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 central to climate action and it should have an immediate and perceptible benefit through improved air quality. There is therefore potential to harness local politics for combating a global problem. However, this requires that coal-fired power decrease air quality satisfaction. This paper provides such evidence using geocoded survey data from 51 countries by demonstrating that people living within 40 km of coal-fired units are more dissatisfied with air quality. We construct a willingness-to-pay measure to show that there are net benefits of replacing coal-fired power with green technologies globally. (*JEL* I31, Q42, Q53, Q58)

I Introduction

There is now widespread recognition among policy-making elites that phasing out coal-fired power is needed as a central plank of climate action to reduce carbon emissions. But there is also much concern that the pace of change is too slow, most often blamed on a failure of political will. Moreover, some countries continue to invest in maintaining their existing coal-fired power plants and building new ones. Coal-fired power is not just bad for carbon emissions, it is also costly in terms of deterioration of air quality, and therefore has a large impact on public health (see, for example, Lelieveld et al. (2015)). The problem gets worse when plants tend to be

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located close to dense population centers.[1] This implies that some benefits from closing coal-fired power should be both rapid and local. Hence, we might expect local political processes to be much more active in spearheading climate action of this kind.

Even though individual citizens may feel these detrimental effects, it will not lead to more public action without it becoming a salient political issue. This is even a challenge in settings with vibrant democratic institutions as Crenson (1971) emphasized long ago in the context of air pollution politics in the United States. Moreover, the dangers of delay in taking such corrective course of action are colossal in terms of great climate-induced migration, socio-economic damages due to severe and extended conflicts, and the destructive impact of more frequent and extreme natural disasters (Stern (2016)). One way to galvanize public action is to provide evidence of collective net benefits from closing down coal-fired power plants.

This paper studies the link between air quality perception and coal-fired power using geocoded data from 51 countries surveyed in the Gallup World Poll. The data gives precise locations where interviews were conducted so that we can tag survey locations based on their proximity to coal-fired power stations. We find that survey respondents who live within 40 km of an operational coal-fired power plant express greater air quality dissatisfaction compared to citizens in the same country/region who are not within 40 km of an operational coal-fired power station. 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. The results are robust to a placebo test using already closed power stations and those that are planned for the future. As a robustness check, we use access to transport links as instruments to address the possibility that location decisions are endogenous to tolerance for air pollution.

Having established this link with air quality perception, we construct a willingness-to-pay (WTP) measure for air quality improvement using responses to a widely-used life satisfaction question that respondents answer in the survey. Specifically, we can compare the coefficient on air quality dissatisfaction (which impacts life satisfaction negatively) and income (which impacts life satisfaction positively). By looking at the size of the population living within 40 km radius of respective coal-fired power stations, we can construct a measure of the benefit from moving to an average level of air quality satisfaction for each country. More interesting still is to compare this benefit to the cost of building additional generation capacity for replacing coal-fired power with renewable energy. We find that just looking at air quality benefits yields a strong case for replacing coal-fired power with clean energy.

We 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 carbon reduction benefits. We also use our estimated benefits "out of sample", i.e.,

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

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 compliment ongoing work on estimating public health benefits from reducing reliance on coal-fired power. For example, Lelieveld et al. (2019) attributes 65% of excess global mortality to fossil fuel-related emissions, with significant heterogeneity across regions.

Reducing anthropogenic emissions has both immediate local benefits, such as lower infant mortality, better test scores, and higher crop productivity, along with meeting long-term sustainable climate goals. Air quality improvement is often talked about as a co-benefit from low-carbon investments (see, for example, Stern (2016)). However, there are two reasons for moving beyond describing it this way when it comes to phased elimination of coal-fired power. First, we show that air quality benefits alone are sufficient to justify phasing out coal-fired power. Second, when it comes to politics, due to their local nature, air quality benefits are likely to have a more direct role to play if they can provide greater impetus to policy action; in that case air quality improvement could be a primary rather than a secondary benefit. When it comes to this, providing evidence of aggregate net benefits at the local level can be useful. Individuals may be aware of poor air quality without being able to attribute it to the proximity to a coal-fired power station. Moreover, they may be aware of their own perceptions but not of the collective benefits that are obtained by aggregating across individuals.

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), faciltating a green transition requires citizens as voters and consumers to embrace green values. Citizens' perceptions of the need for change are likely to be possible 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 link the paper's contribution to existing work and discuss background issues. In Section III, we discuss the data that we use. Section IV discusses how we establish the link between proximity to a coal-fired station and perceptions of air quality. In Section V, we present our core results. The policy implications of our findings are laid out in Section VI, where we also discuss adding in carbon benefits and a few caveats to our core thought experiment. Section VII has some concluding comments.

II Background

Economists are increasingly engaging with questions of how best to measure environmental change damages alongside investigating ways of adapting to and mitigating their consequences (see, for example, Stern (2007) and Aghion et al. (2019)). Research in environmental psychology has picked up pace to uncover relationships between individual characteristics and incentives, location attributes, and perceptions on 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); Zaval et al. (2014); Konisky, Hughes, and Kaylor (2016)) and others leverage a far more granular analysis by implementing bespoke local surveys at a small geographic scale (Kaiser (1998); Bogner and Wiseman (1999)).

These studies have exposed the challenges of studying the relationship between individual-level opinions and location characteristics given the myriad of ways in which locations differ. Data availability has mainly focused on the developed world, primarily the United States and Europe. However, the damages due to global warming are predicted to be disproportionately higher in the Global South (Cruz and Rossi-Hansberg (2021)). Furthermore, the growth in coal-fired power in recent years has predominantly been in low-and-middle income countries. The analysis in this paper is representative of parts of the world that have not previously been studied.

The paper also connects to the strand of literature on life satisfaction and willingness to pay for "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, Luechinger, and Stutzer (2010); Frey and Stutzer (2002)). Previous work in this space has estimated WTP for clean air using objective measures of air pollution such as particulate matter and gaseous content (Luechinger (2009); Welsch (2006)). However, the correlation between objective and perceived air quality is not always strong (Liu, Cranshaw, and Roseway (2020)), and, arguably, perceived air quality seems to matter more for individuals' economic decision-making (Chasco and Gallo (2013)) and possibly for decisions on what climate policy to vote for.

This paper provides estimates of air quality benefits that can result from closing down coal-fired power stations across different countries. We use plant-level data on emissions to estimate plant-by-plant benefits depending on the size of the affected population, alongside the carbon benefits. There is much debate about the appropriate Social Cost of Carbon (SCC) estimate to use, with different methodological approaches suggesting widely different numbers (Tol (2022)).[2] We therefore assume lower and the upper bound values of \$20 and \$100 per ton of CO_2 respectively for our estimated benefits. Following Stern (2007), there is also a debate about the right discount rate to use and we follow existing literature in applying an annual discount rate of 2% for the future (Hassler, Krusell, and Nycander (2016); Nordhaus (2014)).

Air quality, unlike carbon emissions, is place specific. We therefore conduct a spatial cost-benefit analysis based on replacing existing coal-fired power plants with solar or wind farms of

2. 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)).

equivalent capacity for different geographies and extend the analysis to the whole world. This provides a ballpark sense of the value of closing down specific power plants. The context for such policy change is extremely favourable, since some renewable technologies are now sufficiently scalable to match mainstream capacity generation that can be achieved through coal-fired power. 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. 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 non-peak demand without wasting energy. Whereas renewable sources suffer from uncertain fluctuations due to weather conditions and are still not reliable. Therefore, advancement in energy storage technology, which is not limited to batteries[4], holds the key to making a green transition successful because if the surplus power from windmills generated during windy periods can be stored efficiently, it can be used to meet demand during less windy times. In this spirit, 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.[5]

III Data

III.A Geocoded Gallup World Poll Data

The outcomes data is taken from the Gallup World Poll, an annual, nationally-representative survey of citizens which began data collection in 2006 and covers 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 majority of Western European countries with phone surveys as shown in top panel of Figure A.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 A.1 and mapped in the bottom panel of Figure A.1 in the Appendix. The main outcome variable is a binary indicator of the survey respondent's

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

4. Apart from advancement in electrochemical storage technology, such as lithium ion, the energy storage space is witnessing a large investment in research and development as well as investments in non-conventional ways to store energy, such as mechanical storage using liquid CO_2, thermal storage by heating blocks of carbon or metal and delivering them as heat or other forms of energy, and chemical storage using hydrogen. *Source:* The Economist, Technology Quarterly, June 25, 2022

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

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.[6] Here also, we restrict the sample to 51 countries from the main analysis.

III.B Global Energy Monitor Coal Plants Tracker

Data on coal-fired power plants come from the Global Coal Plant Tracker database released by the Global Energy Monitor (GEM).[7] 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 A.2 and A.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.

III.C Transport Links and Other Data

We use global georeferenced data on railways and water-bodies locations to create instrumental variables for endogenous locations of coal-fired power plants. The source of the railways network shapefile is the World Food Program-Logistics Cluster[8], which brings together various

6. 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, women safety, cyber security, etc. (LRF (2020))

7. The Global Coal Plant Tracker (GCPT) provides information on coal-fired power units from around the world generating 30 megawatts and above. The GCPT 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

8. 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.

sources such as OpenStreetMap, American Digital Cartography, Global Discovery, etc. To get the location of water-bodies, we combine data from multiple sources[9] to create an "amalgam" water-bodies shapefile. 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×1 km grid population count from the Gridded Population of the World v4 (GPWv4) database for the year 2020 to compute the population estimates.

We extract country-level estimates of coal, solar, and onshore wind energy generation costs 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.

IV Empirical Approach

IV.A OLS

In our core specification, we suppose that air quality dissatisfaction, y, for an individual, i, surveyed in location, ℓ, can be explained as follows:

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

where $\delta_{i\ell}$ is i's distance to the nearest operating coal-fired power plant and τ_i represents unobserved idiosyncratic distaste for air pollution.

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.

There are however two empirical concerns with this approach. First, policy-makers may choose to locate coal-fired power stations where opposition is lowest, i.e., where people are less concerned about pollution. Second, people who care strongly about pollution could move away from locations where there is heavy pollution from coal-fired power while those with less concern may stay put or even move in to such areas. Both of these concerns would lead us to believe that OLS could underestimate the negative impact of coal-fired power on the general population.

More formally, note that

$$\widehat{\alpha}_{OLS} = \frac{cov\left(y_{i\ell}, \delta_{i\ell}\right)}{var\left(\delta_{i\ell}\right)} = \frac{cov\left(\alpha\delta_{i\ell} + \varepsilon_{i\ell} + \tau_i, \delta_{i\ell}\right)}{var\left(\delta_{i\ell}\right)} = \alpha + \frac{cov\left(\tau_i, \delta_{i\ell}\right)}{var\left(\delta_{i\ell}\right)} \tag{2}$$

9. 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.

Assuming that $cov(\varepsilon_{i\ell}, \delta_{i\ell}) = 0$, the 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. As we discuss further, the most plausible case is where $cov(\tau_i, \delta_{i\ell}) > 0$, implying that the estimated value of α is a lower bound estimate of the average relationship between being located close to a coal-fired power station and air quality dissatisfaction.

IV.B IV

We now 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 log distance of survey locations from the nearest railroad and (ii) the log 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.

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.[10]

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

$$\delta_{i\ell} = \beta\tau_i + \gamma_i z_\ell + \eta_{i\ell} \tag{3}$$

where z are factors, which affect location other than taste for pollution, i.e., "instruments" for location. We allow γ, the relationship between z_ℓ and $\delta_{i\ell}$ to be heterogeneous, which seems reasonable. Now consider an IV estimator of α where we put in $\widehat{\delta}_{i\ell}$, as in the first-stage prediction of δ, under the 2SLS routine. Then

$$\widehat{\alpha}_{IV} = \frac{cov\left(z_\ell, y_{i\ell}\right)}{cov\left(z_\ell, \delta_{i\ell}\right)} = \frac{cov\left(z_\ell, \alpha\left[\beta\tau_i + \gamma_i z_\ell + \eta_{i\ell}\right] + \varepsilon_{i\ell} + \tau_i\right)}{cov\left(z_\ell, \beta\tau_i + \gamma_i z_\ell + \eta_{i\ell}\right)} = \alpha \tag{4}$$

10. 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

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

$$\widehat{\alpha}_{OLS} - \widehat{\alpha}_{IV} = \frac{cov\left(\tau_i, \delta_{i\ell}\right)}{var\left(\delta_{i\ell}\right)} \tag{5}$$

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

V Air Quality Dissatisfaction

V.A Main Results

Our core results come from estimating the following regression using OLS:

$$y_{i\ell} = \alpha_{OLS}\delta_{i\ell} + \beta \mathbf{X}_{i\ell} + \eta_\ell + \varepsilon_{i\ell} \tag{6}$$

where $\mathbf{X}$ contains location and individual-level controls and η captures region fixed effects, which can either be at the country (admin 0) or state/province (admin 1) level. Previous research on perceptions leads us to expect a higher impact on households, which are situated closer to coal-fired power stations (Zhang et al. (2022)). The negative effect of proximity to coal plants on perceptions can also be found when using objective air quality such as concentration of pollutants in areas around coal-burning industrial plants (Ma et al. (2017)) and this poor air quality translates into health costs such as instances of anaemia in children (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.[11]

Table I reports the results. 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_{OLS} 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.[12]

11. 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 A.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.

12. We also run a specification using Equation (6) 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.

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)).[13]

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 less educated ones, *ceteris paribus*. This significant result, along with mixed patterns on age group and income, has been documented in other studies that use different global attitudes datasets (Dechezleprêtre et al. (2022)).[14]

Taken together these results suggest that the mere existence of coal-fired power stations nearby do indeed affect perceptions of air quality negatively.

V.B Additional Findings and Robustness of Results

We first show why the geocoded data, which enables a granular analysis, is essential to our findings. We then consider whether the core results are reflected in risk assessments at the individual level. In addition, we perform placebo tests by checking whether power stations that are non-existent now have a similar effect to those that are currently operational. We also test whether the observed effects are driven by other polluting industries, such as iron and steel production. Moreover, we test the effect of wind direction, which could generate potential heterogeneity based on whether respondents are located on the upwind or downwind side of coal-fired power plants. Finally, a semi-parametric approach attesting the distance cutoff used for the main sample selection is presented.

V.B.1 Data Aggregated at Regional Level

A unique feature of the analysis is being able to use spatially granular data. To see how important this is to the findings, we will now 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 as we can now use the World Poll for all years rather than just 2019, the year for which we have geocoded

13. 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 A.2 with spatial clusters defined at 5 km distance threshold. The results are essentially identical with slightly smaller standard errors.

14. To see if there is a link between the level of emissions and air quality dissatisfaction, we estimate Equation (6) 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 A.3 in the Appendix. This highlights that objective measures of air quality might not be correlated with subjective measures.

data. However, to maintain comparability, we will use the same 51 countries as in our main analysis.

How to define exposure to coal-fired power for regionally aggregated data is less clear given that we do not know precisely where survey respondents live. We therefore experiment with different ways of defining exposure, partly as a point of comparison with the core results obtained from estimating Equation (6). The first exposure variable that we construct measures the number of operational coal-fired plants in a region in a given year divided by the total area of the region. This variable does not require us to know where survey respondents reside.

The second aggregated variable that we use is most analogous to our main variable of interest in Equation (6). It is the log 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.[15]

Results using aggregated data reported in Table II do not show any 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.[16]

This exercise underlines 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 cruder than what can be done using precise locations.

V.B.2 Risk Assessments

Using the data from the World Risk Poll, we estimate a similar specification to Equation (6) but with the left hand side variable now being subjective 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 individuals' location relative to the nearest coal power plant and their pollution risk perception when they are located within the 0-40 km distance band. Nonetheless, no such relationship exists on perception of risk towards climate change damages, thereby highlighting that people tend to respond to immediate risks (air pollution

15. For this to be an accurate exposure measure, the sample collected in 2019 needs to be similar to those in other years.

16. 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 A.5 in the Appendix. It suggests stable air quality perceptions over time across sample countries, thereby allaying concerns around using only a single cross-section for 2019 in our core results.

here) rather than perceiving that pollution will eventually lead to climate change.[17]

These findings reinforce the idea that when looking at global externalities that affect climate change, it may be important to anchor narratives and policy discussions on local manifestations of pollution. In such cases, citizens find it easier to perceive the problem and hence could be more willing to support policies aimed at reducing air pollution.

V.B.3 Placebo Tests using Planned and Retired Plants and Water Quality Perceptions

If the core results are down to proximity to coal-fired power, then we should not expect a relationship between perceptions of air quality and future *planned* coal-fired power plants in new locations i.e., plants that are not operational now, but are either announced, at a pre-permit or permit stage of commissioning as opposed to increasing capacity in an already existing operational plant. We would also not expect to find that coal-fired power plants would be associated with reduced perceptions of other environmental amenities such as water quality when we look for similar effects as found in Table I but with water quality perceptions as the outcome variable.

Formally we expect the α_{OLS} coefficient estimated in a specification like Equation (6) not to be significantly different from zero when looking at planned but as yet unbuilt power stations. This is because the respondents near to planned units have not yet experienced the air pollution externality. We should also not expect to find similar results when we re-run all the specifications for retired and mothballed[18] coal power plants.

Results for both the planned and the retired and mothballed plants are reported in Table IV, showing that the coefficients on distance are not significantly different from zero. Moreover, the effect of distance from nearest operational coal-fired power plant on water quality dissatisfaction is also insignificant, thereby confirming our placebo hypothesis.[19]

V.B.4 Robustness Check using Iron and Steel Production Units

Another concern with our core results is that proximity to coal-fired power plants is not what is important *per se* but that the associated industrial establishments that co-locate with power generation and generate air pollution are more important. A case in point would be iron and steel production plants which tend to be located near coal-fired power plants and are also a major source of local air pollution.

Since the GEM database also provides geolocations of iron and steel plants for the whole world, we use them to conduct robustness check for our core results. Specifically, we consider a sub-sample of coal-fired power plants that are separated by large distances from their nearest

17. Results for 40-80 km and 80-120 km distance band are reported in Table A.4 in the Appendix.
18. 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 mothballed units.
19. Results for 40-80 km and 80-120 km distance band are reported in Table A.5 in the Appendix.

iron and steel plants, and re-estimate Equation (6) on the sub-sample. To do this, we create three distance bins: >50 km, >150 km, and >250 km corresponding to distance between a given coal-fired power plant and the nearest iron and steel plant. Table V report the results and we make two main observations. First, the results are of the same sign and similar magnitude to those reported in Table I. Second, the magnitude is robust to the distance band chosen. These results suggest that the effects of these alternative industries, i.e., iron and steel plants, on air quality perceptions are small compared to coal-fired power plants.

V.B.5 Effect of Wind Direction

Wind is a natural medium for transportation of air pollutants across space and has been shown, in previous work, to be a source of heterogeneity when dealing with the effects of pollution (see, for example, Deryugina et al. (2019)). In the case of coal-fired power plants, the areas lying downwind from the plants will receive more pollution. Moreover, this effect is likely to be continual since wind direction at a terrestrial point remains pretty stable over time after accounting for seasonal variation and occasional climate shocks. Hence, we expect the ranking of regions on the basis of this pollution load to remain fairly constant over time.

We now 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.[20]

We then re-estimate the Equation (6) 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 shown in Column 4. Having established a weak correlation above, it is worthwhile to 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. Also, wind direction predictions at coal plant locations potentially suffer from errors 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

20. We use the monthly averaged u- and v-component of wind at 10 meter elevation from ground surface for single pressure level. 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° 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. *Source:* ERA5 Climate Data Store

propagation of forest fires).

V.B.6 A Semi-parametric Approach to Distance

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

To explore the robustness of the 40 km distance band, Figure I gives the result of estimating a semi-parametric locally smoothed polynomial to show how air quality dissatisfaction varies with distance. It shows that air quality dissatisfaction decays to a level that is basically zero at around 20 km from power plants. However, if we used this as a our core distance measure, we would have a much smaller number of survey respondents on the basis of which to estimate the effect; around 6% of the survey respondents live within 20 km of a coal-fired power plant whereas around 13% live within 40 km. So it is interesting that we do get significant results when we use the 0-40 km distance.

As a further robustness check, we run our main as well as the placebo regressions for the 0-20 km bandwidth to see whether our results continue to hold. Table A.6 reports the results and shows that 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.

V.C IV Estimates

To assess the robustness of our results, we also do an IV estimation. Here, we expect to find a larger coefficient on proximity to a coal-fired plant compared to the OLS. Specifically, we estimate the following regression for households located in distance band 0-40 km from an operational coal-fired power plant:

$$y_{i\ell} = \alpha_{IV}\widehat{\delta}_{i\ell} + \beta\mathbf{X}_{i\ell} + \eta_\ell + \varepsilon_{i\ell} \tag{7}$$

where $\mathbf{X}$ contains location and individual-level controls and $\widehat{\delta}_{i\ell}$ is predicted from the first-stage using the vector of instruments, Λ:

$$\delta_{i\ell} = \theta\Lambda_{i\ell} + \gamma\mathbf{X}_{i\ell} + \zeta_\ell + \nu_{i\ell}. \tag{8}$$

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

The results are reported in Table VII. 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 log 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_{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.[21] 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.[22] 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 A.9 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 are insignificant, meaning that distance from railroads and water-bodies do 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.[23] 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.

VI Policy Implications

The results so far have established that perceptions of air quality are indeed related to proximity to coal-fired power plants. Moreover, there are approximately 1.12 billion people living within 40 km of an operational coal-fired power plant in our sample of countries. And this number increases to 2.18 billion i.e., about one-third of the global population, if we consider the whole world.

But how our findings affect the case for closing down coal-fired power plants is not so clear. To explore this, three steps are needed. First, we need a way of constructing a hypothetical WTP measure from the survey data. Second, we need to aggregate this across the affected population. Third, we need to get a ballpark cost of replacing coal-fired power generation with a non-polluting source such as solar or wind energy. This section explores these issues to produce a quantitative measure of the benefits of closing down coal-fired power plants.

Using WTP as a way of valuing public goods has been popular in the public finance literature (Layard, Mayraz, and Nickell (2008); Kahneman and Deaton (2010)). And it has been

21. The first-stage and reduced-form results are presented in Table A.7 in the Appendix.
22. Table A.8 in the Appendix reports the results
23. See Figures A.6 and A.7 in the Appendix.

used by environmental economists to estimate the value of eliminating air pollutants, such as Nitrogen Oxides (NO_x) and Sulphur Oxides (SO_x) (Frey and Stutzer (2002); Frey, Luechinger, and Stutzer (2010); Luechinger (2009)). Data limitations mean that the scope of these studies has generally been limited to the US and parts of Europe.

To construct a WTP measure, we first show that there is a negative correlation between a standard subjective wellbeing measure from the Gallup survey data and air quality dissatisfaction. We then use the standard finding that subjective wellbeing and income are also correlated to generate a WTP measure for air quality improvements. We then use the measure to examine the aggregate air quality benefits from switching away from coal-fired power and compare this with an estimate of the cost of making the transition to clean energy.

As well as looking at this in aggregate terms, we also show more granular results at the plant level to look at the impact of different ways of scheduling the closure of coal-fired power around the world. Then, we explore the politics of air pollution by looking at country-level heterogeneity and discuss the political economy and policy priorities of air pollution. Finally, we compare the immediate air quality benefits using our measure with more long-term benefits that come from carbon reduction due to the shut down of coal-fired power plants. Unlike the air quality benefits which are local, the overall benefits are global. We end the section with some caveats around balancing energy systems through renewables and the role of technology in relaxing some of those constraints.

VI.A Approach

We start by estimating a standard equation relating life satisfaction scores in the survey data to a range of variables that are generally included in the extensive empirical literature on wellbeing. We also include the perception of air quality as a regressor. Specifically, we use OLS to estimate the following specification:[24]

$$u_{i\ell} = \gamma \log(a_{i\ell}) + \beta \log(y_{i\ell}) + \alpha_\ell + \delta \mathbf{X}_{i\ell} + \varepsilon_{i\ell} \tag{9}$$

where the dependent variable, $u_{i\ell}$, is the life satisfaction score on a 0-10 Cantril ladder for individual i in location ℓ, α_ℓ controls for region fixed effects, y stands for household income in 1000 USD, a 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 same as in our previous specifications.

We are interested in estimates of β and γ, which quantify the relationship between income and air quality dissatisfaction with life satisfaction. We estimate Equation (9) for all 51

24. 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 log 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)).

countries in our sample. The results are reported in Table VIII.[25] In order to be cautious, we consider upper and lower bound estimates, from a 95% confidence interval, rather than just point estimates.[26]

To gauge the willingness to pay, we use a standard equivalent variation measure for a reference level of air quality based on a Cobb-Douglas utility function. The equivalent variation, e, i.e., the amount needed to get to the reference air quality satisfaction level, $a_r < a$, in this case is given by

$$\gamma \log(a_r) + \beta \log(y - e) = \gamma \log(a) + \beta \log(y)$$

which implies

$$e = y\left[1 - \exp\left\{\frac{\gamma}{\beta}\log\left(\frac{a}{a_r}\right)\right\}\right] \tag{10}$$

To estimate e in Equation (10), we use the parameter estimates for $\frac{\gamma}{\beta}$ and a reference level of air quality dissatisfaction, a_r. For the former, we use the estimates that control for admin-1 fixed effects as reported in Column 2 of Table VIII.[27] And for the reference air quality level, we use 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 IX 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 VIII.

To obtain the Aggregate WTP (AWTP) measure, we multiply e by the number of affected households, based on the number of residences located within 40 km of an operational coal plant. The population figure reported in Column 7 of Table IX is the total number of people living within 40 km of coal plants in our sample. We adjust this downwards by household size in order to get to the total residences within 40 km of coal-fired plants. Finally, we multiply total residences by per capita WTP in order to get AWTP, which we report in Column 9 of Table IX.

To represent a green transition, we consider replacing coal-fired power plants with either solar or wind farms of equivalent generation capacity over a period of time. To give a ballpark estimate of the cost of this, we use the total power generation capacity of coal plants and

25. As with the OLS estimation results in Section V, there is a potential concern about selection issues and, as we argued there, this is likely to lead to a downward bias in the OLS estimates. 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)).

26. Figure A.8 in the Appendix shows 95% confidence interval bounds on β and γ estimates for each of the 51 countries in our main sample. There is 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.

27. 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 A.10. Our estimate of $\frac{\gamma}{\beta}$ in this case is -1.047 which is close to the value of -0.989 that we get from the OLS estimation. Hence, we use the OLS results in the analysis that follows.

the source-specific average global Levelized Cost of Energy (LCOE)[28] to compute the cost of supplying an equivalent amount of energy through solar and onshore wind energy generation. We assume a gradual "linear" transition process over twenty-five years where 4% of coal-fired power production is converted to solar or wind each year.

VI.B Findings

VI.B.1 Aggregate Estimates

In Figure II, we show the present-discounted benefits over time for the twenty-five year time horizon, where all the values are discounted at a constant rate of 2% per annum. We report point estimates along with a shaded area for lower and upper bound of AWTP. It is striking that even at the lower bound, and only considering air quality benefits, a green energy transition at the global scale looks worthwhile. Moreover, these results are not particularly sensitive to the exact choice of discount factor.[29]

An additional concern is that the green energy transition might create an undue fiscal burden if it is financed publicly. However, when viewed in terms of costs relative to GDP, this is probably not the case since, when we express the amounts involved as a fraction of annual household income, they are of the order of only 1% of annual household income.[30] Hence, even as a tax-financed proposition, our proposed green transition looks feasible.

VI.B.2 Plant-level Estimates

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. Our analysis allows us to look at a policy strategy of that kind by looking at the benefits of closing specific coal-fired power stations.

A useful starting point is to construct a "league table" of the most polluting power stations according to our AWTP estimates. Specifically, we rank all power stations according to the total population that is affected by poor air quality. Table X presents a list of the "top" 25 coal-fired power plants based on the affected population for our sample of 51 countries. It is notable that most of the plants on this list are in India and China, the two most populous countries in

28. 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 A.9 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.

29. We have tested the robustness of the results to using alternative values of discount rates; see Figure A.10 in the Appendix.

30. See Figure A.11 in the Appendix.

the world.[31]

Table X also presents the benefits and the costs of closing 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.

We can also look at the benefits from closing coal-fired power stations in countries that are not in our sample of 51 countries by using our estimates of $\frac{\gamma}{\beta}$ to estimate benefits for these countries. Specifically, we take operational coal power plants across the globe in 2019 outside the 51 countries in our survey sample with Table XI 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 X, 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 net benefits of air quality improvement.

VI.C Political Economy Implications

It is interesting to speculate on the implications of our findings for the political economy of climate action. In principle, we might expect that having a high AWTP for air quality improvement coupled with a high net benefit when factoring in the cost of replacing the system with renewables would create a compelling case for action to reduce coal-fired power production. Indeed, such a policy conclusion would follow from the findings above. But whether it would lead to such action depends upon the politics of the decision-making process, which depends, in part on whether citizens have the voice needed to channel their discontent and a willingness to use it in the case of coal-fired power.

Given the results that we have found, it is not clear whether citizens will actually perceive the scale of aggregate benefits even if they are personally unhappy about air quality. First, they may not be able to attribute low air quality to coal-fired power. And, at best, they would know their own level of dissatisfaction rather than the aggregate costs and benefits. One way to think of our findings is as an input to a policy process that has the potential to galvanize policy action.

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

And, as we have seen, the benefits vary not only across countries but from one power plant to another.

For political economy purposes, therefore, it is interesting to focus on two countries: China and India. As we saw above, they are home to most of the plants with large affected populations, perhaps not surprising given their population sizes. But, of course, when it comes to thinking about climate action, they have very different political institutions. We explore this by studying results where we allow the parameters relating life satisfaction to income and air quality dissatisfaction to be country-specific.[32] We then consider what this says about the prospects for policy action on coal-fired power in both countries.

In the Appendix, we calculate the aggregate benefits for each country using the same method as for our sample of 51 countries.[33] These reveal that WTP for better air quality is quite a bit lower in India compared to China, i.e., the parameters that go into the AWTP calculation are different.

Taken at face value, this would say that Indians appear less concerned, on average, about air quality than the Chinese (and the average person in our wider sample). Thus, based on this crude money metric, this would imply lower welfare gains from decommissioning coal-fired power plants in India.[34] This could explain why even if they have political voice, Indian citizens may be less inclined to put pressure on their government to do this even though, as in most democracies, Indians can organise and participate in public protests and demonstrations to shut-down coal plants and regulate associated industries, and potentially inform debates and discussions related to policy-making. That said, whether air quality is likely to be salient relative to other issues is far from clear. The classic work in political science by Crenson (1971) highlights how air quality has frequently been a non-political issue in the U.S. which at best is explained by the lack of salience amongst citizens.

In contrast, the results for China suggest a compelling case based on air quality net benefits, more similar to what we found for the world as a whole. The positive net benefits result for China is reassuring from an economic feasibility point of view, but how it could translate into policy action given the nature of the political system is less clear. It is more likely to come from the Chinese government finding the case, implicit in our findings, compelling rather than via bottom-up pressure from citizen voice.

Heterogeneity by education level is also interesting; we assume that $\frac{a}{a_r}$ is common across all education categories and set it to the global level. The differences in WTP 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., $\frac{\gamma}{\beta}$ ratio across the categories as reported

32. See Table A.12 in the Appendix.
33. See Table A.13 in the Appendix.
34. Figure A.12 in the Appendix gives the benefits and costs over time for each country. 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 A.14 in the Appendix.

in Table A.15 in the Appendix. Again, using Equation (10), we find that the WTP for better air quality among highly educated individuals is more than double that of those with only primary or intermediate-level education as reported in Table A.16 in the Appendix. Overall, it suggests that educational elites have much higher willingness to get rid of coal-fired power. This is an important finding as people who are more educated are also more likely to vote and engage in other political activities.

VI.D Further Issues

Alternative approaches to assessing the value of clean air: The implied valuations based on citizens' perceptions are complementary with public health approaches such as Lelieveld et al. (2015); Lelieveld et al. (2019). Contingent Valuation Methods are also widely used in environmental impact assessment (Arrow et al. (1993); Hanemann (1994)).[35] Our approach makes use of survey responses and avoids the criticism of such approaches that they "prime" survey respondents since the Gallup World Poll surveys do not mention coal-fired power explicitly.

To benchmark our findings against Contingent Valuation studies, we a willingness to pay value of \$0.025 per kWh of electricity used from Kim, Lee, and Yoo (2018) and find that the average willingeness to pay is about 0.358 trillion USD,[36] which, although smaller, is the same order of magnitude as our reported estimate in Table IX.

There is also a strand of literature that estimates the value of clean air using hedonic analysis (Chay and Greenstone (2005); Ito and Zhang (2020)). It would be interesting, in future, to compare this with an approach based on subjective wellbeing.

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.[37] Therefore, shutting down coal-fired power plants has an additional dividend in terms of carbon reduction benefits, which can help mitigate the climate change problem.

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)). To add such considerations, we take upper and lower bound estimates on the SCC varying from a \$20 lower bound to \$100 upper

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

36. The total operational capacity of coal-fired power plants in the 51 countries in 2019 was 1633.9 GW. We first take the product of total capacity and $10^3 \times 24 \times 365$ to get to the energy equivalent in kWh and then rescale it by 0.025 to get to the monetary equivalent.

37. 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

bound. 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.[38]

The cost of air quality deterioration, using our measure of benefits, may be lower in future if governments move coal-fired plants away from densely populated areas to please voter and there is evidence that this happening. Planned coal plants in future are, on average, located farther away from large population centers, when compared to the existing ones.[39]

Generation balance: A key challenge for future energy systems is to balance stochastic supply and demand, until better energy storage technologies exist. As highlighted above, we need to ensure that any excess demand is fulfilled both during and after the transition process. However, in light of "excess" coal power capacity in many countries, including China (Lin, Kahrl, and Liu (2018)), this transition could pay dividends in other forms also i.e., by overcoming the sunk cost fallacy around investments in coal-fired power.[40]

Employment 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 A.17 shows, it is unclear that clean energy would lead to 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)). 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. This, along with many other factors, are areas of radical uncertainty *à la* Kay and King (2020) around the consequences of making a green energy transition that may have consequences, which are impossible to foresee, let alone being quantifiable at present.

VII Conclusion

Many countries and international organizations have put phasing out of coal-fired electricity generation at the centre of their environmental strategies. But, although the climate narrative

38. We can also look at plant-level net benefits after adding the carbon reduction benefits; see Figure A.13 in the Appendix. The net benefits from closing almost every coal-fired power plant is positive.
39. On average, an existing operational coal plant affects 3,457,731 individuals, while a typical planned plant, which is non-existent in 2019, is expected to affect 1,328,480 individuals in future.
40. 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

is front and centre to this, it is important not to lose sight of the other detrimental effects of coal-fired power that are sometimes downgraded to “secondary” benefits. Chief amongst these is its impact on local air quality. There is now a fairly advanced debate about the social cost of carbon and its measurement. But there is a challenge also to value benefits of air quality improvement and to factor them into policy discussions.

This paper uses a unique source of geocoded perceptions data, which we match to the location of coal-fired power stations, including for a number of countries in the Global South. We have used these subjective perceptions of reduced air quality to create an empirical measure of the benefits of phasing out coal-fired power, and we show a statistically significant difference between the air quality dissatisfaction of those who live close to and further away from coal-fired power stations. By using data on life satisfaction, we can create a money metric or “willingness-to-pay” measure for improvements in air quality. A key finding is that these benefits alone (without factoring-in carbon benefits) can make a credible case for phasing out coal-fired power. This is important for environmental policy discourse since this brings the debate about the urgency in closing down coal-fired power more squarely into the domain of local politics. Moreover, it comes from the perceptions of the citizens themselves rather than “expert” opinion.

On top of this, the survey data show a difference between how citizens pay attention to air quality and how they perceive climate risks. In particular, citizens do not show more concern about climate risk compared to pollution risk, thereby suggesting that it is reduced air quality rather than the consequences of carbon emissions that are likely to be more salient to the extent that they can be linked to coal-fired power. In systems where politics is responsive to what citizens want, harnessing citizen discontent can be an important driver of change. But whether policy action will take place is moot; citizens may know how dissatisfied they are but be unaware of the source of their problem. By laying bare this connection, our results have the potential to contribute towards arguments for policy action in situations where citizens are empowered to demand change.

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Main Tables and Figures

Table I: **OLS 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 (6) 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 A.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 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 log distance from nearest plant, which is the straight-line distance between 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), log household income in 1000 USD, and whether the respondent has children under 15 years of age.

Table II: **OLS Results for Regional Exposure to Operational Coal Plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss
#Coal plants over total area of region	-2.337 (1.7254)	-1.870 (1.4962)		
Log avg. region-level distance from coal plant			-0.015 (0.0112)	-0.015 (0.0111)
Regional vegetation index	-0.299* (0.1247)	-0.046 (0.1219)	-0.124 (0.0752)	-0.101 (0.0770)
Area is urban	0.150*** (0.0103)	0.149*** (0.0103)	0.180*** (0.0206)	0.180*** (0.0204)
Respondent's age is 26-60 years	0.003 (0.0025)	0.003 (0.0025)	0.003 (0.0033)	0.003 (0.0034)
Respondent's age is more than 60 years	-0.033*** (0.0041)	-0.032*** (0.0040)	-0.032*** (0.0059)	-0.031*** (0.0057)
Respondent's gender is male	-0.016*** (0.0027)	-0.016*** (0.0027)	-0.018*** (0.0047)	-0.018*** (0.0046)
Respondent's education is intermediate	0.032*** (0.0040)	0.033*** (0.0041)	0.034** (0.0101)	0.036** (0.0105)
Respondent's education is high	0.072*** (0.0055)	0.074*** (0.0055)	0.076*** (0.0123)	0.079*** (0.0129)
Log annual hh income in '000 USD	-0.001 (0.0018)	-0.000 (0.0018)	0.002 (0.0043)	0.003 (0.0047)
Respondent has children under 15 yrs	-0.001 (0.0024)	-0.001 (0.0024)	-0.001 (0.0028)	-0.002 (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 (6) 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) log 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 A.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 (6). 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 A.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 do (do 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 geocode's log distance from nearest plant, which is the straight-line distance between 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 (6) 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 A.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 result 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 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 log distance from nearest plant, which is the straight-line distance between survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

Table V: **Results for Distant Coal Plants from Iron and Steel Production Units**

	(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	-0.056***	-0.055**	-0.055*	-0.046**	-0.049**	-0.044*
	(0.0144)	(0.0189)	(0.0204)	(0.0146)	(0.0185)	(0.0191)
Geocode's vegetation index	-0.083*	-0.032	-0.045	-0.055	-0.029	-0.037
	(0.0383)	(0.0401)	(0.0436)	(0.0314)	(0.0316)	(0.0328)
Geocode area is urban	0.100***	0.108***	0.111***	0.081**	0.045*	0.016
	(0.0224)	(0.0220)	(0.0283)	(0.0253)	(0.0211)	(0.0228)
Respondent's age is 26-60 years	0.016	0.009	0.002	0.014	0.011	0.004
	(0.0116)	(0.0160)	(0.0193)	(0.0117)	(0.0154)	(0.0187)
Respondent's age is more than 60 years	-0.021	-0.005	-0.003	-0.016	0.001	0.004
	(0.0193)	(0.0239)	(0.0295)	(0.0155)	(0.0199)	(0.0242)
Respondent's gender is male	-0.009	-0.028*	-0.032*	-0.010	-0.029**	-0.033**
	(0.0092)	(0.0123)	(0.0127)	(0.0078)	(0.0101)	(0.0108)
Respondent's education is intermediate	0.058***	0.052**	0.047**	0.060***	0.055***	0.053**
	(0.0126)	(0.0186)	(0.0169)	(0.0113)	(0.0142)	(0.0172)
Respondent's education is high	0.086***	0.071***	0.065**	0.084***	0.065***	0.056**
	(0.0131)	(0.0194)	(0.0206)	(0.0143)	(0.0161)	(0.0186)
Log annual hh income in '000 USD	-0.008	-0.001	0.005	-0.005	0.005	0.008
	(0.0059)	(0.0076)	(0.0103)	(0.0061)	(0.0083)	(0.0104)
Respondent has children under 15 yrs	0.003	0.012	0.009	-0.002	0.004	0.007
	(0.0102)	(0.0139)	(0.0145)	(0.0091)	(0.0124)	(0.0148)
Number of observations	12,964	7,144	5,255	12,964	7,144	5,255
Adj R-squared	0.148	0.203	0.199	0.188	0.241	0.231
Mean of dependent variable	0.314	0.327	0.357	0.314	0.327	0.357
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
Distance b/w coal and nearest steel plant	$>$ 50 km	$>$ 150 km	$>$ 250 km	$>$ 50 km	$>$ 150 km	$>$ 250 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 (6) for survey locations that are in 0-40 km distance band of an operational coal-fired power plant. The sample used in each column is further conditioned on the distance between the coal plant and the nearest operational iron and steel plant i.e., how far the coal plant is from the nearest iron and steel production plant. Results are presented for three distance bins viz. $>$ 50 km, $>$ 150 km, and $>$ 250 km i.e., for coal plants that are situated at respective distances from nearest iron and steel plants. 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. 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 log distance from nearest plant, which is the straight-line distance between survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

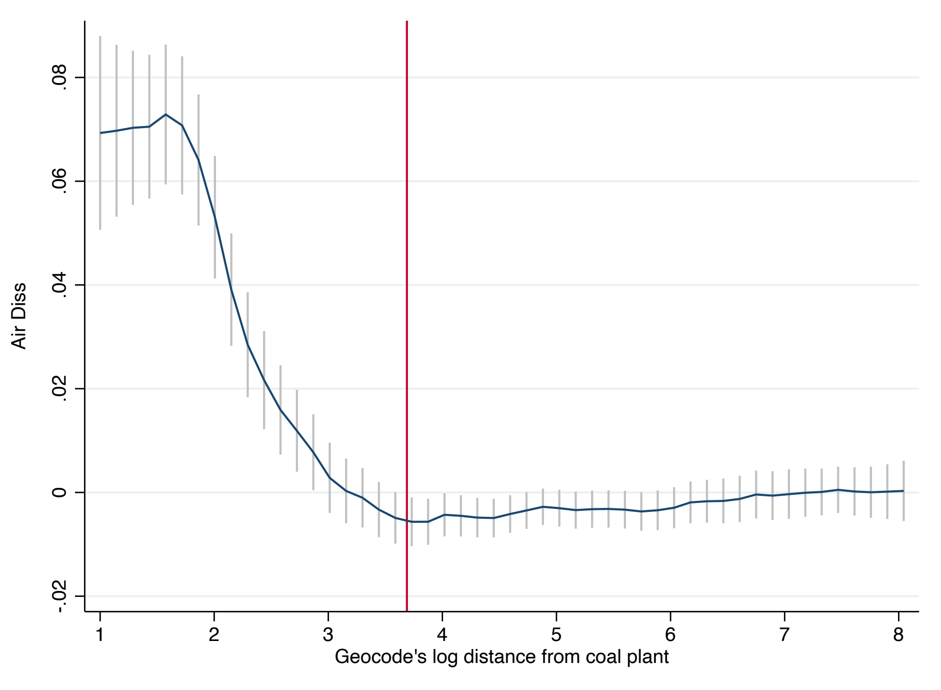
Table VI: **OLS Results for Operational Plants with Wind Direction Interaction**

	(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 (6) 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 log distance from nearest plant is a measure of straight-line distance between 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 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 Coal Plants on Air Quality Dissatisfaction**



Notes: The graph above shows local polynomial regression results with 90% confidence intervals spikes for the effect of log 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 (6) 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 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 log distance from nearest plant, is the straight-line distance between survey and nearest coal plant location.

Table VII: **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		1.553		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 (7) for operational coal-fired power plants. The two instruments used are: (i) log distance of survey locations from nearest railroad and (ii) log 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 A.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 log distance from nearest plant, which is the straight-line distance between 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 A.7 in the Appendix.

Table VIII: **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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

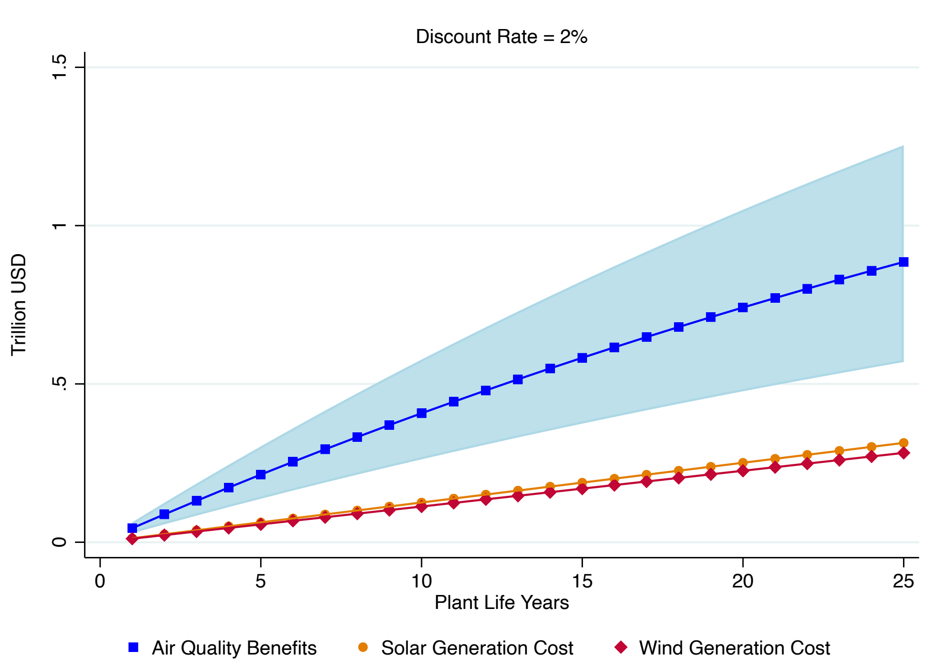
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within 40 km distance from the nearest coal power plant. Table A.1 provide the 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 log of air quality dissatisfaction and log 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 log of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table IX: **Aggregate Willingness to Pay Results**

(1) Estimate Type	(2) γ	(3) β	(4) y (in \$)	(5) a/a_r	(6) e (in \$)	(7) Affected Population	(8) HH Size (# persons)	(9) AWTP (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 γ and β parameters respectively. Estimates on log annual household income, β, log air quality dissatisfaction, γ, and average income, y, are taken from Table VIII. $\frac{a}{a_r}$ 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 (10). The population data comes from the Gridded Population of the World, v4 (GPWv4) database for year 2020. AWTP 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 Coal Power Plants**



Notes: Chart shows the cost-benefit analysis results for all 51 countries combined as listed in Table A.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 X: **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

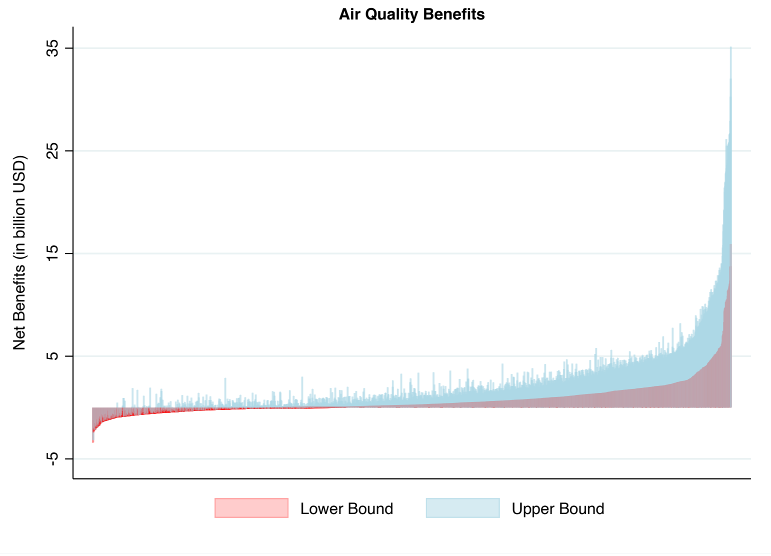
Notes: The table lists 25 coal power stations in our sample in decreasing order of total population affected, which is reported in Column 4. The population figures are the total number of individuals located within 40 km of respective plants. Solar and wind costs report the cost of green transition through 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 (10), with the total number of residences in the 0-40 km distance band. For EV calculations, global parameter values for γ, β, $\frac{a}{a_r}$, 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 XI: **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

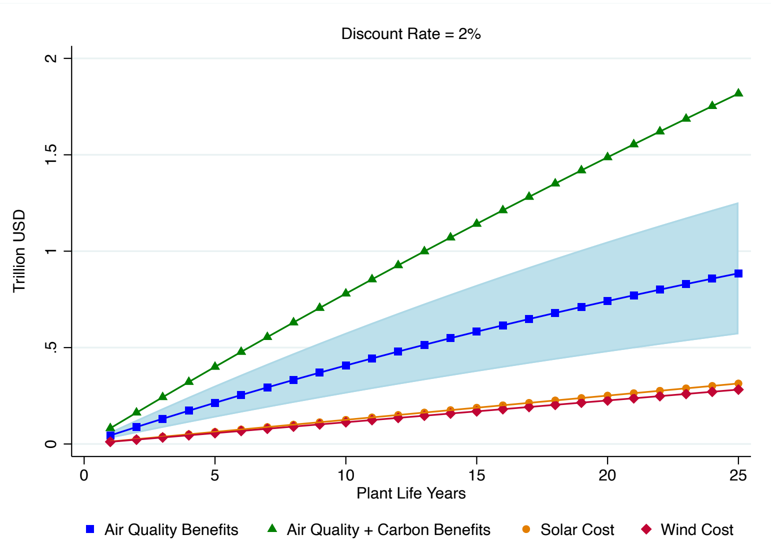
Notes: The table lists 25 coal power stations in the rest of the world i.e., countries outside our 51 country sample in the decreasing order of total population affected, which is reported in Column 4. The population figures are total number of individuals located within 40 km of respective plants. Solar 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 (10), with the total number of residences in the 0-40 km distance band. For EV calculation, global parameter values for γ, β, $\frac{a}{a_r}$, 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 Coal Power 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 γ, β, $\frac{a}{a_r}$, 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.

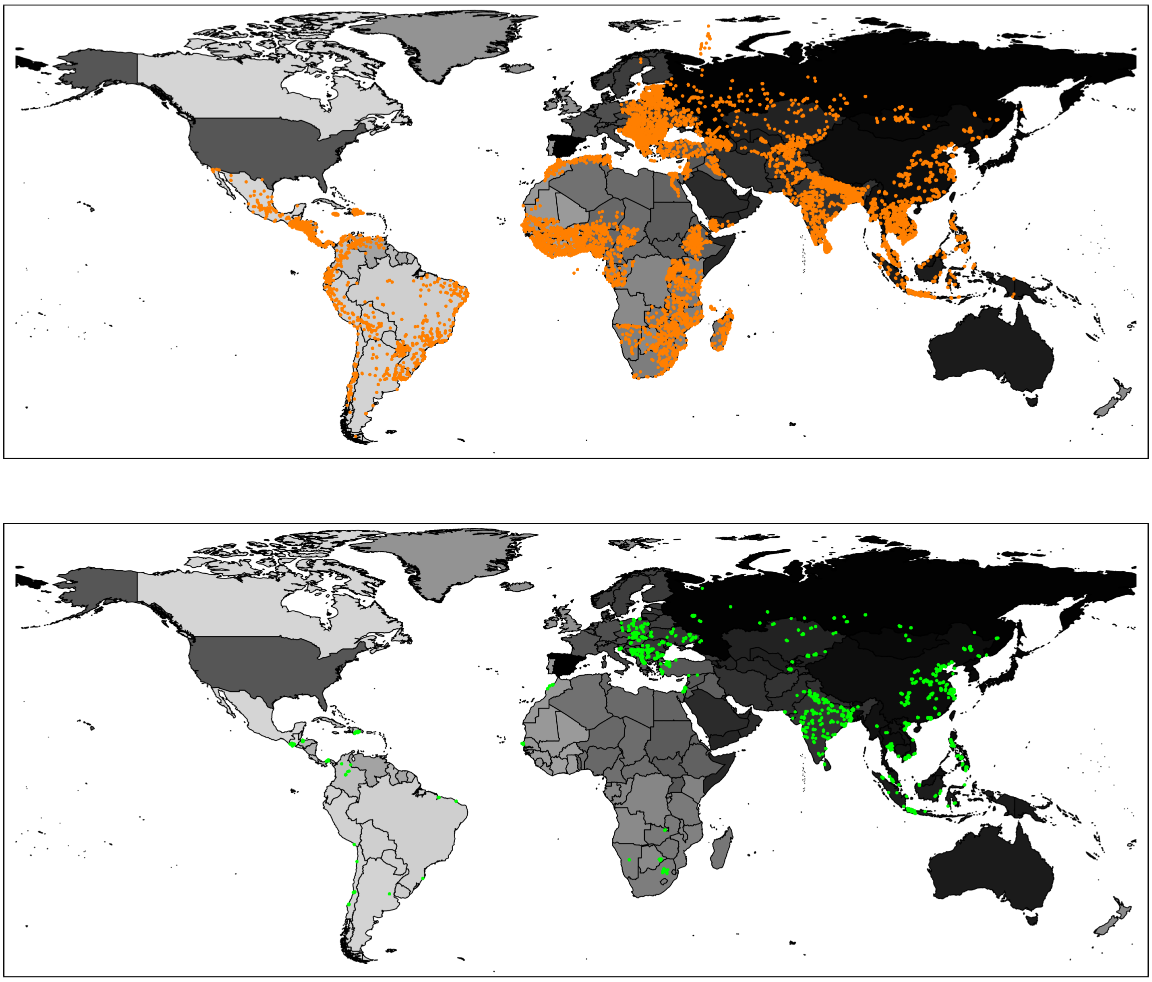
Figure IV: **Overall Aggregate Benefits and Costs of Closing Coal Power Plants**



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 Tables and Figures

Figure A.1: **2019 Gallup World Poll Survey Geocodes**



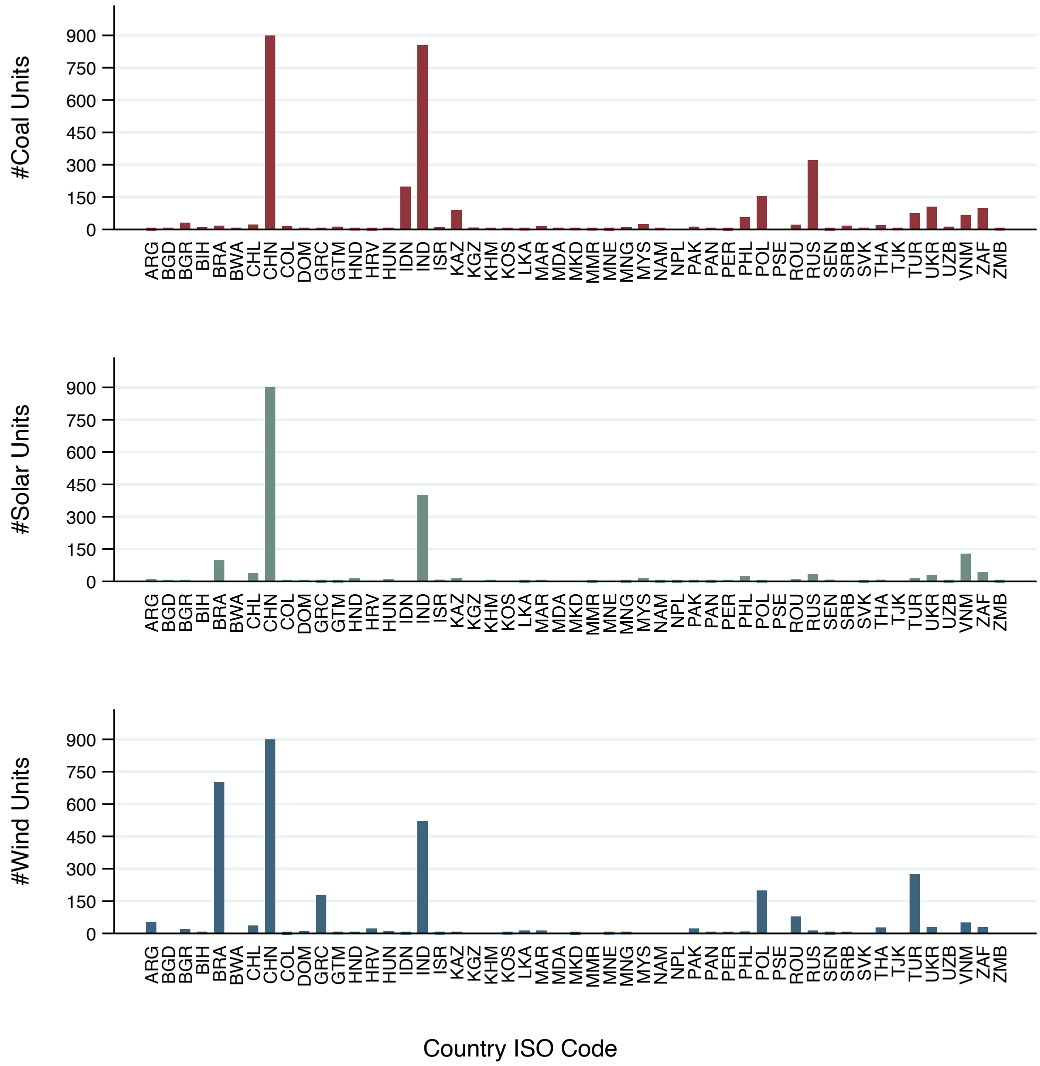
Notes: Top map shows all the surveys (in orange dots) where precise GPS coordinates were recorded in the 2019 round of the Gallup World Poll – a total of 138,242 surveys spread across 140+ countries worldwide. Bottom map shows the subset of surveys (in green dots) that are located in the 0-40 km distance 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 A.1.

Table A.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

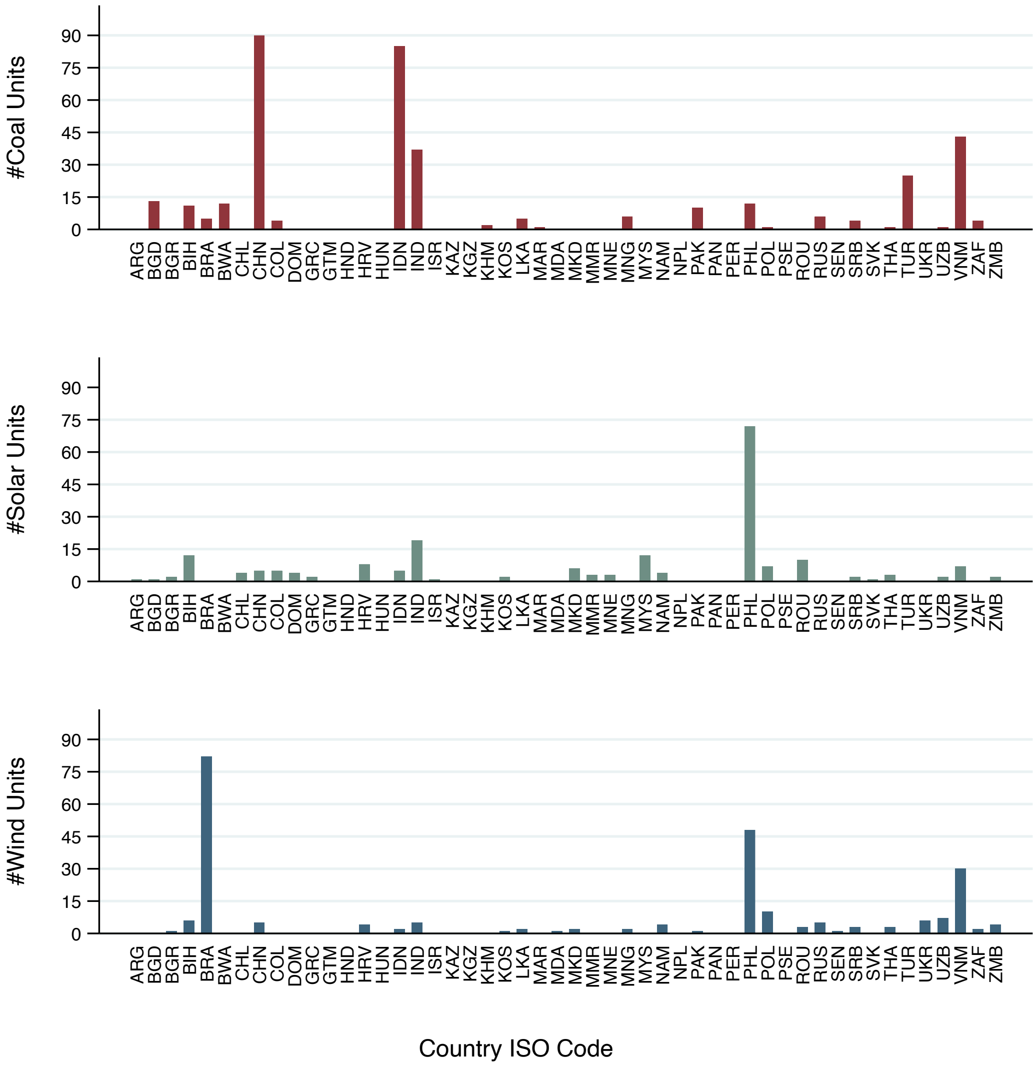
Notes: These countries contain the sample of surveys that are used in the main analysis. Some of the survey locations within these countries qualify under the distance band 0-40 km i.e., survey locations that are located within 40 km of the nearest operational coal-fired power plants. Bottom panel of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

Figure A.2: **Distribution of Operational Energy Sources in Sample Countries**



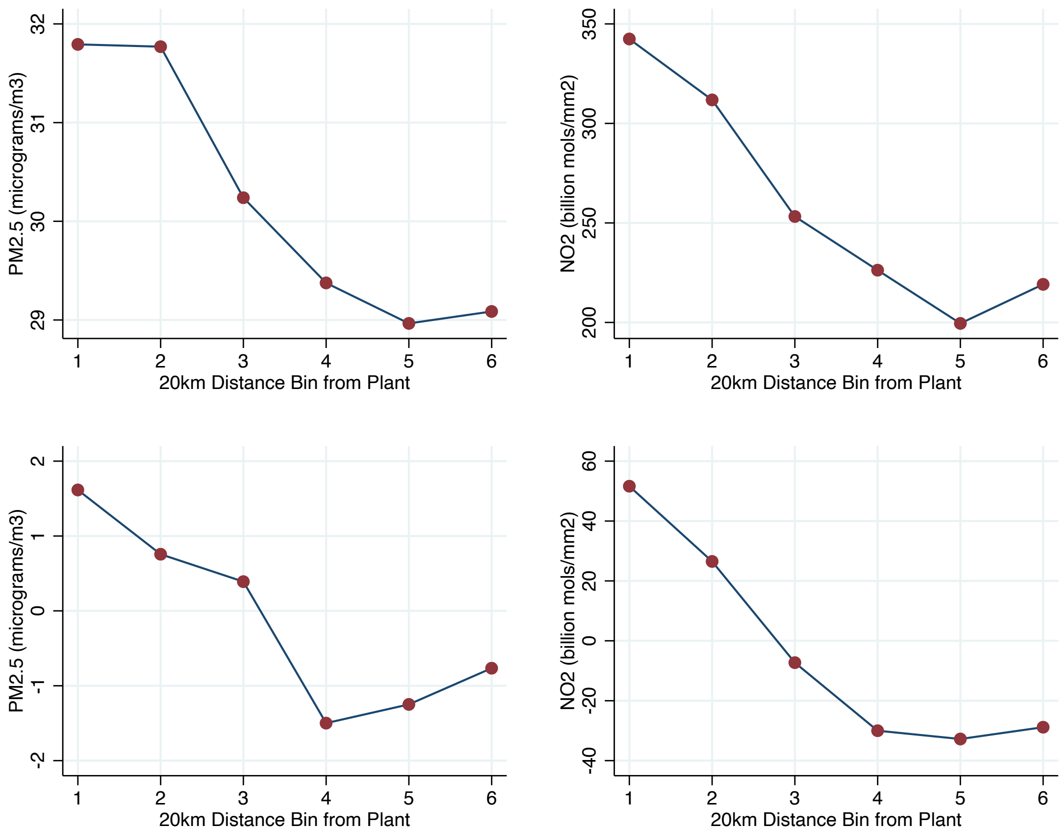
Notes: The graph shows the count of operational coal plants (top), solar farms (middle), and wind farms (bottom) for 51 countries in the main sample as listed in Table A.1. The number of units have been capped at 900 for display purpose, thereby censoring all units counts for China (CHN). The actual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

Figure A.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 A.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 A.4: **Air Pollution Level Indicators Around Operational Coal Power 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 A.2: **OLS 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
	(0.0088)	(0.0305)	(0.0581)	(0.0087)	(0.0312)	(0.0630)
Geocode's vegetation index	-0.097**	-0.097**	-0.084*	-0.063*	-0.104**	-0.139**
	(0.0301)	(0.0365)	(0.0393)	(0.0281)	(0.0337)	(0.0470)
Geocode area is urban	0.106***	0.144***	0.142***	0.089***	0.120***	0.125***
	(0.0139)	(0.0148)	(0.0181)	(0.0152)	(0.0143)	(0.0187)
Respondent's age is 26-60 years	0.020*	0.016	0.027**	0.015	0.022**	0.030***
	(0.0089)	(0.0086)	(0.0093)	(0.0088)	(0.0081)	(0.0091)
Respondent's age is more than 60 years	-0.022	0.011	0.018	-0.020	0.017	0.027*
	(0.0121)	(0.0115)	(0.0128)	(0.0117)	(0.0112)	(0.0124)
Respondent's gender is male	-0.018*	-0.020**	-0.016*	-0.015*	-0.015*	-0.012
	(0.0071)	(0.0071)	(0.0073)	(0.0068)	(0.0066)	(0.0072)
Respondent's education is intermediate	0.057***	0.039***	0.037***	0.059***	0.036***	0.035***
	(0.0093)	(0.0087)	(0.0097)	(0.0091)	(0.0083)	(0.0090)
Respondent's education is high	0.089***	0.066***	0.059***	0.089***	0.059***	0.062***
	(0.0129)	(0.0142)	(0.0153)	(0.0125)	(0.0129)	(0.0141)
Log annual hh income in '000 USD	-0.006	-0.003	-0.009	-0.004	-0.006	-0.010*
	(0.0045)	(0.0046)	(0.0047)	(0.0044)	(0.0043)	(0.0046)
Respondent has children under 15 yrs	0.004	0.000	0.010	0.001	0.001	0.008
	(0.0078)	(0.0080)	(0.0086)	(0.0075)	(0.0076)	(0.0086)
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 (6) 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 A.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 log distance from nearest plant, which is the straight-line distance between survey and nearest coal plant location. Please refer to Table I notes for details on other variables.

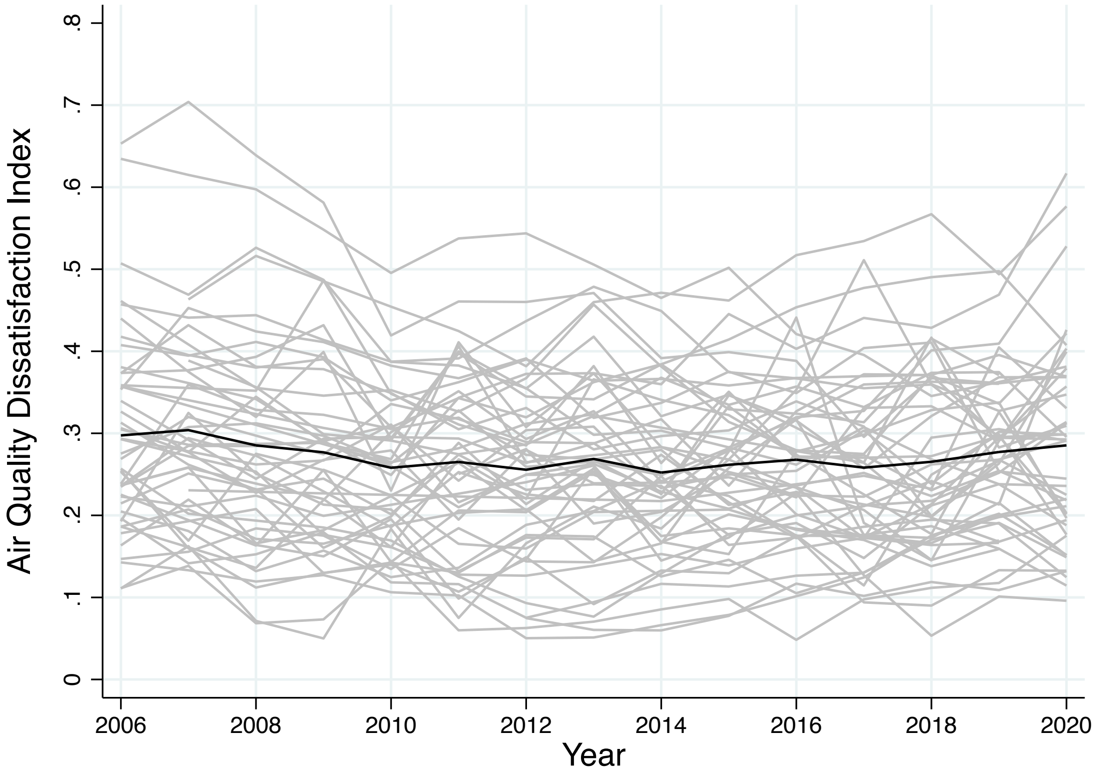
Table A.3: **OLS Results with CO_2 Interaction for Operational Plants**

	(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 (6) 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 log distance from nearest plant is a measure of straight-line distance between 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 A.5: **Air Quality Dissatisfaction Trends Across Sample Countries**



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

Table A.4: **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 (6). 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 A.5: **Placebo OLS 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 (6) 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.

Table A.6: **OLS 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 (6) 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 A.7: **First-stage and Reduced-form Results on IV Estimation**

	(1)	(2)	(3)	(4)
Air Diss				
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 plant				
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 (7). The columns correspond to Table VII, which reports IV results.

Table A.8: **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-determinded 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.

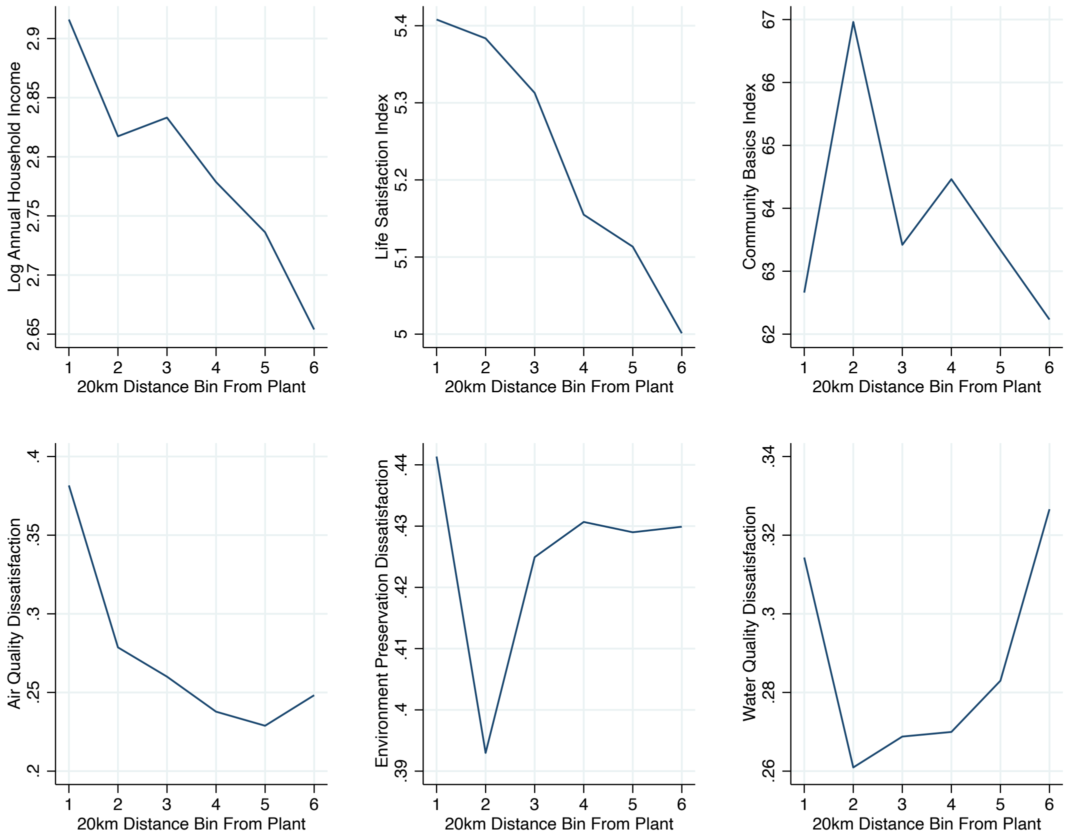
Table A.9: **First-stage and Reduced-form Results for Retired Plants**

	(1)	(2)	(3)	(4)
Air Diss				
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 plant				
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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

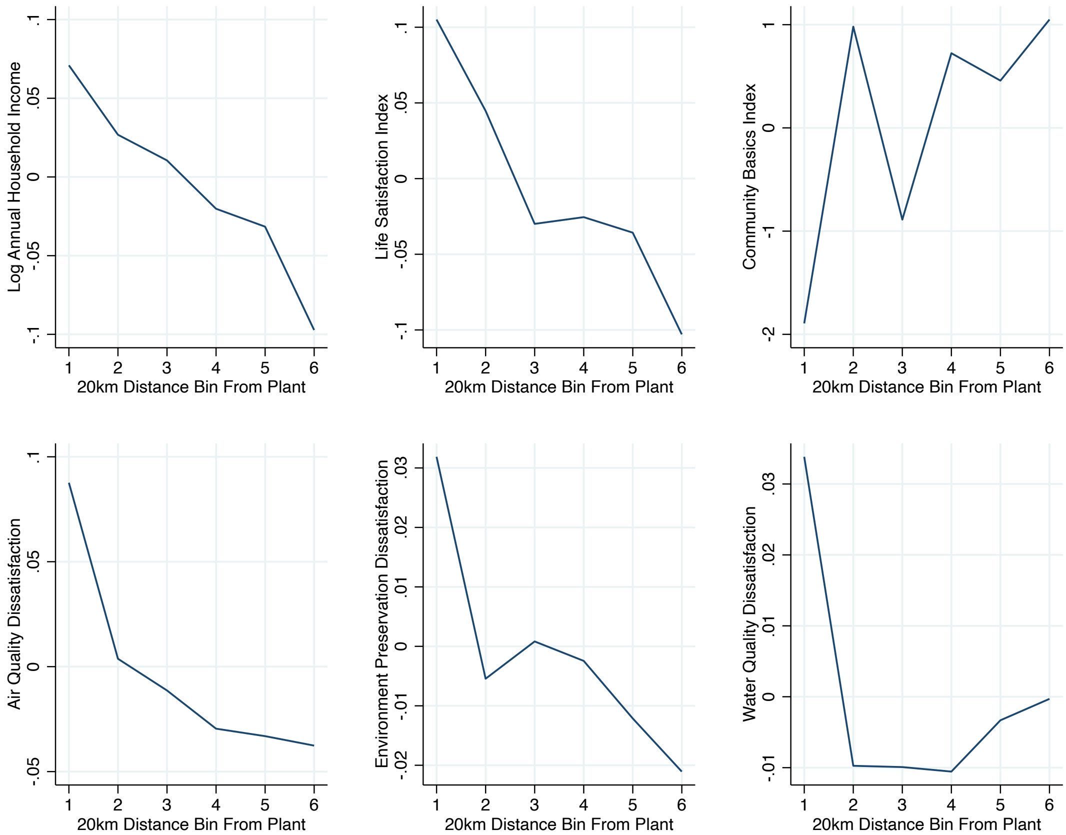
Notes: Top table reports reduced-form results and bottom reports first-stage results of IV regression using Equation (7) for retired plants. The columns correspond to Table VII.

Figure A.6: **Descriptive Plots - I**



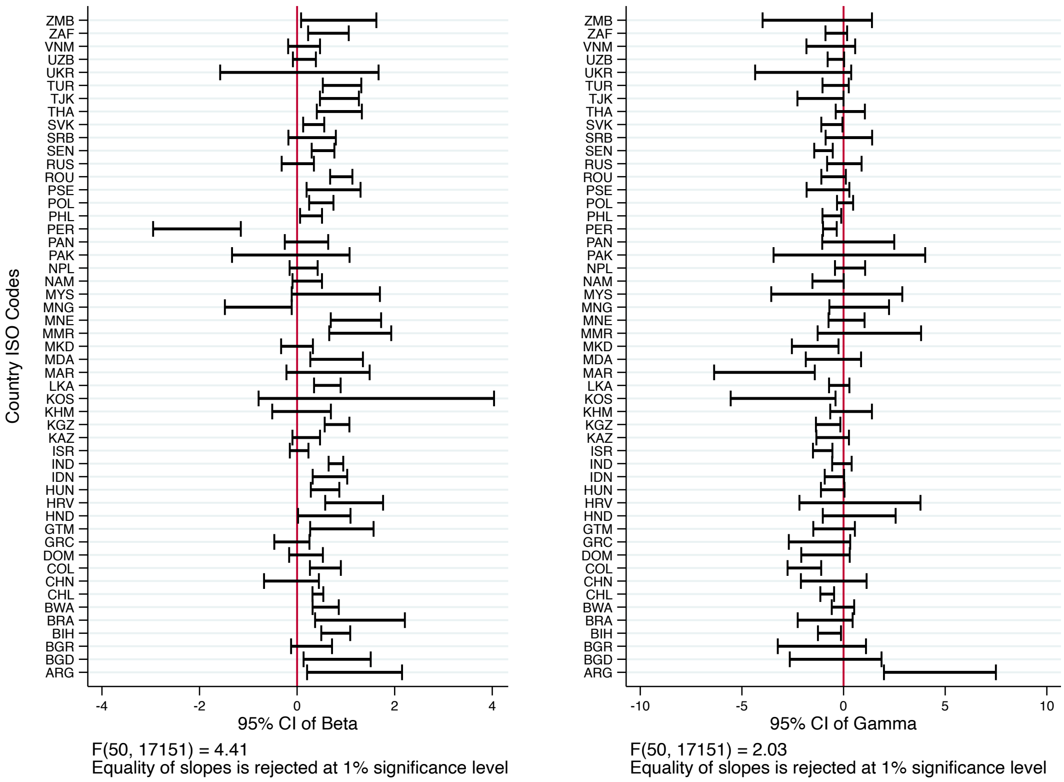
Notes: All the variables are taken from the 2019 Gallup World Poll. The label on x-axis should be multiplied by 20 to get the distance bin of the survey location from the nearest coal plant.

Figure A.7: **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.

Figure A.8: **Estimates of Beta and Gamma Parameters for Sample Countries**



Notes: The chart shows 95% confidence interval for β and γ estimates for each of the 51 countries in the main sample by running a pooled regression with country interactions corresponding to Equation (9). Equality of slopes across countries for both β and γ is rejected at 1% significance level, thereby highlighting the heterogeneous effect of both air quality satisfaction and income on overall life satisfaction across countries.

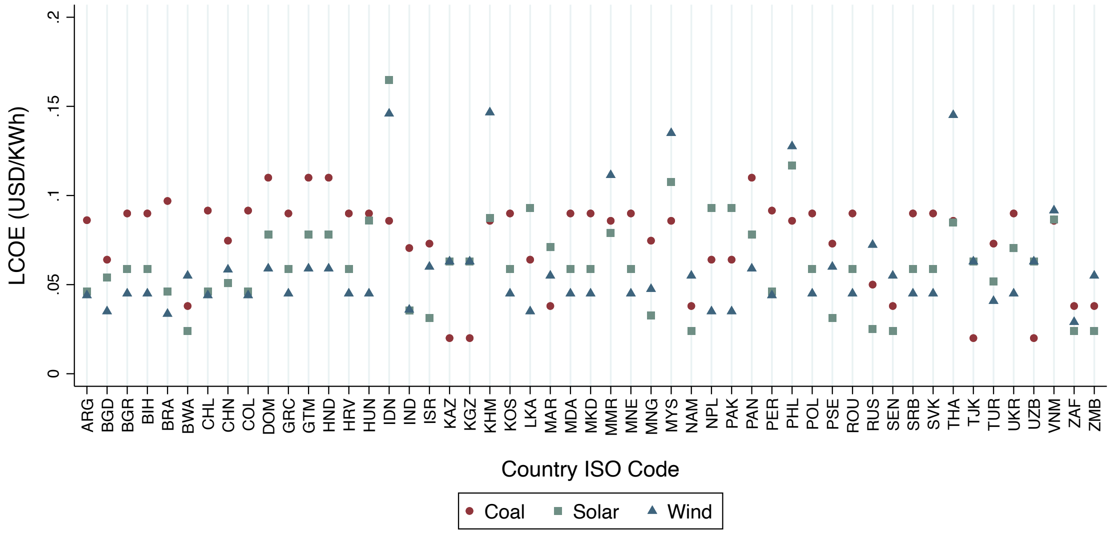
Table A.10: **Ordered Logit Estimation Results for Life Satisfaction Regression**

	(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	17,701
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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

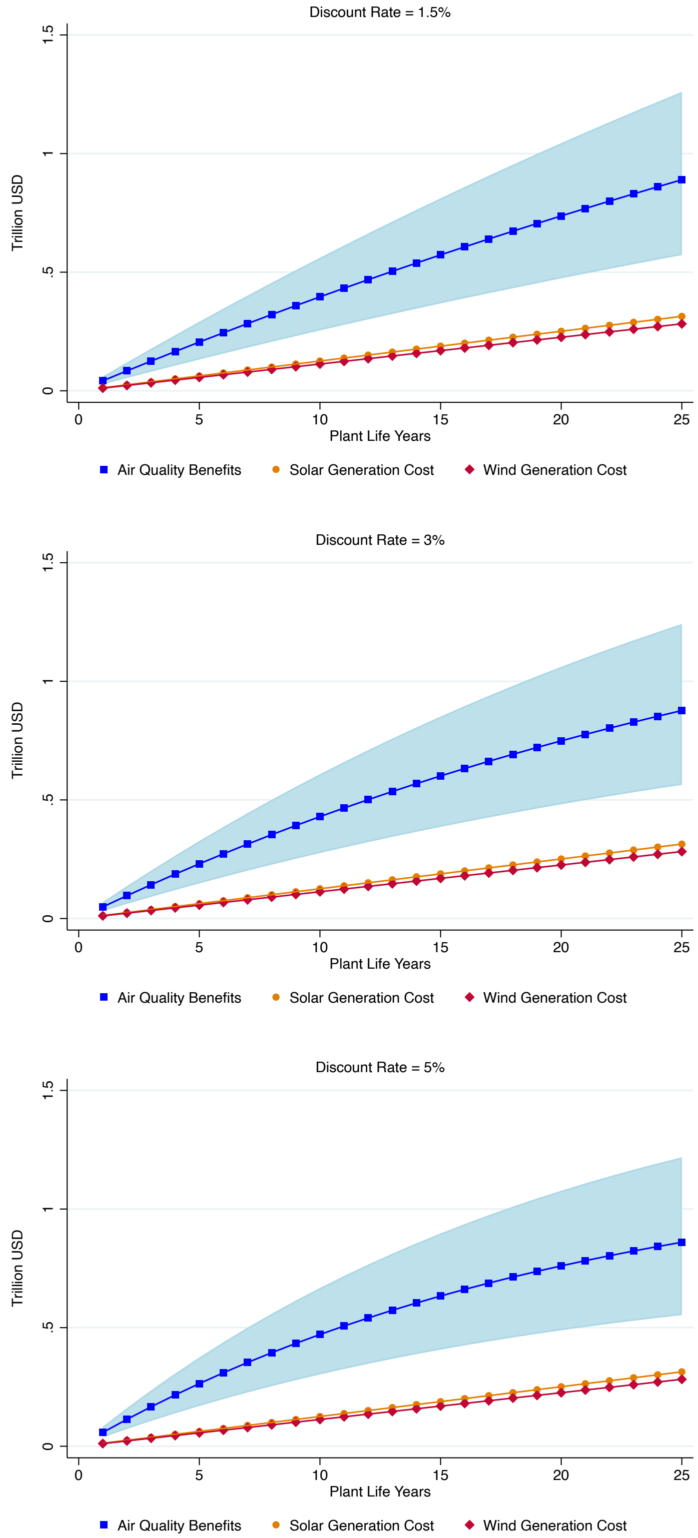
Notes: The table above reports results for ordered logit estimation with fixed effects corresponding to OLS estimation results reported in Table VIII. We implement a robust estimation for fixed effects ordered logit models using the estimator proposed by Baetschmann et al. (2020).

Figure A.9: **Unit Cost of Energy for Different Generation Technologies**



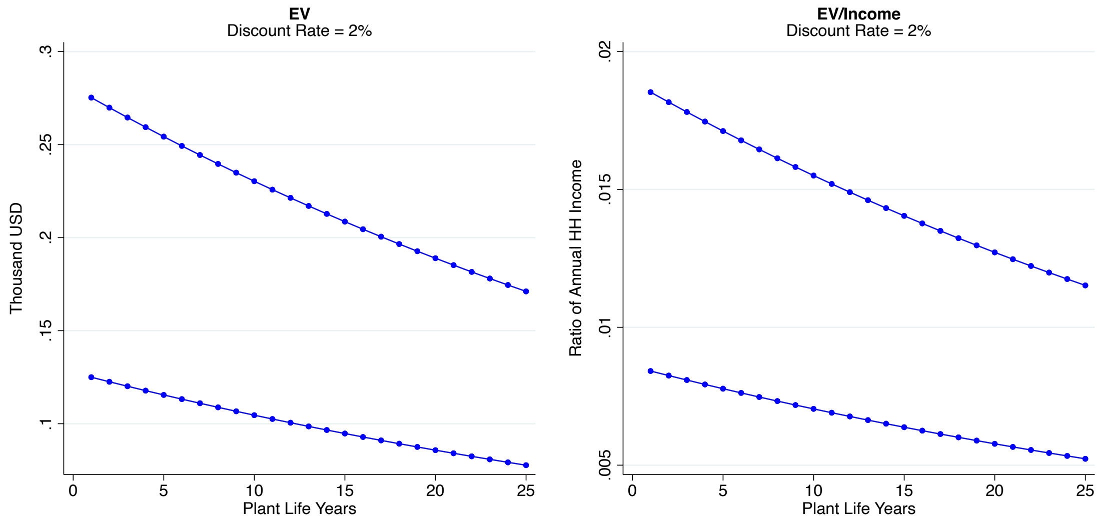
Notes: The graph shows LCOE values for all 51 countries in the main sample as listed in Table A.1. LCOE measures lifetime costs divided by energy production. It accounts for present value of the total cost of building and operating a power plant over an assumed lifetime. This measure allows comparison 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 A.10: **Cost-Benefit Analysis for Alternative Discount Rates**



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

Figure A.11: **EV and EV/Income During 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 A.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 (10), with the total number of residences in 0-40 km distance band. For EV calculations, global parameter values for γ, β, $\frac{a}{a_r}$, 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 A.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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

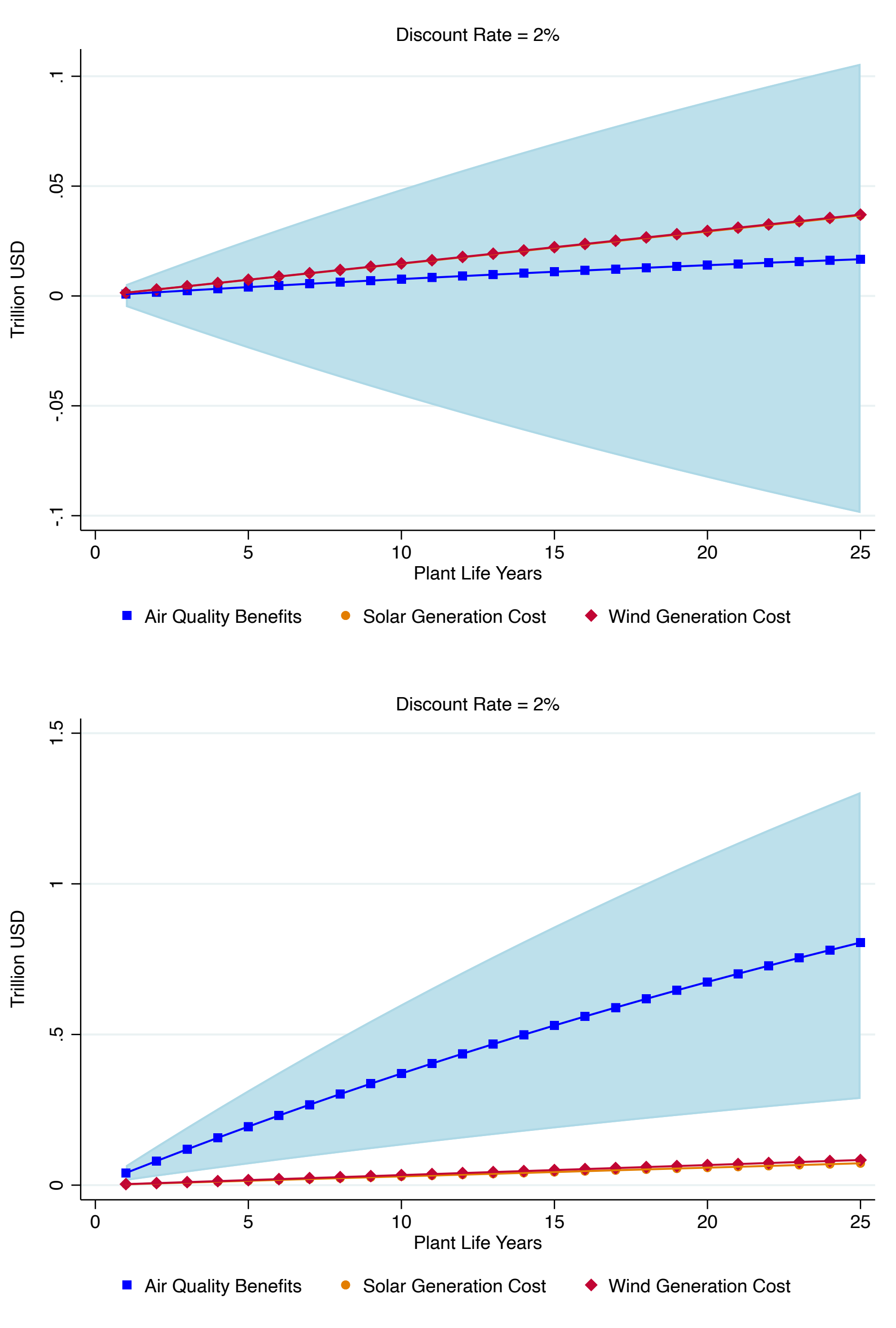
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants in India and China. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. 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 log of air quality dissatisfaction and log 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 log of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table A.13: **Aggregate Willingness to Pay Results for India and China**

(1) Geographical Category	(2) γ	(3) β	(4) y (in \$)	(5) a/a_r	(6) e (in \$)	(7) Affected Population	(8) HH Size (# persons)	(9) AWTP (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 γ and β parameters respectively. Estimates on log annual household income, β, log air quality dissatisfaction, γ, and average income, y, are taken from Columns 3 and 4 of Table A.12 for respective countries. $\frac{a}{a_r}$ 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 (10). 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. AWTP 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 A.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 A.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 γ and β for all categories.

Table A.15: **Life Satisfaction Regression Results for Different 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

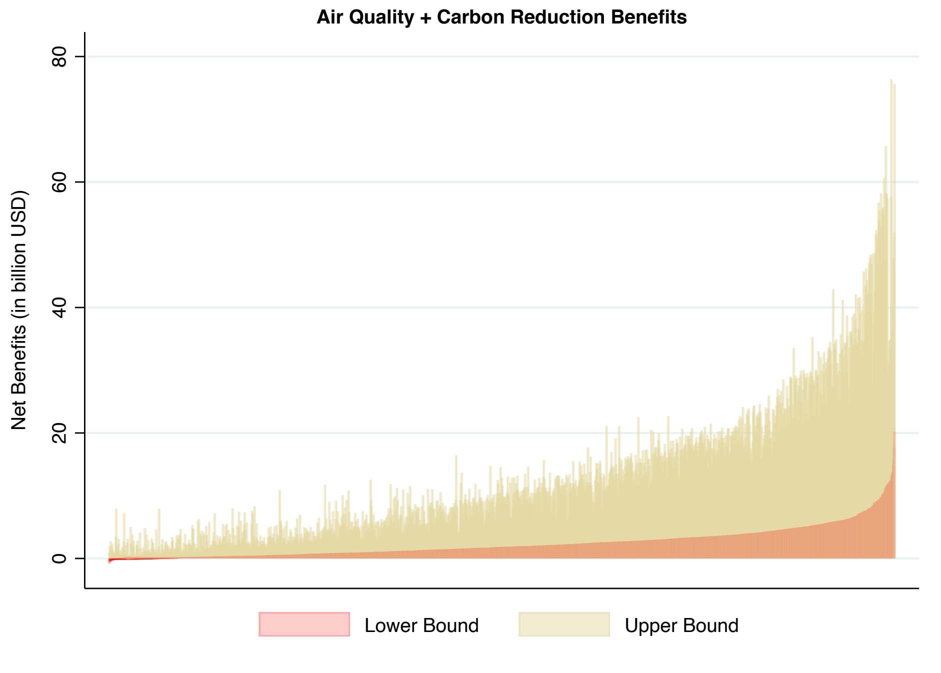
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants for each education group separately. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. Table A.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 log of air quality dissatisfaction and log 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 log of household reported total annual income in 1000 USD. Please refer to Table I notes for details on other variables.

Table A.16: **Willingness to Pay Results for Different Education Groups**

(1) Education Category	(2) γ	(3) β	(4) y (in $)	(5) a/a_r	(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: $\underline{\gamma}$ and $\underline{\beta}$					
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: $\overline{\gamma}$ and $\overline{\beta}$					
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 γ and β parameters respectively. Estimates on log annual household income, β, log air quality dissatisfaction, γ, and average income, y, are taken from Columns 4, 5, and 6 of Table A.15 for respective education categories. $\frac{a}{a_r}$ is the ratio of air quality dissatisfaction level in the 0-40 km distance band and that outside of the band for global. e is the equivalent variation computed using Equation (10).

Figure A.13: **Plant-level Net Overall Benefits from Closing Coal Power 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 γ, β, $\frac{a}{a_r}$, 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 A.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 coal sector for 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.

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