0.279]
Geocode's vegetation index	0.020
	[-0.155,0.195]
Geocode area is urban	0.093
	[-0.029,0.215]
Respondent's age is 26-60 years	-0.301***
	[-0.384,-0.219]
Respondent's age is more than 60 years	-0.397***
	[-0.529,-0.264]
Respondent's gender is male	-0.133***
	[-0.210,-0.057]
Respondent's education is intermediate	0.247***
	[0.146,0.348]
Respondent's education is high	0.608***
	[0.472,0.744]
Log annual hh income in '000 USD	0.377***
	[0.318,0.436]
Respondent has children under 15 yrs	0.031
	[-0.047,0.108]
Number of observations	163,029
Pseudo R-squared	0.034
Log likelihood	-61,047
Mean of dependent variable	5.411
Mean household income in USD	14855
Region fixed effects	Admin-1
Countries included	Global

95% confidence interval in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

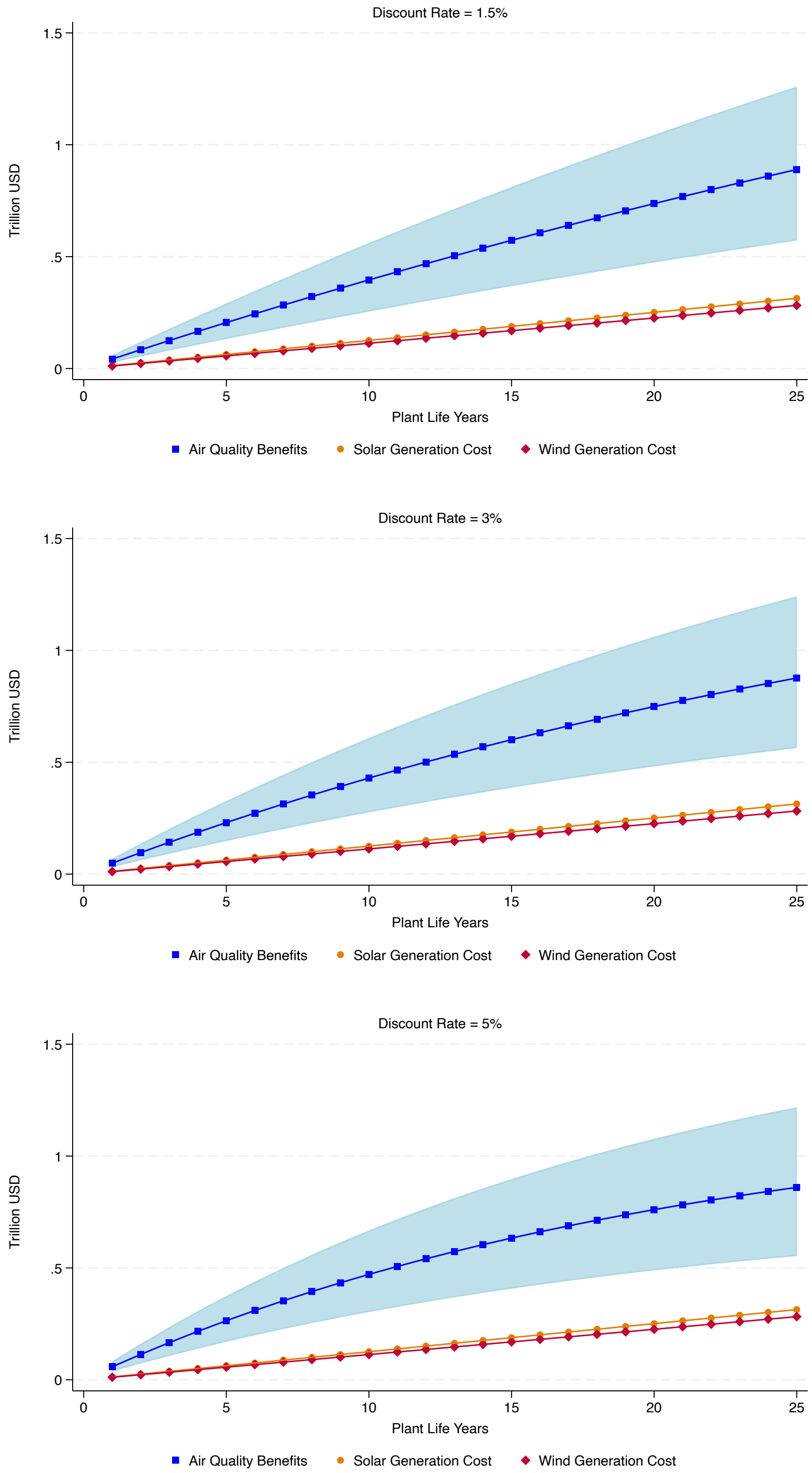
Notes: The table above reports results for ordered logistical model estimation with fixed effects corresponding to OLS estimation results reported in Table VII. We implement a robust estimation for fixed effects ordered logit models using the estimator proposed by Baetschmann et al. (2020).

Figure B.8: **Unit cost of energy for different generation technologies**



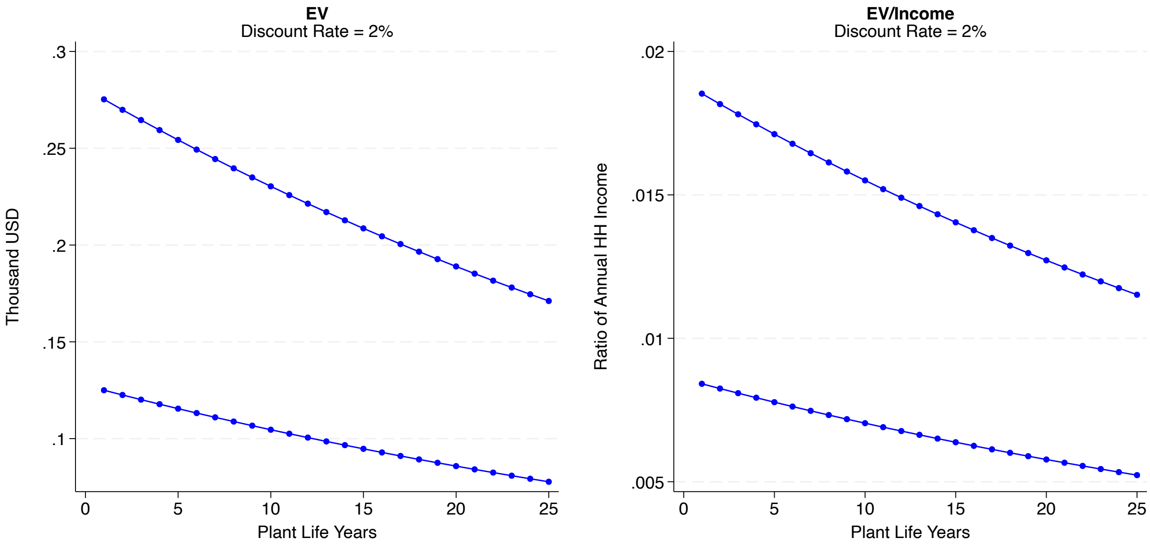
Notes: The graph shows LCOE values for all 51 countries in the main sample as listed in Table B.1. LCOE measures lifetime costs divided by energy production. It accounts for present value of the total cost of building and operating a power plant over an assumed lifetime. This measure allows comparison of different technologies (e.g., wind, solar, coal) of unequal life spans, project size, different capital cost, risk, return, and capacities for each of the respective sources. LCOE also accounts for different capacity factors across energy sources and plants.

Figure B.9: **Cost-benefit analysis for alternate discount rates**



Notes: Top/mid/bottom row show results for 1.5/3/5% discount rate. Refer to Figure II for more details.

Figure B.10: **EV and EV/Income during transition project life cycle**



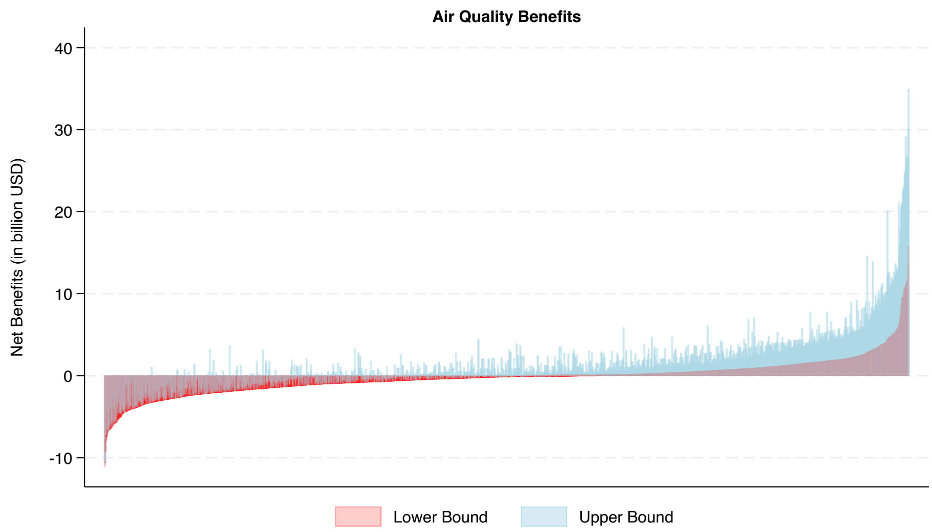
Notes: The chart shows the present-discounted value of estimated EV and EV to annual household income ratio in left and right plots respectively assuming an annual discount rate of 2% for an energy transition project life cycle of 25 years.

Table B.11: **Combined top-25 coal power stations based on affected population**

(1) Country	(2) State/Province	(3) Name of Plant	(4) Population	(5) Ann. Emission (in mil. tons)	(6) Capacity (in MW)	(7) Plant Life (in years)	(8) Solar Cost (in mil. $)	(9) Wind Cost (in mil. $)	(10) Gross Benefits (in mil. $)	(11) Gross Benefits LB (in mil. $)
India	Delhi	Rajghat Delhi	30871582	0.8	135	2	78.64	70.72	24874.62	15998.17
China	Shanghai	Wujing	29310080	11.9	2537.5	17	1478.20	1329.26	23616.45	15188.97
China	Shanghai	Shanghai Gaoqiao	26608464	0.9	150	9	87.38	78.58	21439.64	13788.95
China	Shanghai	Waigaoqiao	25449414	22.6	5240	22	3052.51	2744.96	20505.74	13188.31
China	Shanghai	Baoshan Works	24979818	5.9	1050	11	611.67	550.04	20127.36	12944.96
China	Shanghai	Shidongkou	24205972	17.6	3820	13	2225.30	2001.10	19503.84	12543.94
India	West Bengal	Budge Budge	23684622	4.1	750	23	436.91	392.89	19083.77	12273.77
India	West Bengal	Southern CESC	23486538	0.8	135	11	78.64	70.72	18924.16	12171.12
India	West Bengal	Titagarh	23426320	1.2	240	5	139.81	125.72	18875.64	12139.91
China	Guangdong	Hengyun-D	22829176	3.2	660	28	384.48	345.74	18394.49	11830.46
China	Guangdong	Hengyun-C	22803540	2.3	420	5	244.67	220.02	18373.84	11817.18
India	Haryana	Faridabad	22755274	0.9	165	2	96.12	86.43	18334.95	11792.16
China	Guangdong	Jiulong Paper Mill	22686148	3.2	620	25	361.17	324.79	18279.25	11756.34
China	Guangdong	Yuehua Huangpu	22633900	3.4	660	2	384.48	345.74	18237.15	11729.27
China	Guangdong	Guangzhou Refinery	22396020	1.0	200	28	116.51	104.77	18045.48	11605.99
Indonesia	West Java	Cikarang Babelan	21297338	1.4	280	38	163.11	146.68	17160.23	11036.64
India	Maharashtra	Trombay	21296044	4.0	810	12	471.86	424.32	17159.18	11035.97
China	Guangdong	Guangzhou Lixin	20995940	2.8	660	33	384.48	345.74	16917.37	10880.45
China	Guangdong	Mawan	20927798	9.4	1940	19	1130.13	1016.27	16862.47	10845.13
China	Guangdong	Guangzhou Nansha	20716364	2.8	600	30	349.52	314.31	16692.11	10735.57
China	Guangdong	Lee & Man Paper	20536522	1.3	216	28	125.83	113.15	16547.20	10642.37
China	Guangdong	Shunde Desheng	20437078	2.8	600	29	349.52	314.31	16467.07	10590.83
India	Uttar Pradesh	National Capital Dadri	19695644	4.8	840	14	489.33	440.03	15869.67	10206.61
Japan	Kanto	Isogo	19357188	5.0	1200	27	699.05	628.62	15596.96	10031.22
China	Guangdong	Dongtang Plant	19029100	1.5	285	2	166.02	149.3	15332.60	9861.20

Notes: The table lists the top 25 coal power stations in the world in decreasing order of total population affected, which is reported in Column 4. The population figures are the total number of individuals located within 40 km of respective plants. Solar and wind costs report the cost of green transition through solar and wind technology respectively. These costs are calculated by using source-specific average global LCOE values and respective capacities of coal plants as reported in Column 6. Air quality benefits in Column 10 are computed by multiplying EV values, which are computed by using Equation (4), with the total number of residences in 0-40 km distance band. For EV calculations, global parameter values for ψ, ϕ, $\frac{AirDiss}{\widetilde{AirDiss}}$, and y are used. Column 11 reports the lower bound on the gross air quality benefits from shutting down each of the listed plants.

Figure B.11: **Plant-level net air quality benefits from closing operational plants**



Notes: Chart shows the net benefits from closing all the operational coal-fired power in 2019 located across the whole world. The parameter values for ψ, ϕ, $\frac{\widehat{AirDiss}}{\widetilde{AirDiss}}$, and y are taken from the global estimates using all 51 countries combined. The policy experiment entails phasing out coal-fired power and replacing that freed capacity with 50% solar and 50% wind generation. The costs of solar and wind energy generation are calculated by multiplying respective source-specific global average LCOE values in USD/kWh with the total energy demand. The LCOE values for solar and wind are inflated by a factor of 4 and 2 respectively.

Table B.12: **Life satisfaction regression results for India and China**

	(1) Life Sat	(2) Life Sat	(3) Life Sat	(4) Life Sat
Log air quality dissatisfaction	-0.080	-0.803***	-0.124	-0.646**
	[-0.553,0.393]	[-1.137,-0.469]	[-0.709,0.461]	[-1.051,-0.241]
Geocode's vegetation index	-0.363	-0.973**	-0.038	-0.331
	[-1.224,0.497]	[-1.635,-0.311]	[-1.142,1.066]	[-1.430,0.768]
Geocode area is urban	0.352*	0.018	0.118	0.130
	[0.066,0.637]	[-0.219,0.254]	[-0.413,0.650]	[-0.447,0.708]
Respondent's age is 26-60 years	-0.181	-0.017	-0.414**	-0.121
	[-0.475,0.113]	[-0.279,0.246]	[-0.679,-0.150]	[-0.392,0.149]
Respondent's age is more than 60 years	-0.474*	0.550**	-0.730**	0.409*
	[-0.902,-0.047]	[0.200,0.899]	[-1.174,-0.285]	[0.017,0.800]
Respondent's gender is male	-0.345**	0.142	-0.183	0.187
	[-0.604,-0.086]	[-0.054,0.337]	[-0.484,0.118]	[-0.065,0.438]
Respondent's education is intermediate	0.586***	0.253*	0.332*	0.267*
	[0.291,0.880]	[0.029,0.477]	[0.008,0.655]	[0.041,0.492]
Respondent's education is high	0.708**	0.424*	0.545	0.544***
	[0.200,1.216]	[0.075,0.774]	[-0.065,1.155]	[0.266,0.822]
Log annual hh income in '000 USD	0.797***	0.427***	0.681***	0.454***
	[0.649,0.944]	[0.317,0.536]	[0.512,0.850]	[0.309,0.599]
Respondent has children under 15 yrs	-0.297*	-0.122	-0.025	-0.068
	[-0.549,-0.045]	[-0.324,0.079]	[-0.202,0.152]	[-0.285,0.149]
Number of observations	2,131	2,099	2,131	2,099
Adj R-squared	0.093	0.072	0.171	0.127
Mean of dependent variable	3.262	5.213	3.262	5.213
Mean household income in USD	4626	19365	4626	19365
Region fixed effects	-	-	Admin-1	Admin-1
Countries included	India	China	India	China

95% confidence interval in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

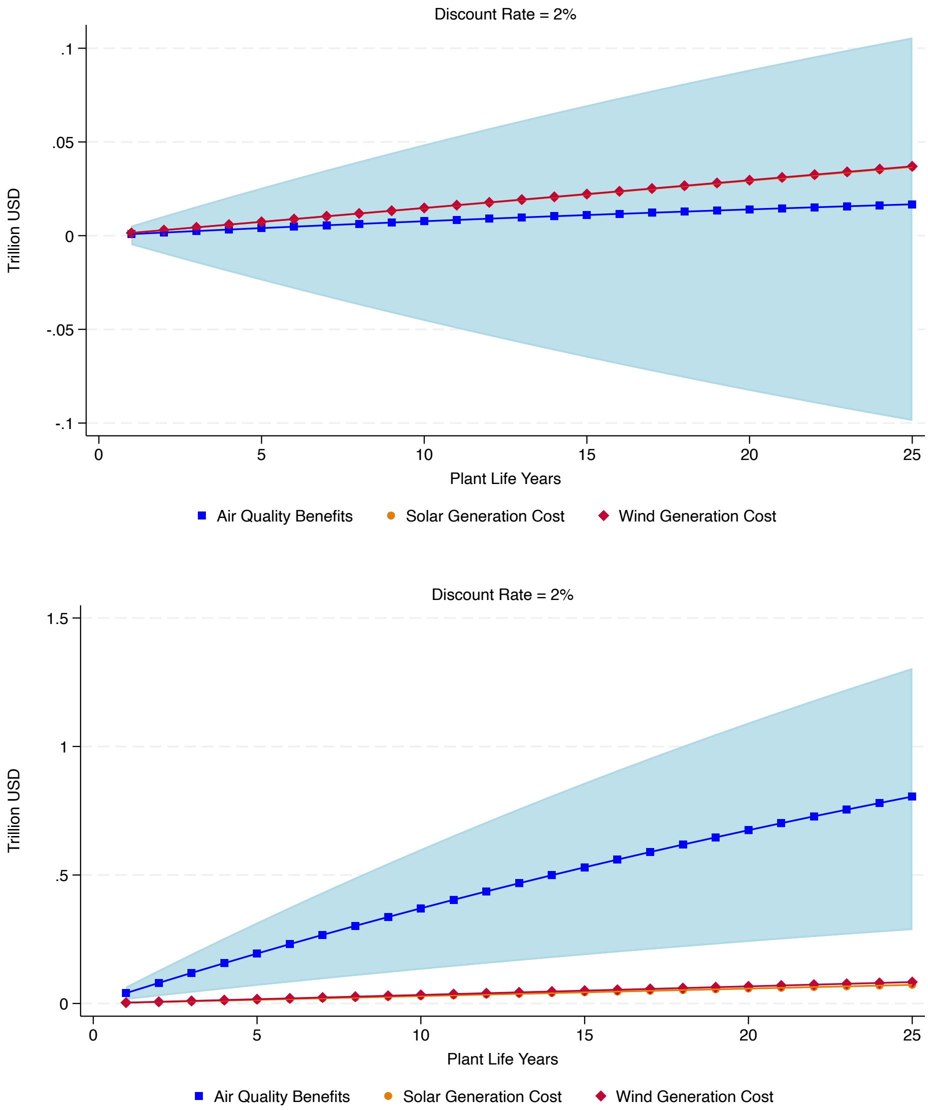
Notes: This table presents estimates using the specification in Equation (3) for operational coal-fired power plants in India and China. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. 95% confidence interval bounds are reported in square brackets. Columns 3 and 4 control for admin-1 fixed effects. The dependent variable, *Life Sat*, is a shorthand for life satisfaction, which takes values between 0 ("the worst possible life") and 10 ("the best possible life") based on what surveyed individuals reports as their current life satisfaction. The main variables of interest are logarithm of air quality dissatisfaction and logarithm of annual household income. The first variable takes value 2 (1) if an individual is dissatisfied (satisfied) with ambient air quality and the second variable is logarithm of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table B.13: **Aggregate equivalent variation results for India and China**

(1) Geographical Category	(2) ψ	(3) ϕ	(4) y (in $)	(5) $AirDiss/\widetilde{AirDiss}$	(6) e (in $)	(7) Affected Population	(8) HH Size (# persons)	(9) AEV (in tril. $)
Panel 1: Point estimates								
India	-0.124	0.681	4626	1.38	264	375,939,467	5.8	0.017
China	-0.646	0.454	19365	1.62	9617	374,225,419	4.4	0.818
Panel 2: $\underline{\gamma}$ and $\underline{\beta}$								
India	-0.709	0.512	4626	1.38	1665	375,939,467	5.8	0.108
China	-1.051	0.309	19365	1.62	15612	374,225,419	4.4	1.328
Panel 3: $\overline{\gamma}$ and $\overline{\beta}$								
India	0.461	0.850	4626	1.38	-883	375,939,467	5.8	-0.057
China	-0.241	0.599	19365	1.62	3416	374,225,419	4.4	0.291

Notes: The three rows correspond to point estimates and lower and upper bounds of 95% confidence intervals of ψ and ϕ parameters respectively. Estimates on logarithm of annual household income, ϕ, logarithm of air quality dissatisfaction, ψ, and average income, y, are taken from Columns 3 and 4 of Table B.12 for respective countries. $\frac{AirDiss}{\widetilde{AirDiss}}$ is the ratio of air quality dissatisfaction level in the 0-40 km distance band and that outside of the band for each country. e is the equivalent variation computed using Equation (4). The population is computed by adding the number of individuals living in a circle of radius 40 km around each coal plant. The population data comes from the Gridded Population of the World, v4 (GPWv4) database for year 2020. AEV is generated by multiplying e with population estimates downscaled by the number of persons living in a typical household taken from the Area Database v4.1 of the Global Data Lab.

Figure B.12: **Cost-benefit analysis results for India and China**



Notes: Charts show the cost-benefit analysis results for India (top) and China (bottom). The blue line represents point estimates of air quality benefits with the shaded area showing upper and lower bounds on the estimates calculated using country-specific parameter values. The costs of solar and wind energy generation are calculated by multiplying their respective source-geography-specific LCOE values in USD/kWh with the total excess energy demand because of closing of coal plants. Please refer to Figure II for more details.

Table B.14: **Total benefits of energy transition for different regions**

(1) Geographical Category	(2) Gross Benefits (in tril. $)	(3) Net Benefits (in tril. $)	(4) Gross Benefits LB (in tril. $)	(5) Net Benefits LB (in tril. $)
Panel 1: Actual parameters				
Global	.903	.605	.581	.283
India	.017	-.02	-.057	-.094
China	.821	.743	.292	.214
Panel 2: Global preference parameters				
Global	.903	.605	.581	.283
India	.081	.044	.053	.016
China	.628	.555	.416	.338

Notes: The table reports gross and net benefits of closing coal plants in different geographical categories using point estimates for the respective categories in Columns 2 and 3 respectively. Columns 4 and 5 report the lower bound on the benefits. The policy experiment entails phasing out coal-fired power at a constant rate of 4% per year and replacing that freed capacity with 50% solar and 50% wind generation over a period of 25 years. The benefits shown here are for the last year i.e., 25th year of plant operation. The costs of solar and wind energy generation are calculated by multiplying their respective source-geography-specific LCOE values in USD/kWh with the total excess energy demand because of closing of coal plants. Panel 1 reports results when respective parameter values for each category is used to calculate benefits, while in Panel 2, we use Global category parameter values of ψ and ϕ for all categories.

Table B.15: **Life satisfaction regression results for education categories**

	(1) Life Sat	(2) Life Sat	(3) Life Sat	(4) Life Sat	(5) Life Sat	(6) Life Sat
Log air quality dissatisfaction	-0.621***	-0.447***	-0.468***	-0.650***	-0.407***	-0.511***
	[-0.922,-0.320]	[-0.647,-0.247]	[-0.734,-0.202]	[-0.914,-0.386]	[-0.586,-0.229]	[-0.771,-0.251]
Geocode's vegetation index	-0.413	0.106	0.006	-0.184	0.036	0.236
	[-1.090,0.263]	[-0.090,0.303]	[-0.440,0.452]	[-0.800,0.431]	[-0.208,0.280]	[-0.206,0.678]
Geocode area is urban	-0.043	0.134	0.178	-0.084	0.170*	0.233
	[-0.244,0.157]	[-0.012,0.280]	[-0.070,0.426]	[-0.340,0.173]	[0.014,0.327]	[-0.038,0.504]
Respondent's age is 26-60 years	-0.561***	-0.305***	-0.087	-0.608***	-0.335***	-0.204*
	[-0.844,-0.277]	[-0.426,-0.185]	[-0.312,0.138]	[-0.816,-0.400]	[-0.452,-0.219]	[-0.395,-0.013]
Respondent's age is more than 60 years	-0.315	-0.575***	-0.426**	-0.353**	-0.615***	-0.494**
	[-0.669,0.039]	[-0.894,-0.255]	[-0.732,-0.121]	[-0.611,-0.095]	[-0.812,-0.418]	[-0.809,-0.178]
Respondent's gender is male	-0.227	-0.153	-0.145	-0.219*	-0.148*	-0.131
	[-0.482,0.027]	[-0.317,0.012]	[-0.298,0.008]	[-0.394,-0.044]	[-0.269,-0.028]	[-0.275,0.012]
Log annual hh income in '000 USD	0.565***	0.481***	0.393***	0.549***	0.456***	0.391***
	[0.418,0.711]	[0.344,0.619]	[0.204,0.582]	[0.452,0.645]	[0.361,0.550]	[0.248,0.534]
Respondent has children under 15 yrs	-0.176*	0.043	-0.011	-0.065	0.058	0.022
	[-0.312,-0.040]	[-0.104,0.190]	[-0.204,0.181]	[-0.221,0.090]	[-0.075,0.192]	[-0.133,0.177]
Number of observations	5,572	9,166	2,957	5,547	9,161	2,911
Adj R-squared	0.190	0.155	0.166	0.229	0.182	0.213
Mean of dependent variable	4.665	5.611	6.196	4.666	5.610	6.190
Mean household income in USD	8872	15291	24735	8865	15289	24810
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1
Countries included	Global	Global	Global	Global	Global	Global
Education level	Primary	Intermediate	High	Primary	Intermediate	High

95% confidence interval in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

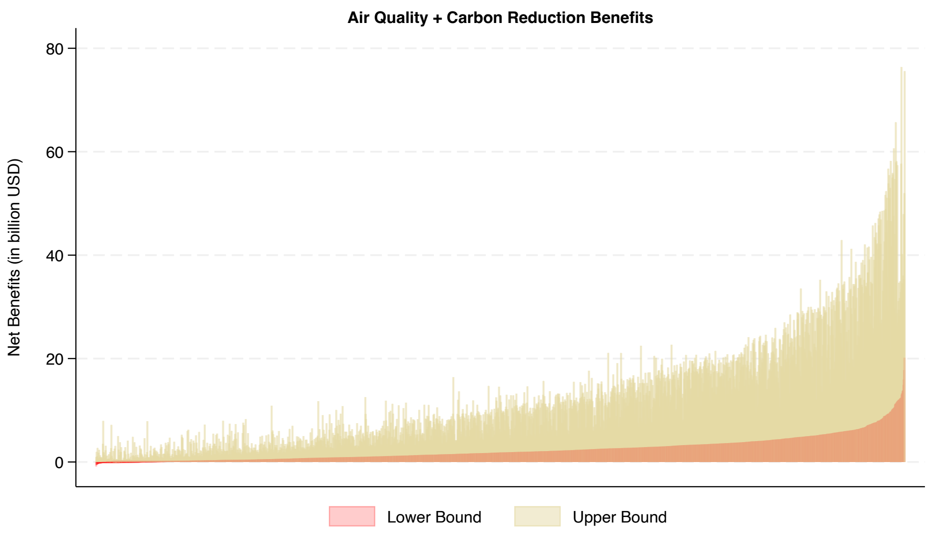
Notes: This table presents estimates using the specification in Equation (3) for operational coal-fired power plants for each education group separately. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. Table B.1 provides the list of countries from which sample surveys are used in this specification. 95% confidence interval bounds are reported in square brackets. Columns 1-3 control for admin-0 fixed effects while Columns 4-6 control for admin-1 fixed effects. The dependent variable, *Life Sat*, is a shorthand for life satisfaction, which takes values between 0 ("the worst possible life") and 10 ("the best possible life") based on what surveyed individuals report as their current life satisfaction. The main variables of interest are logarithm of air quality dissatisfaction and logarithm of annual household income. The first variable takes value 2 (1) if an individual is dissatisfied (satisfied) with ambient air quality and the second variable is logarithm of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table B.16: **Equivalent variation results for education categories**

(1) Education Category	(2) ψ	(3) ϕ	(4) y (in \$)	(5) $AirDiss/\widetilde{AirDiss}$	(6) e (in \$)
Panel 1: Point estimates					
Primary	-0.650	0.549	8865	1.37	2758
Intermediate	-0.407	0.456	15289	1.37	3745
High	-0.511	0.391	24810	1.37	8368
Panel 2: $\underline{\psi}$ and $\underline{\phi}$					
Primary	-0.914	0.452	8865	1.37	4175
Intermediate	-0.586	0.361	15289	1.37	6117
High	-0.771	0.248	24810	1.37	15487
Panel 3: $\overline{\psi}$ and $\overline{\phi}$					
Primary	-0.386	0.645	8865	1.37	1522
Intermediate	-0.229	0.550	15289	1.37	1878
High	-0.251	0.534	24810	1.37	3413

Notes: The three panels correspond to point estimates and lower and upper bounds of 95% confidence intervals of ψ and ϕ parameters respectively. Estimates on logarithm of annual household income, ϕ, logarithm of air quality dissatisfaction, ψ, and average income, y, are taken from Columns 4, 5, and 6 of Table B.15 for respective education categories. $\frac{AirDiss}{\widetilde{AirDiss}}$ is the ratio of average air quality dissatisfaction level in the 0-40 km distance band to that outside of the 40 km band for global category. e is the equivalent variation computed using Equation (4).

Figure B.13: **Plant-level net benefits from closing operational plants**



Notes: Chart shows the sum of net air quality and carbon benefits from closing all the operational coal-fired power in 2019 across the whole world. The parameter values for ψ, ϕ, $\frac{AirDiss}{\widetilde{AirDiss}}$, and y are taken from the global estimates using all 51 countries combined. The policy experiment entails phasing out coal-fired power and replacing that freed capacity with 50% solar and 50% wind generation. The costs of solar and wind energy generation are calculated by multiplying respective source-specific average global LCOE values in USD/kWh with the total energy demand.

Table B.17: **Employment in energy generation sectors for sample countries**

ISO	Country	Solar			Wind			Coal		
		Jobs (000)	Capacity (MW)	Jobs/MW	Jobs (000)	Capacity (MW)	Jobs/MW	Jobs (000)	Capacity (MW)	Jobs/MW
ARG	Argentina	2.2	764.1	2.9	1.7	2623.9	0.6			
BGD	Bangladesh	110	284	387.3	0.1	2.9	34.5			
BIH	Bosnia and Herzegovina	0.1	34.9	1.7	0.2	135.0	1.5			2.8
BWA	Botswana	0.04	5.9	6.5	0.04	170.2	0.3			
BRA	Brazil	68	7879.2	8.6	40.2	17198.3	2.3			
BGR	Bulgaria	1	1097.4	0.9	0.5	702.8	0.8	55.3	3733	14.8
KHM	Cambodia	7.1	315.0	22.4	0.005	0.3	20.6			
CHL	Chile	7.1	3205.4	2.2	7.5	2149	3.5			
CHN	China	2300	253417.8	9.1	550	282112.7	2	3209	1064400	3
COL	Colombia	0.4	85.5	4.2	2.1	18.4	114	44.3	1633.5	27.1
HRV	Croatia	0.1	108.5	0.5	2.3	801.3	2.9			2.8
DOM	Dominican Republic	0.3	385.6	0.8	0.3	370.3	0.8			
GRC	Greece	6.1	3287.7	1.9	6.8	4119.3	1.7	6.1	4337	1.4
GTM	Guatemala	0.1	100.8	0.8	0.1	107.4	0.8			
HND	Honduras	0.4	514	0.8	0.2	241.3	0.8			
HUN	Hungary	8.9	2131	4.2	0.8	321	2.5	2.2	783	2.8
IND	India	163.5	39042.7	4.2	44	38558.6	1.1	416.2	231900	1.8
IDN	Indonesia	4.2	185.3	22.4	3.2	154.3	20.6	240	40200	6
ISR	Israel	2.3	2230	1	0.1	27.3	3.7			
KAZ	Kazakhstan	5	1718.6	2.9	2.6	486.3	5.3	29.7	12986	2.3
KOS	Kosovo	0.1	10	6.3	0.02	32	0.5			2.8
KGZ	Kyrgyzstan	0.03	584.3	0.1	0.9	162.5	5.3			
MYS	Malaysia	54.9	1482.6	37	7.7	374.6	20.6			
MDA	Moldova	0.01	4.3	2.4	0.1	37	1.6			2.8
MNG	Mongolia	0.04	89.6	0.4	0.1	156	0.6			
MNE	Montenegro	0.01	6	1.7	0.9	118	7.6			2.8
MAR	Morocco	1	194	5.2	3.5	1405	2.5			
MMR	Myanmar	1.9	84.5	22.4	0.0001	0.006	20.6			
NAM	Namibia	0.5	145	3.2	0.001	5.2	0.3			
NPL	Nepal	0.1	66.9	2.2	0.0002	0.2	1.0			
MKD	North Macedonia	0.9	94.2	9.6	0.03	37.0	0.8			2.8
PAK	Pakistan	1.9	860.3	2.2	1	1235.9	0.8			
PSE	Palestine	0.1	116.8	1	0.1	27.3	3.7			
PAN	Panama	0.2	242.1	0.8	0.2	270	0.7			
PER	Peru	0.4	334.8	1.1	0.3	409	0.7			
PHL	Philippines	41	1057.9	38.8	23.8	442.9	53.7			
POL	Poland	29.4	3955	7.4	9.7	6298.3	1.5	91.4	27244	3.4
ROU	Romania	1	1382.5	0.7	2.3	3012.5	0.8	16	4465	3.6
RUS	Russia	3.5	1427.8	2.5	12	945.3	12.7	150.1	41800	3.6
SEN	Senegal	1.1	171	6.5	0.04	158.7	0.3			
SRB	Serbia	0.1	30.5	3	0.1	398	0.2	18.4	5314	3.5
SVK	Slovakia	0.2	535	0.4	0.007	3	2.2	2.4	926	2.6
ZAF	South Africa	21.5	5489.6	3.9	18.8	2516	7.5	74.8	43400	1.7
LKA	Sri Lanka	0.8	370.9	2.2	2.7	179	15.1			
TJK	Tajikistan	0.9	584.3	1.5	0.9	162.5	5.3			
THA	Thailand	18.7	2982.6	6.3	2	1506.8	1.3	0.9	5933	0.1
TUR	Turkey	7.7	6667.4	1.2	23	8832.4	2.6	51.8	19700	2.6
UKR	Ukraine	29.8	7331	4.1	3.8	1402	2.7	44.3	21842	2
UZB	Uzbekistan	0.005	3.5	1.5	0.004	0.8	5.3			
VNM	Vietnam	126.3	16660.5	7.6	3.5	518	6.8	86.4	20917	4.1
ZMB	Zambia	1.2	96.4	12.4	0.043	170.2	0.3			

Notes: The table reports country-level estimates of jobs present in different energy generation sectors. We could not come up with estimates for the coal sector of all the countries and that is why there are blanks in the table. Also, estimates for some of the countries are imputed from nearby countries. For example, for Jobs/MW of wind for Kyrgyzstan, Tajikistan, and Uzbekistan, we use the estimates for Kazakhstan as it is a neighbouring country to all three of them. References used for deriving the numbers, which are reported in the table above, are in the Appendix.

Table B.18: **IV results for air quality dissatisfaction and operational plants location**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss
Geocode's log dist from nearest plant	-0.441**	-0.324***	-0.305**	-0.301**
	(0.1413)	(0.0889)	(0.1057)	(0.0978)
Geocode's vegetation index	0.078	0.026	0.053	0.051
	(0.0714)	(0.0531)	(0.0547)	(0.0520)
Geocode area is urban	0.013	0.040	0.023	0.024
	(0.0456)	(0.0357)	(0.0347)	(0.0325)
Respondent's age is 26-60 years	0.023	0.022*	0.019	0.019
	(0.0116)	(0.0109)	(0.0107)	(0.0108)
Respondent's age is more than 60 years	-0.021	-0.021	-0.018	-0.018
	(0.0193)	(0.0176)	(0.0135)	(0.0135)
Respondent's gender is male	-0.010	-0.013	-0.014	-0.014
	(0.0123)	(0.0110)	(0.0077)	(0.0077)
Respondent's education is intermediate	0.054***	0.055***	0.054***	0.055***
	(0.0123)	(0.0111)	(0.0106)	(0.0106)
Respondent's education is high	0.064**	0.071***	0.075***	0.075***
	(0.0213)	(0.0190)	(0.0155)	(0.0154)
Log annual hh income in '000 USD	-0.009	-0.008	-0.009	-0.009
	(0.0087)	(0.0074)	(0.0058)	(0.0057)
Respondent has children under 15 yrs	0.010	0.008	0.007	0.007
	(0.0104)	(0.0093)	(0.0083)	(0.0082)
Number of observations	17,964	17,964	17,964	17,964
Under-id LM test statistic	8.743	8.787	13.172	15.084
Under-id LM test p-value	0.003	0.012	0.000	0.001
Weak-id F statistic (first stage)	16.302	11.888	15.872	9.404
Hansen J test statistic	0.000	1.553	0.000	0.006
Hansen J test p-value		0.213		0.939
Mean of dependent variable	0.327	0.327	0.327	0.327
Number of instruments	1	2	1	2
Region fixed effects	Admin-0	Admin-0	Admin-1	Admin-1

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents IV estimates using the specification in Equation (8) for operational coal-fired power plants. The two instruments used are: (i) logarithm of distance of survey locations from nearest railroad and (ii) logarithm of distance of survey locations from nearest water-body. Columns 1 and 3 use instrument (i) only, while Columns 2 and 4 use both instruments. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within 40 km distance from the nearest coal power plant. Table B.1 provides the list of countries for which sample surveys are used in this specification. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for the first two columns and state/province/admin-1 level for the last two columns. Columns 1-2 and Columns 3-4 control for admin-0 and admin-1 fixed effects respectively. The dependent variable, *Air Diss*, is a shorthand for Air Quality Dissatisfaction, which takes value 1 (0) if the surveyed individual is dissatisfied (satisfied) with the ambient air quality. The main variable of interest is geocode's logarithm of distance from the nearest plant, which is the straight-line distance between the survey and nearest coal plant location. Please refer to Table I notes for details on other variables. First-stage and reduced-form results are reported in Table B.19 in the Appendix.

Table B.19: **First-stage and reduced-form results for operational plants**

	(1)	(2)	(3)	(4)
Geocode's log dist from nearest railroad	-0.020***	-0.020***	-0.017***	-0.017***
	(0.0038)	(0.0037)	(0.0045)	(0.0045)
Geocode's vegetation index	-0.118***	-0.115***	-0.079**	-0.068*
	(0.0313)	(0.0325)	(0.0283)	(0.0282)
Geocode area is urban	0.102***	0.101***	0.086***	0.084***
	(0.0225)	(0.0234)	(0.0219)	(0.0220)
Respondent's age is 26-60 years	0.018	0.018	0.015	0.015
	(0.0108)	(0.0108)	(0.0099)	(0.0099)
Respondent's age is more than 60 years	-0.023	-0.023	-0.020	-0.020
	(0.0154)	(0.0154)	(0.0128)	(0.0128)
Respondent's gender is male	-0.018*	-0.018*	-0.016*	-0.016*
	(0.0090)	(0.0091)	(0.0072)	(0.0072)
Respondent's education is intermediate	0.055***	0.055***	0.058***	0.058***
	(0.0103)	(0.0103)	(0.0100)	(0.0100)
Respondent's education is high	0.090***	0.090***	0.091***	0.091***
	(0.0157)	(0.0158)	(0.0145)	(0.0145)
Log annual hh income in '000 USD	-0.007	-0.007	-0.003	-0.003
	(0.0053)	(0.0053)	(0.0050)	(0.0050)
Respondent has children under 15 yrs	0.004	0.004	0.001	0.001
	(0.0075)	(0.0075)	(0.0078)	(0.0078)
Geocode's log dist from nearest waterbody		-0.002		-0.010
		(0.0071)		(0.0062)
Geocode's log dist from nearest railroad	0.045***	0.046***	0.056***	0.055***
	(0.0112)	(0.0110)	(0.0142)	(0.0141)
Geocode's vegetation index	0.443**	0.394*	0.432***	0.394***
	(0.1655)	(0.1591)	(0.0921)	(0.0908)
Geocode area is urban	-0.202**	-0.189**	-0.208***	-0.201***
	(0.0680)	(0.0694)	(0.0561)	(0.0569)
Respondent's age is 26-60 years	0.010	0.009	0.015	0.015
	(0.0175)	(0.0177)	(0.0134)	(0.0135)
Respondent's age is more than 60 years	0.004	0.000	0.007	0.006
	(0.0255)	(0.0260)	(0.0190)	(0.0191)
Respondent's gender is male	0.017	0.018	0.005	0.007
	(0.0132)	(0.0129)	(0.0084)	(0.0083)
Respondent's education is intermediate	-0.002	-0.001	-0.012	-0.013
	(0.0213)	(0.0202)	(0.0164)	(0.0163)
Respondent's education is high	-0.059**	-0.057*	-0.051*	-0.051*
	(0.0225)	(0.0225)	(0.0227)	(0.0228)
Log annual hh income in '000 USD	-0.003	-0.004	-0.018*	-0.018*
	(0.0148)	(0.0141)	(0.0087)	(0.0087)
Respondent has children under 15 yrs	0.013	0.013	0.019	0.018
	(0.0146)	(0.0141)	(0.0118)	(0.0117)
Geocode's log dist from nearest waterbody		0.040**		0.036
		(0.0157)		(0.0223)
Observations	17964	17964	17964	17964

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Top table reports reduced-form results and bottom reports first-stage results of IV regression using Equation (8). The columns correspond to Table B.18, which reports IV results.

Table B.20: **Robustness test results on instruments**

	(1) Gender	(2) Agegroup	(3) Religion	(4) Gender	(5) Agegroup	(6) Religion
Geocode's log dist from nearest railroad	0.003	-0.000	-0.008	0.000	0.005	-0.008
	(0.0031)	(0.0062)	(0.0065)	(0.0036)	(0.0049)	(0.0074)
Number of observations	18,902	18,888	16,310	18,902	18,888	16,310
Adj R-squared	0.014	0.078	0.606	0.027	0.104	0.664
Mean of dependent variable	0.441	1.987	2.196	0.441	1.987	2.196
Region fixed effects	Admin-0	Admin-0	Admin-0	Admin-1	Admin-1	Admin-1

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table above reports robustness checks on the railroad instrument using three pre-determined variables: gender (male/female), age group (young/middle-aged/old), and religion. Standard errors, which are reported in parentheses, are clustered at country/admin-0 level for Columns 1-3 and at state/province/admin-1 level for remaining columns. Columns 1-3 control for admin-0 fixed effects and remaining control for admin-1 fixed effects.

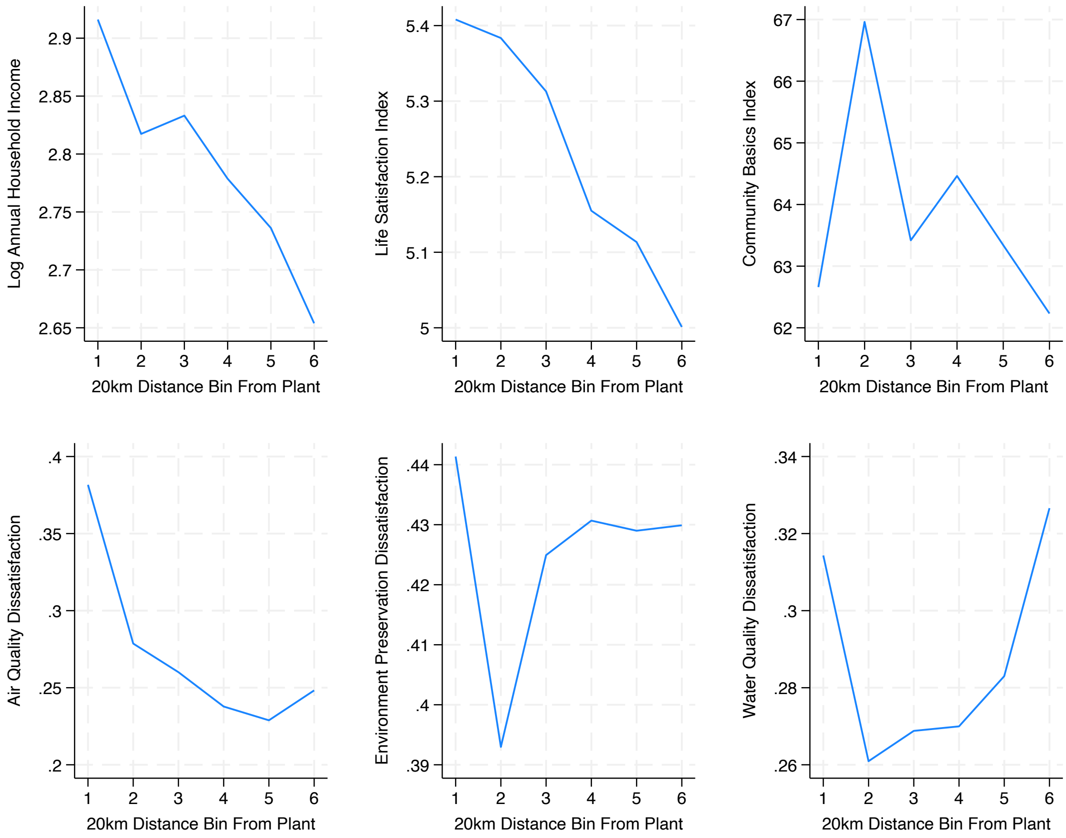
Table B.21: **First-stage and reduced-form results for retired plants**

	(1)	(2)	(3)	(4)
Geocode's log dist from nearest railroad	-0.009	-0.009	-0.005	-0.005
	(0.0057)	(0.0055)	(0.0087)	(0.0088)
Geocode's vegetation index	-0.551***	-0.551***	-0.444	-0.450
	(0.1248)	(0.1403)	(0.2403)	(0.2449)
Geocode area is urban	0.064	0.064	0.074	0.074
	(0.0344)	(0.0344)	(0.0568)	(0.0564)
Respondent's age is 26-60 years	-0.005	-0.005	0.010	0.010
	(0.0192)	(0.0193)	(0.0325)	(0.0324)
Respondent's age is more than 60 years	-0.046	-0.046	-0.024	-0.025
	(0.0268)	(0.0265)	(0.0327)	(0.0328)
Respondent's gender is male	-0.028**	-0.028**	-0.030	-0.030
	(0.0105)	(0.0106)	(0.0205)	(0.0205)
Respondent's education is intermediate	0.070**	0.070**	0.074***	0.074***
	(0.0269)	(0.0265)	(0.0219)	(0.0217)
Respondent's education is high	0.078**	0.078**	0.067	0.067
	(0.0270)	(0.0266)	(0.0356)	(0.0349)
Log annual hh income in '000 USD	-0.016*	-0.016*	-0.015	-0.015
	(0.0071)	(0.0074)	(0.0095)	(0.0095)
Respondent has children under 15 yrs	-0.016	-0.016	-0.042	-0.042
	(0.0253)	(0.0253)	(0.0301)	(0.0300)
Geocode's log dist from nearest waterbody		0.000		0.003
		(0.0183)		(0.0158)
Geocode's log dist from nearest railroad	0.153***	0.153***	0.152**	0.149**
	(0.0440)	(0.0438)	(0.0471)	(0.0464)
Geocode's vegetation index	1.623	1.654	2.150**	2.264**
	(0.9679)	(1.0040)	(0.7958)	(0.8063)
Geocode area is urban	-0.432**	-0.432**	-0.365**	-0.370**
	(0.1430)	(0.1422)	(0.1111)	(0.1126)
Respondent's age is 26-60 years	-0.027	-0.025	-0.048	-0.048
	(0.0488)	(0.0505)	(0.0430)	(0.0433)
Respondent's age is more than 60 years	-0.018	-0.014	-0.088	-0.080
	(0.0794)	(0.0853)	(0.0578)	(0.0599)
Respondent's gender is male	0.031	0.032	0.045	0.048
	(0.0470)	(0.0462)	(0.0297)	(0.0296)
Respondent's education is intermediate	-0.044	-0.045	-0.068	-0.071
	(0.0359)	(0.0352)	(0.0517)	(0.0501)
Respondent's education is high	-0.033	-0.035	-0.044	-0.054
	(0.0570)	(0.0545)	(0.0517)	(0.0486)
Log annual hh income in '000 USD	-0.000	-0.001	0.001	0.001
	(0.0313)	(0.0294)	(0.0248)	(0.0246)
Respondent has children under 15 yrs	0.019	0.018	0.055	0.056
	(0.0427)	(0.0437)	(0.0348)	(0.0337)
Geocode's log dist from nearest waterbody		-0.015		-0.061
		(0.0391)		(0.0709)
Observations	2317	2317	2317	2317

Region-clustered robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

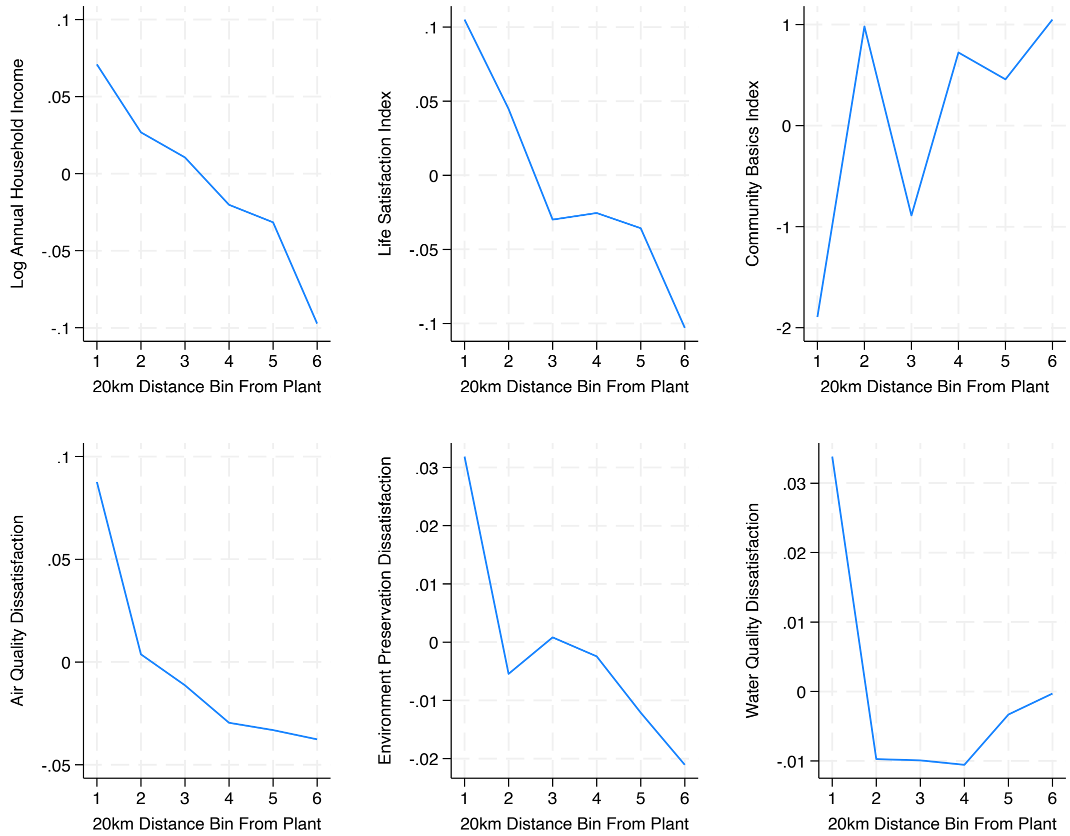
Notes: Top table reports reduced-form results and bottom reports first-stage results of IV regression using Equation (8) for retired plants.

Figure B.14: **Descriptive plots - I**



Notes: All the variables are taken from the 2019 Gallup World Poll. The label on x-axis should be multiplied by 20 to get the distance bin of the survey location from the nearest coal plant.

Figure B.15: **Descriptive plots - II**



Notes: All the variables are taken from the 2019 Gallup World Poll. The label on x-axis should be multiplied by 20 to get the distance bin of the survey location from the nearest coal plant. The estimates on y-axis have been demeaned of country fixed effects.

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