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GLOBAL GAINS FROM A GREEN ENERGY TRANSITION: EVIDENCE ON COAL-FIRED POWER AND AIR QUALITY DISSATISFACTION

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Abstract

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JEL Classification: N/A

Keywords: N/A

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

Timothy Besley† Azhar Hussain‡

March 20, 2023

Abstract

Phasing out coal-fired power in favor of renewables is now a central plank of climate action. But, in contrast to many other policy actions, coal-fired power should have an immediate and perceptible benefit through improved air quality. If this is true, there is potential to harness local politics in combating a global problem. However, this line of argument is only valid if coal-fired power does indeed lead to greater air quality dissatisfaction. This paper provides such evidence using geocoded survey data from 51 countries by demonstrating that people living within 40 km of coal-fired power stations are, on average, more dissatisfied with the ambient air quality. We then construct a willingness-to-pay measure to show that there are net benefits from replacing coal-fired power generation capacity with green technologies globally, solely based on air quality improvements.

JEL codes: I31, Q42, Q53, Q58

Keywords: Coal-fired power plants, air quality, clean energy transition, renewable energy, climate action, life satisfaction

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1 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 to 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 large impact on public health (see, for example, Lelieveld et al. (2020)). The problem gets worse when plants tend to be 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 is not necessarily going to lead to more public action unless the issue becomes politically salient. Even in settings with vibrant local political democratic processes, this is a challenge 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 destruction impact of more frequent and more 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 can provide an input into the policy process and potentially be a catalyst for change.

This paper provides new evidence on the link between air quality perception and coal-fired power using geocoded data from 51 countries, which are covered in the Gallup World Poll. The data gives precise locations where interviews were conducted so we can tag survey locations 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 to coal-fired power cannot be ex-

1. There are at least 10 thermal power plants in Punjab, Haryana, and Uttar Pradesh that are located in vicinity of Delhi, which is the most densely populated city of India. *Source:* Economic Times - Energy News, 4 June, 2021.

plained by a priming effect since respondents were not asked about coal-fired power before 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 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 conduct a "thought experiment" at the power plant-level to find that there is a case for closing the largest 25 coal-fired power stations in our sample of countries, even without looking at the carbon reduction benefits. The benefits are large enough to justify those investments. We also use our estimates "out of sample", i.e. for countries that are not in our survey data. We project the valuations of air quality from our sample countries into these countries and find a similarly strong case for closing coal-fired power stations elsewhere based on just 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 have both immediate local benefits, such as lower infant mortality, better test scores, and higher crop productivity, along with meeting long-term sustainable climate goals (Wen and Burke (2022); Burney et al. (2022)). 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 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 contribution of the paper to existing work and discuss background issues. In Section 3, we discuss the data that we use. Section 4 discusses how we establish the link between proximity to a coal-fired station and perceptions of air quality. In Section 5, we present our core results. The policy implications of our findings are laid out in Section 6, where we also discuss adding in carbon benefits and a few caveats to our core thought experiment. Section 7 has some concluding comments.

2 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); Capstick et al. (2015); Egan and Mullin (2017); Poortinga et al. (2019)). Some of these studies have established correlations using variations in existing datasets at state or 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); Diekmann and Preisendörfer (2003)).

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 damage due to global warming is 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

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)).

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 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, R&D investments in energy storage technologies promise finding a way of balancing out supply and demand [3], the transition looks technologically feasible in 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, advancement in energy storage technology, which is not limited to batteries[4], holds the key to making 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.[5]

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

3 Data

We use data from a variety of sources, including individual-level primary surveys, satellite observations, and reanalysis products that are developed and validated through ground-based observations. Below, we discuss the main datasets, which we have used, in detail.

3.1 Geocoded Gallup World Poll Data

The outcomes data comes from the Gallup World Poll, an annual, nationally-representative survey of citizens which began data collection in 2006 and covers around 99% of world's adult population living in more than 160 countries. We only use the 2019 data where 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 1. 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 1 and mapped in the bottom panel of Figure 1. The main outcome variable is a binary indicator of the survey respondent's dissatisfaction with ambient air quality. The exact question (translated into English) is: *"In the city or area where you live, are you satisfied or dissatisfied with the quality of air?"*

We also use survey responses to a question on current life satisfaction as a proxy for overall wellbeing. It asks respondents to rate their present life on an eleven-point scale from 0 ("the worst possible life") to 10 ("the best possible life"). This measure of life satisfaction is popular among researchers and has been used extensively to make cross-country comparisons of wellbeing, particularly for less-developed countries (Deaton (2008); Kahneman and Deaton (2010)). Apart from these two "outcome" variables, we also use controls for education, age, income, gender, and whether or not they have children under 15 years of age (also from the Gallup World Poll). We also make use of a different, but related, attitudinal survey based on a subset of countries included in the Gallup World Poll: the Lloyd's Register Foundation World Risk Poll.[6] Here also, we restrict the sample to 51 countries from the main analysis.

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))

3.2 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.[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 generation, 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. Figures 6 and 7 in the Appendix section show the distribution of operational and planned units respectively for coal, solar, and wind energy generation across 51 countries that constitute the main analysis sample.

3.3 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 railways network shapefile is the World Food Program-Logistics Cluster[8], which brings together various sources such as OpenStreetMap, American Digital Cartography, Global Discovery, etc. To get the location of water-bodies, we combine data from multiple sources[9] to create an "amalgam" water-bodies shapefile. We also use remote-sensing data on a vegetation index from the NASA Earth Observations project to control for green cover of each survey location and a 1 km$\times$1 km grid population count from the Grid-level Population of the World v4 (GPWv4) database for year 2020 to compute population.

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.

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.

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 detailed in the Appendix.

4 Empirical Approach

Our empirical analysis estimates the elasticity of air quality dissatisfaction with respect to the distance of survey locations from the nearest operating coal-fired power plants.

4.1 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, τ_i represents unobserved idiosyncratic distaste for air pollution.

If coal plants were randomly assigned to different locations, or equivalently, if individuals are randomly assigned to 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 compared to the general population.

More formally, note that

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

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 below, 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.

4.2 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 navigable water, such as a river or the 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 have an impact 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 implausible to think that there is a direct effect of railway locations on air quality.[10]

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

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

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

where z are things 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 $\hat{\delta}_{i\ell}$, as in the first-stage prediction of δ, under the 2SLS routine. Then

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

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

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

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.

5 Air Quality Dissatisfaction

In this section, we establish the relationship between ambient air quality dissatisfaction at individual level and their geographical proximity to a coal-fired power plant.

5.1 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. A number of case studies in different geographies have tried to define the domain of detrimental effects of coal-fired power stations on air quality (Iordanidis et al. (2008); Kravchenko and Lyerly (2018)). These studies suggest that most-affected residences tend to be located within 30 km radius of a coal power station. Previous research on perceptions also 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 respiratory ailments (Barrows, Garg, and Jha (2019)). We therefore present our main findings for three distance bands: 0-40 km, 40-80 km, and 80-120 km, measured as the distance between survey location and nearest coal-fired power plant.

Table 2 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.[11]

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)).

Table 2 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 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)).

To see if there is a link between level of emissions and air quality dissatisfaction, we run the above specifications for distance band 0-40 km and include either discrete (high/low) or a continuous interaction of the nearest plant-level annual CO_2 emissions (in million tonnes) with the distance regressor. We find that the interaction term is not statistically significant

11. We 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.

in any of the cases, as reported in Table 3. This highlights that objective measures of air quality (total annual CO_2 emissions in this case) might not be correlated with subjective measures – something we discussed early on in the paper and has also been documented in other studies (Crenson (1971)).

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

5.2 Additional Findings and Robustness of Results

We first show why geocoded data, which enables a granular analysis, is essential to our findings. We also consider whether the core results are also reflected in risk assessments. In addition, we perform a placebo test by testing whether power stations that are non-existent now have a similar effect to those that are currently operational.

5.2.1 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 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 nearest operational coal-fired power plant at the region level for survey locations that are within 40 km of the plant in 2019.[12]

Results using aggregated data reported in Table 4 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 in the main results reported in Table 2, is of same order of magnitude.[13]

This exercise underlines the usefulness of using geocoded 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 that what we were able to do by knowing precisely where the surveys are conducted. This lesson on the value of granular data does therefore give an important pointer for future research in terms of the need to have geographically granular data.

5.2.2 Risk Assessments

Using the data from the World Risk Poll, we implement a specification similar to Equation (6) but with the left hand side variable being risk assessments on pollution and climate. Table 5 reports the results.

For both of the risk assessment variables 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 here) rather than perceiving that pollution will eventually lead to climate change.[14]

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

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

13. The results in Table 4 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 8 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.

14. Results for 40-80 km and 80-120 km distance band are reported in Table 12 in the Appendix.

manifestations of pollution. In such cases, citizens find it easier to perceive the problem and hence more willing to support policies aimed at reducing air pollution.

5.2.3 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 2 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[15] coal power plants.

Results for both the planned and the retired and mothballed plants are reported in Table 6, 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.[16]

5.2.4 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 showed 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 2 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

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

16. Results for 40-80 km and 80-120 km distance band are reported in Table 13 in the Appendix.

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. Nonetheless, 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 14 reports the results and shows that the main and placebo results continue to hold even though we lose some statistical significance on the main results due to lower statistical power.

5.3 IV Estimates

To assess the robustness of our results, we also do an IV estimation. Here we also expect 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 7. 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.[17] As a robustness test on the railroad instrument, we also check whether it predicts pre-determined variables such as, gender and age, thereby violating exclusion restriction.[18] 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 17 in Appendix. As expected, the first-stage results are significant i.e., railroads and water-bodies predict retired coal plants locations, but reduced-form is 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 also highlights the importance of selection-bias introduced due to citizens, who value air quality, choosing to locate further away from coal plants, even though these areas are likely to be richer neighbourhoods with higher overall life satisfaction.[19] This is plausible since, once a government sets up a coal plant in an area, this may bring other economic and cultural activities into the area.

6 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

17. The first-stage and reduced-form results are presented in Table 15 in the Appendix.
18. Table 16 in the Appendix reports the results
19. See Figures 9 and 10 in the Appendix.

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 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.[20]

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.

6.1 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

20. Even though remote-sensing data on some pollutants are now available worldwide at a fine spatial scale, they are not suitable for a granular analysis, such as ours. There has been some recent advancements in getting accurate measurements on local air pollution through remote-sensing methods, but the estimates are not widely available for the whole world, and some of them are not validated against ground-based reference data (Nassar et al. (2022)).

on wellbeing. We also include the perception of air quality as a regressor. Specifically, we use OLS to estimate the following specification:[21]

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

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 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 countries in our sample. The results are reported in Table 8.[22] In order to be cautious, we consider upper and lower bound estimates, from a 95% confidence interval, rather than just point estimates.[23]

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

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

21. There is no consensus in the literature on the exact econometric equation that should be used here, but the majority of previous work in this vein has used a specification similar to ours. The coefficient on 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)).

22. As with the OLS estimation results in Section 5, there is a potential concern about selection issues 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)).

23. Figure 11 in 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.

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 8.[24] 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 9 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 8.

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 9 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 9.

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 the source-specific average global Levelized Cost of Energy (LCOE)[25] 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.

24. 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 18. 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.

25. 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 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 12 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.

6.2 Findings

Using the above methodology, we compute aggregate and plant-level estimates of net air quality benefits that come from clean energy transition based on our thought experiment.

6.2.1 Aggregate Estimates

In Figure 3, we present 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.[26]

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 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.[27] Hence, even as tax-financed proposition, our proposed green transition looks feasible.

6.2.2 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 10 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

26. We have tested the robustness of the results to using alternative values of discount rates; see Figure 13 in the Appendix.
27. See Figure 14 in the Appendix.

most populous countries in the world.[28]

Table 10 gives the benefits and cost of closing each power station while replacing it 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 11 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 10, 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.

As a final step, Figure 4 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 for air quality improvement.

6.3 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

28. Table 19 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.

processes, which depends, in part 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 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. 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.[29] 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.[30] 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.[31] 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

29. See Table 20 in the Appendix.
30. See Table 21 in the Appendix.
31. Figure 15 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 22 in the Appendix.

inform debates and discussions related to policy-making. [32] 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 among most 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 in Table 23 in 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 24 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.

6.4 Alternative Approaches to Assessing the Value of Clean Air

The implied valuations based on our approach are *citizen-centric* and exploit the fact that citizens' perceptions are likely to be important in their roles as voters or activists. This is complementary to approaches that look at the value of clean air through the lens of public health benefits such as reduced disease burden, higher excess mortality, or reduced life expectancy. How far they are perceived directly by citizens is unclear. Public health-based approaches are often based on sophisticated models, such as Global Atmospheric Chemistry and Global Exposure Mortality models (Lelieveld et al. (2015); Lelieveld et al.

32. For example, Srivastav and Singh (2022) argue for constitutional amendments on land acquisition laws for businesses and firms in India.

(2020)). The resulting benefit estimates suggest that ambient air pollution-related death numbers are as high as 10 million per year. We are not aware of studies that have tried to link these estimates to citizens' perceptions of air quality and detrimental impacts. It would be interesting to know how far priming citizens with information about public health costs of air pollution changes their perceptions of air quality and/or encourages greater citizen engagement in the political process.

Priming is, of course, a key feature of Contingent Valuation Methods (CVM), which are also widely used in cost-benefit analysis and environmental impact assessment (Ciriacy-Wantrup (1947); Arrow et al. (1993); Hanemann (1994)). In particular, the case for shutting down coal-based power generation has been strengthened by a number of CVM studies for both developed and developing countries (Chikkatur, Chaudhary, and Sagar (2011); Wang and Mullahy (2006)). Nonetheless, research using CVM are often criticized precisely because they prompt citizens to think about issues differently than they might in their everyday lives. So, it is important to be aware of concerns around interview-bias along with other sources of biases due to non-response and other factors (Kahneman and Knetsch (1992)). Although, our approach makes use of survey responses, there is no priming towards thinking about proximity to coal-fired power plants, so the link that we have found between perceptions of air quality are not due to having subjects worry directly about coal-fired power. Therefore, we are uncovering a "latent" valuation for closing down coal-fired power stations that citizens themselves may not be aware of.

To check how our estimate of aggregate benefits derived from shutting down coal-fired power plants compare to those in the CVM literature, we make use of WTP value of \$0.025 per kWh of electricity used from Kim, Lee, and Yoo (2018) and recalculate AWTP using aggregate installed capacity of coal plants across 51 countries in our sample. We find that the new value of AWTP obtained using alternative WTP estimates comes out to be 0.358 trillion USD,[33] which is smaller but reassuringly of the same order of magnitude as AWTP reported in Table 9. Also, the difference in magnitude is expected because what we are recovering in this paper is just the WTP to shut down coal plants, while Kim, Lee, and Yoo (2018) estimate the WTP of transition from coal to natural gas, which, though far less

33. 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.

polluting, do contribute towards air pollution.

There is also a strand of literature that estimates the value of clean air using hedonic analysis on house prices (Chay and Greenstone (2003); Chay and Greenstone (2005)). We view our work as complementary with such approaches. It would be interesting, in future, to find contexts where the findings from this approach and ones based on subjective wellbeing data could also be compared. For example, to use WTP estimates from Ito and Zhang (2020), we would need reliable granular data on PM_{10} emissions for all the 51 countries in our sample.

6.5 Further Issues

Our results suggest positive net benefits of a switch towards green energy. Nevertheless, there are a few issues at hand that warrant some discussion to render more credibility to the conclusions reached in this section.

6.5.1 Benefits from Carbon Reduction

So far, we have not allowed carbon benefits from decommissioning coal-fired power to be considered as part of the benefits. And yet, 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.[34] Therefore, shutting down coal-fired power plants has an additional dividend in terms of carbon reduction benefits, which can help mitigate the growing climate change problem.

Recent work on estimating the carbon benefits of emission reduction due to the closure of coal plants across the world finds it to be in 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)). There are well-known controversies around the right magnitude of SCC. In the spirit of how we approached air quality benefits, we take upper and lower bound estimates on SCC, with \$20 at the lower bound and \$100 at the upper bound (Hassler,

34. 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

Krusell, and Nycander (2016); Nordhaus (2014)).[35]

Figure 5 reports the results from adding in carbon reduction benefits from closing down coal-fired power stations over a twenty-five year period with 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. It is not surprising that these benefits strengthen the case for making a green energy transition globally. We can also look at plant-level net benefits after adding the carbon reduction benefits.[36] The net benefits from closing almost every coal-fired power plant on earth are positive.

Although we have taken an unweighted sum of air quality and carbon reduction benefits to get to the overall figure, one key difference between the two is worth highlighting. Air quality benefits are likely to appear more immediately whereas carbon reduction benefits could take much longer to be realised, with benefits mainly accruing globally and to future generations. This difference is important in political economy terms. Indeed, as we saw above, living within 40 km of a coal-fired power station did not appear to be accompanied by a greater concern about the risks from climate change. Economists typically simply add up air pollution and carbon emissions in conventional cost-benefit calculations, but political weights could be rather different.

6.5.2 The Need for Generation Balance

While the push towards renewable energy sources is an important element of a green transition, our focus on replacing coal with wind and solar does come with an important caveat. A key challenge for energy systems is to manage imbalances that can arise with stochastic supply and demand. Until viable storage technologies exist, there is a need for insurance against days when the sun does not shine or there is insufficient wind.

A complete treatment of the issues that our analysis raises would have to embrace such concerns. Gas-fired power is one alternative that is widely used and is flexible when balancing a system. Moreover, it comes without negative air quality externalities even if it still produces carbon emissions. But that means our analysis is particularly relevant to gas as

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

36. See Figure 16 in the Appendix.

the air quality benefits would be paramount. That said, the invasion of Ukraine by Russia and the ensuing sanctions have highlighted the uncertainties in the supply of gas across some geographies. In future, using hydrogen as an alternative to natural gas may be a useful way of storing excess energy from renewables. Thus, power generated via hydrogen can be attractive in achieving system balance without either producing carbon emissions or having major detrimental effects on air quality.

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.[37] In addition, idle capacity of existing coal plants, reflected in low utilization rate, which is around 50% for the whole world (54% for China and 58% for India),[38] also points towards "unwanted" capacity that one can get rid of without derailing the energy generation system.

6.5.3 Effects on Employment

There has been some evidence suggesting that people who benefit from the coal economy through the local job base in coal mining, thermal power plants, and associated activities, tend to express lower dissatisfaction with its existence (Eyer and Kahn (2020)). Employment margins could be important for shaping citizens' debates and policy design around a green energy transition. However, as reported in Table 25, it is not clear that clean energy would lead to job losses. Job creation would depend 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)). Nevertheless, if we believe that people have specific human capital and they cannot be retrained, then there would be losses, which should be considered in the bigger picture around the issues studied here.

There is also a potential threat from intensive mining of elements such as aluminium,

37. 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

38. The global average utilisation of coal-fired power plants is on track to hit an all-time low, affecting the profitability of both existing and planned capacity. *Source:* CarbonBrief.org

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 which may have consequences that are impossible foresee, let alone quantify.

7 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 is front and centre to this, it is important not to lose sight of the other detrimental effects of coal-fired power which are sometimes downgraded to "secondary" benefits. Chief among these is its impact on 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 to arguments for policy action in situations where citizens are empowered to demand change.

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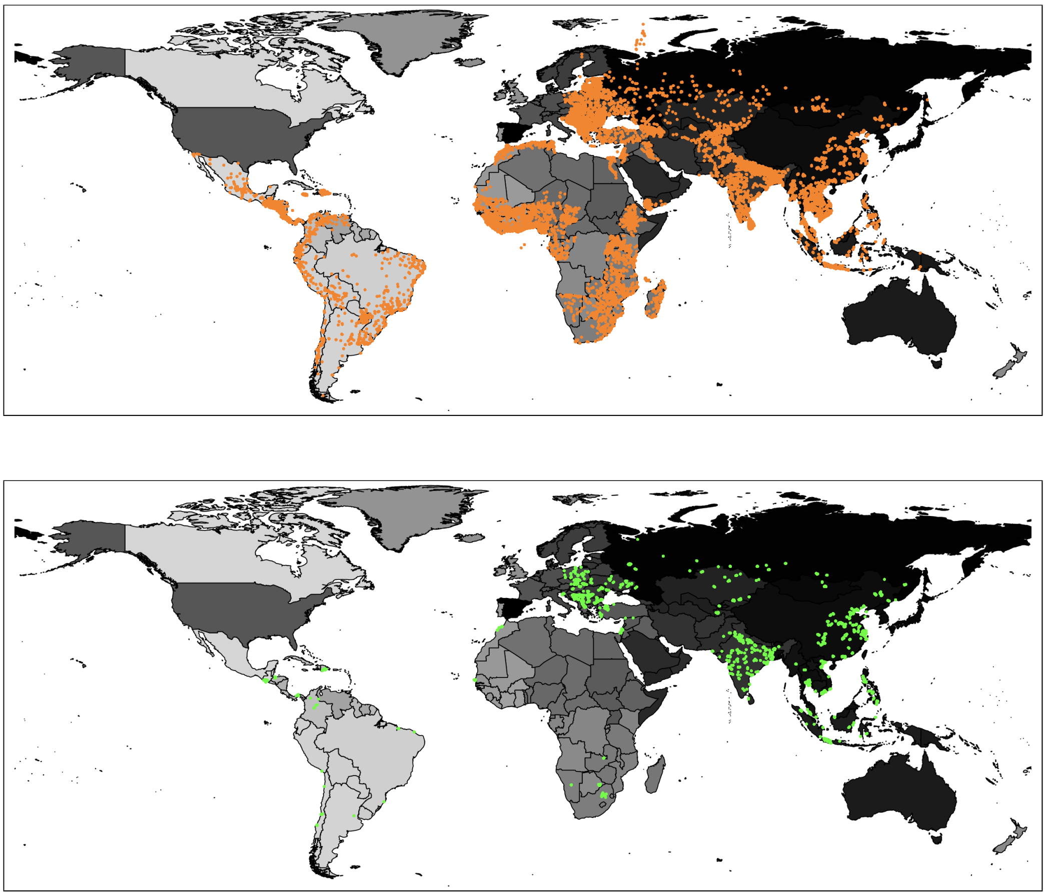
Tables and Figures

Figure 1: **Geocoded Gallup World Poll 2019**



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 1.

Table 1: **List of Countries in the 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. Figure 1 maps the geocodes of survey locations.

Table 2: **OLS Estimation Results for Operational Plants**

	(1) Air Diss	(2) Air Diss	(3) Air Diss	(4) Air Diss	(5) Air Diss	(6) Air Diss
Geocode's log dist from nearest plant	-0.044***	-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

Clustered 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 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 3: **OLS Estimation Results with CO_2 Level 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

Clustered 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 2 notes for details on other variables.

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

Clustered 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 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 2 notes for details on other variables.

Table 5: **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

Clustered 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 1 in Appendix 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 2 notes for details on other variables.

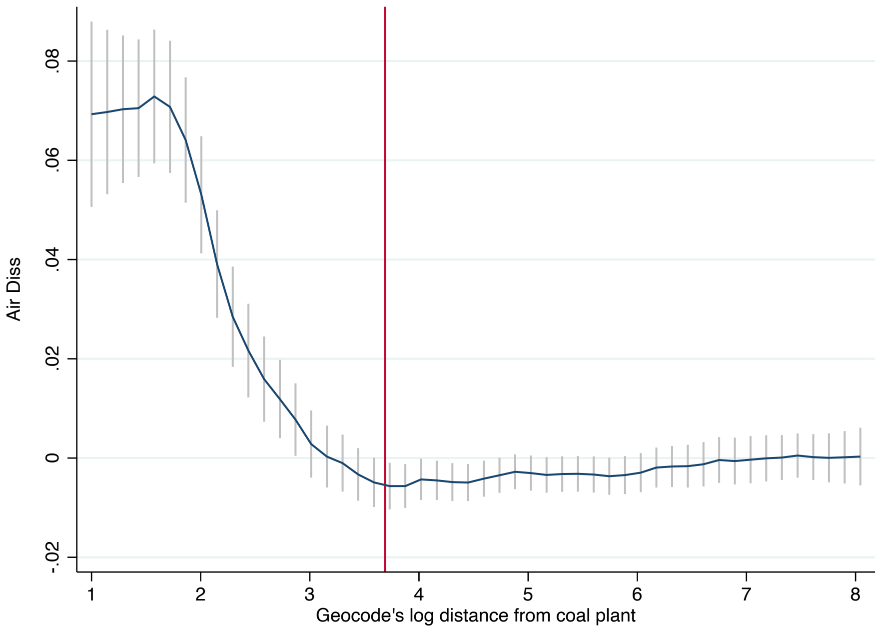
Table 6: **Placebo Results for Non-operational Plants and Water Quality Perception**

	(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

Clustered 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 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 2 notes for details on other variables.

Figure 2: **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 be equal to 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 7: **IV Results for Operational Plants**

	(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

Clustered 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 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 2 notes for details on other variables. First-stage and reduced-form results are reported in Table 15 in the Appendix.

Table 8: **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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

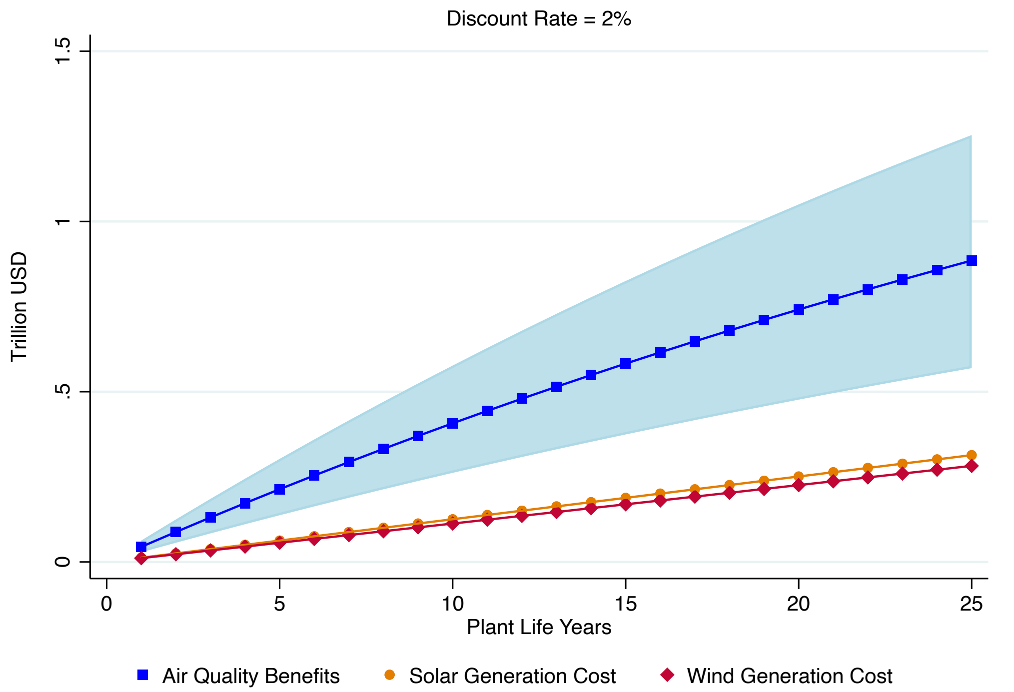
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within 40 km distance from the nearest coal power plant. Table 1 provide the 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 2 notes for details on other variables.

Table 9: **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 8. $\frac{a}{a_r}$ 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 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 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 3: **Cost-Benefit Analysis Results**



Notes: Chart shows the cost-benefit results for all 51 countries combined as listed in Table 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. Air quality benefits include the immediate benefits that the exposed population i.e. households located within a 40 km distance from an operational coal plant, derive from an improvement in their ambient air quality due to lower pollution. 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 10: **Top 25 Coal Power Stations in Sample 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

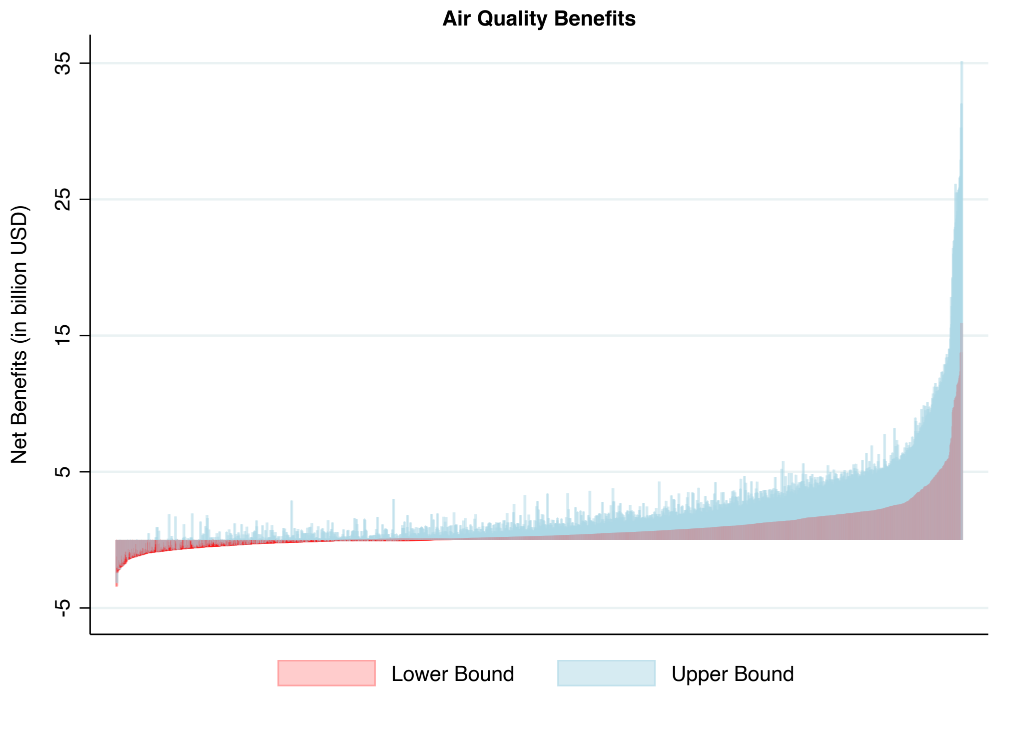
Notes: The table lists 25 coal power stations in our sample in decreasing order of total population affected, which is reported in Column 4. The population figures are the total number of individuals located within 40 km of respective plants. Solar and wind costs report the cost of green transition through 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 11: **Top 25 Coal Power Stations Out-of-Sample Countries 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

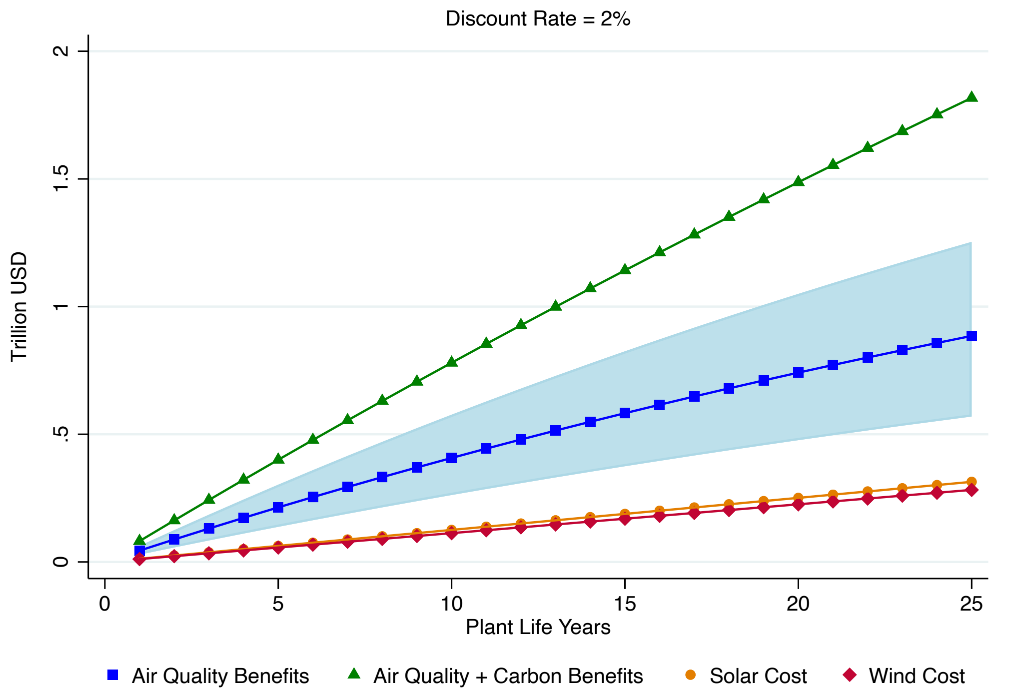
Notes: The table lists 25 coal power stations in the rest of the world i.e. countries outside our 51 countries sample in the decreasing order of total population affected, which is reported in Column 4. The population figures are total number of individuals located within 40 km of respective plants. 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 4: **Plant-level Net 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 two shaded regions in both plots represent upper and lower bounds of the benefits estimates. Air quality benefits include the immediate benefits that the exposed population, i.e. households located within a 40 km distance from an operational coal plant, derive from an improvement in their ambient air quality due to lower pollution. 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 excess energy demand because of shutting down respective coal plants.

Figure 5: **Carbon Reduction Benefits from Closing Coal Plants**

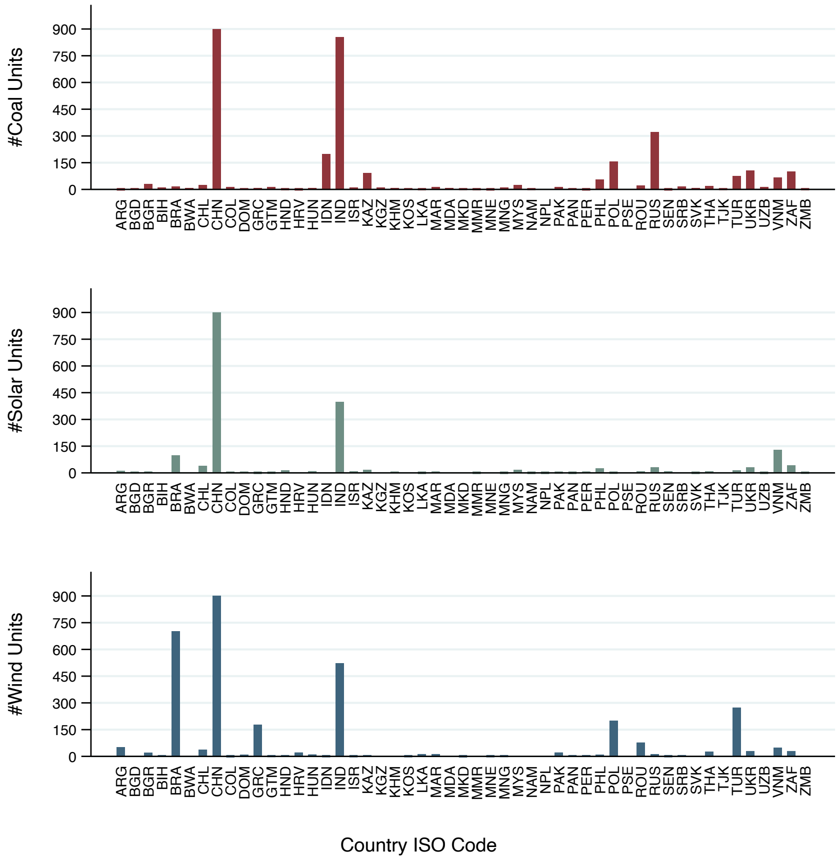


Notes: Chart shows the cost-benefit results accounting for carbon reduction benefits for all 51 countries combined as listed in Table 1. The policy experiment entails phasing out coal-fired power at a constant rate of 4% per year and replacing that freed capacity with solar or wind generation over a 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. Air quality benefits include the immediate benefits that the exposed population, i.e. households located within a 40 km distance from an operational coal plant, derive from improvement in their ambient air quality due to lower pollution. The green line shows the estimates resulting from adding the lower bound of carbon reduction benefits to the air quality benefits. Carbon reduction benefits are more long-term benefits that realise after some period due to lower concentration of carbon in the atmosphere. The costs of solar and wind energy generation are calculated by multiplying their respective source-specific global average LCOE values in USD/kWh with the total excess energy demand because of shutting down respective coal plants. All the costs and benefits are expressed in present-discounted value terms with the annual discount rate set at 2% per year.

Appendix

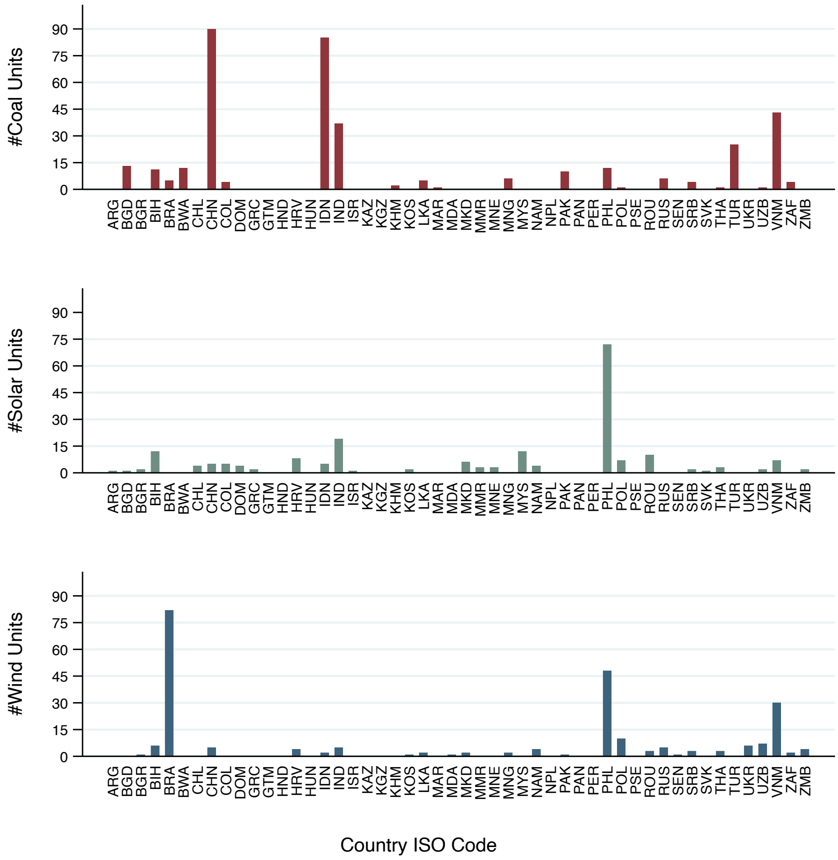
Tables and Figures

Figure 6: **Distribution of Operational Energy Sources**



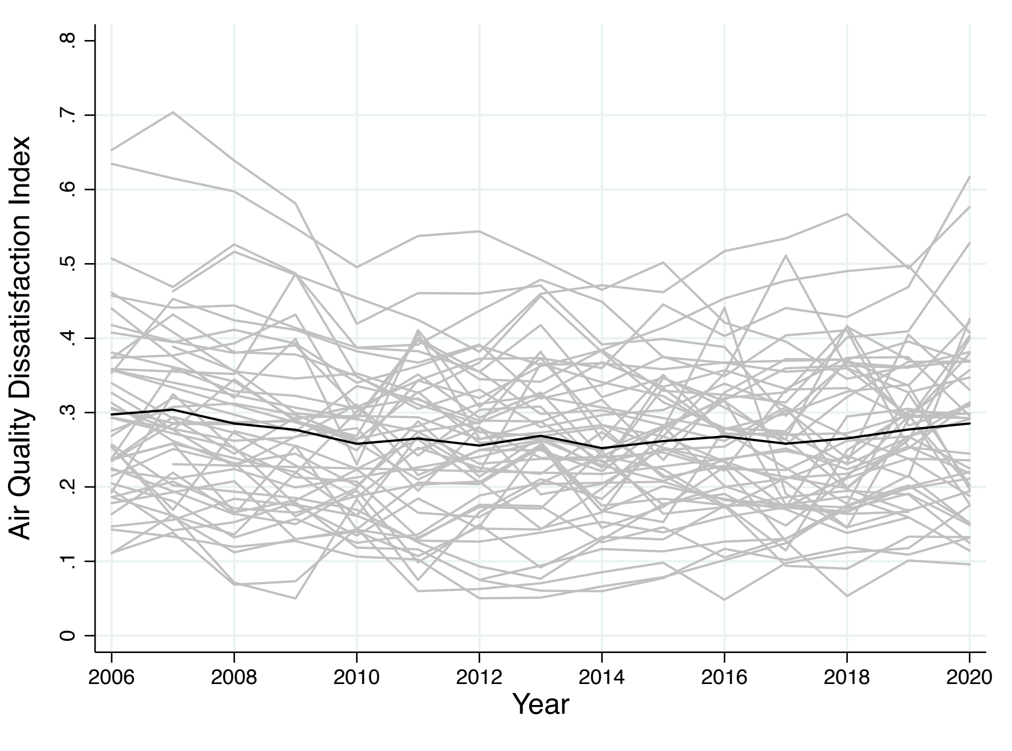
Notes: The graph shows the count of operational coal plants (top), solar farms (middle), and wind farms (bottom) for 51 countries in the main sample as listed in Table 1. The number of units have been capped at 900 for display purpose, thereby censoring all units counts for China (CHN). The actual count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

Figure 7: **Distribution of Planned Energy Sources**



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 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 8: **Air Quality Dissatisfaction Across Countries**



Notes: Each grey line represents one country from the list of countries in Table 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 12: **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

Clustered 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 5 notes for more details.

Table 13: **Placebo OLS Estimates 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

Clustered 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 6 notes for more details.

Table 14: **OLS Estimates 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

Clustered 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 6 notes for more details.

Table 15: **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

Clustered 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 7, which reports IV results.

Table 16: **Robustness Check on IV**

	(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

Clustered 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.

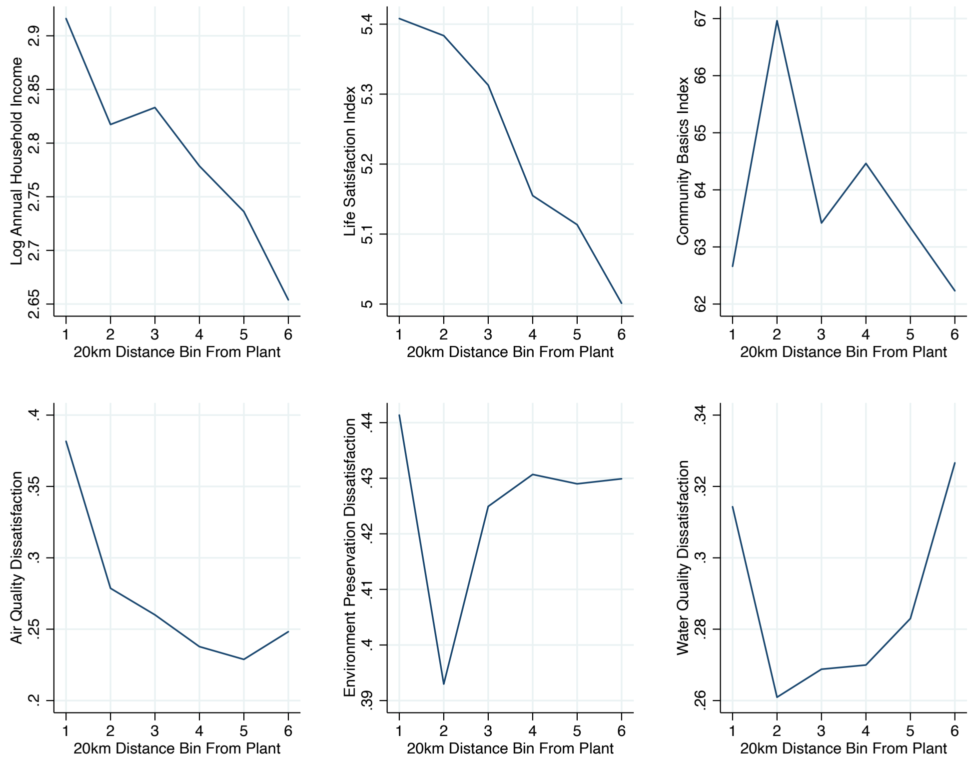
Table 17: **First-stage and Reduced-form Results for Retired Plants**

	(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

Clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

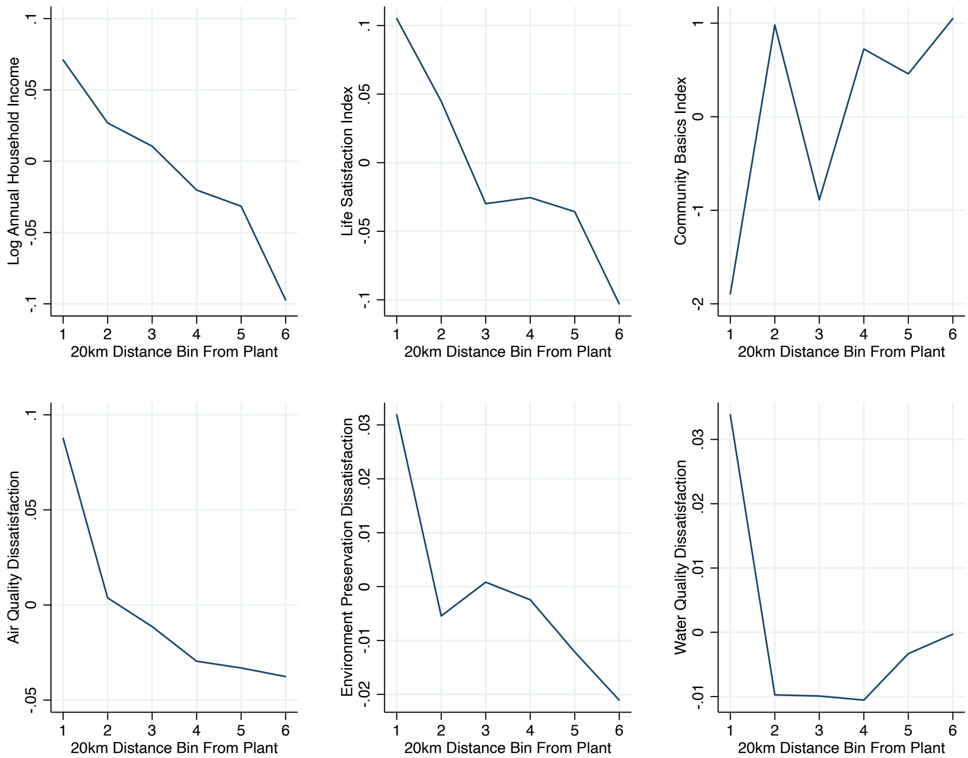
Notes: Top table reports reduced-form results and bottom reports first-stage results of IV regression using Equation (7) for retired plants. The columns correspond to Table 7.

Figure 9: **Descriptive Plots - I**



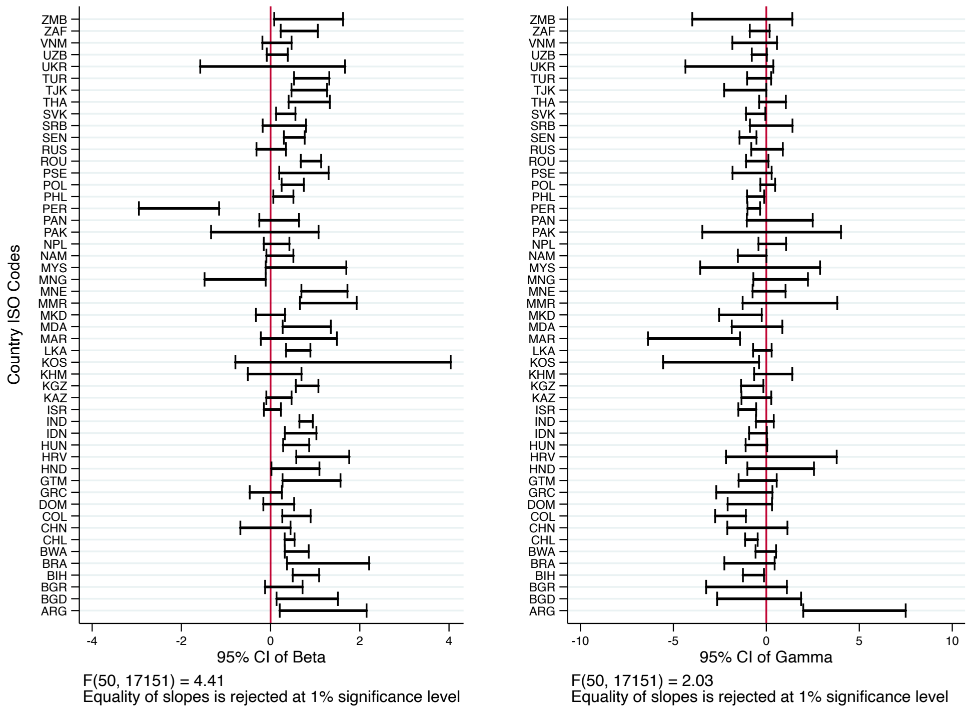
Notes: All the variables are taken from the 2019 Gallup World Poll. The label on x-axis should be multiplied by 20 to get the distance bin of the survey location from the nearest coal plant.

Figure 10: **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 11: **Beta and Gamma Estimates 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.

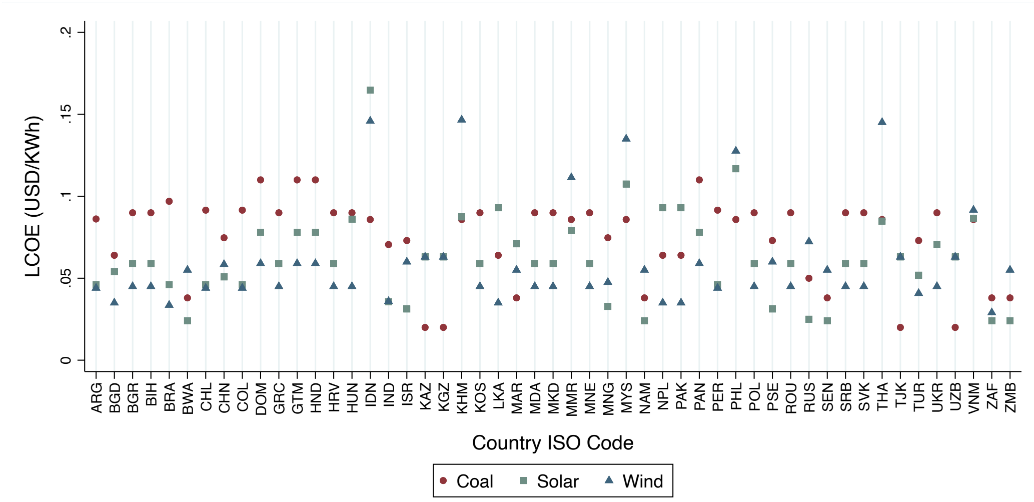
Table 18: **Robustness Test Results for Life Satisfaction Regression**

	(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	163,029
Pseudo R-squared	0.034
Log likelihood	-61,047
Mean of dependent variable	5.411
Mean household income in USD	14855
Region fixed effects	Admin-1
Countries included	Global
Estimator	Ordered Logit
FE Correction	Robust

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

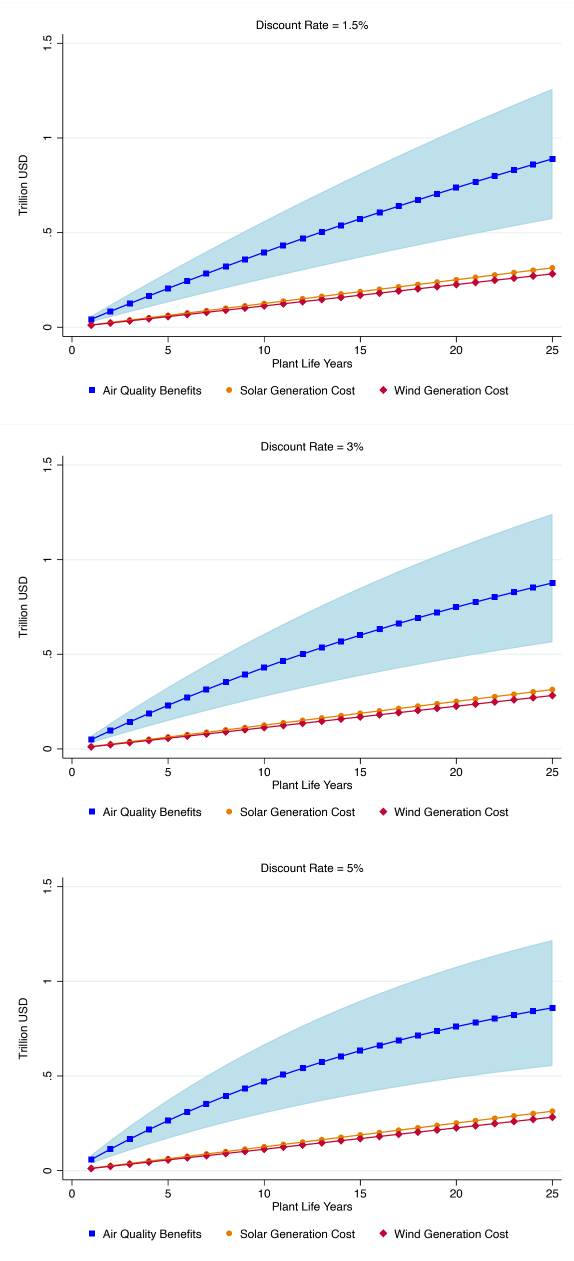
Notes: The table above reports results for ordered logit estimation with fixed effects corresponding to OLS estimation results reported in Table 8. We implement a robust estimation for fixed effects ordered logit models using the estimator proposed by Baetschmann et al. (2020).

Figure 12: **Cost of Energy for Different Sources**



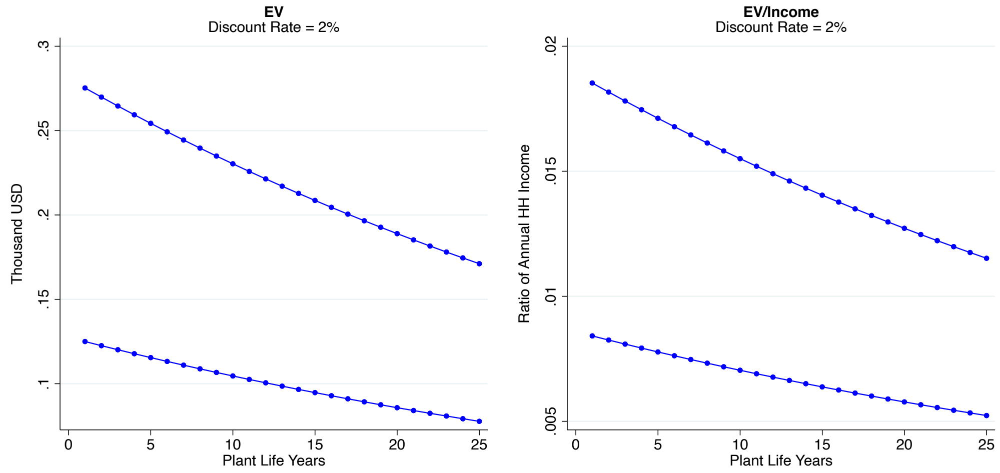
Notes: The graph shows LCOE values for all 51 countries in the main sample as listed in Table 1. LCOE measures lifetime costs divided by energy production. It accounts for present value of the total cost of building and operating a power plant over an assumed lifetime. This measure allows comparison 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 13: **Cost-Benefit Analysis for Alternative Discount Rates**



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

Figure 14: **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 energy transition project life cycle of 25 years.

Table 19: **Top 25 Coal Power Stations in World 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 20: **Life Satisfaction Regression Results for Plants in 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

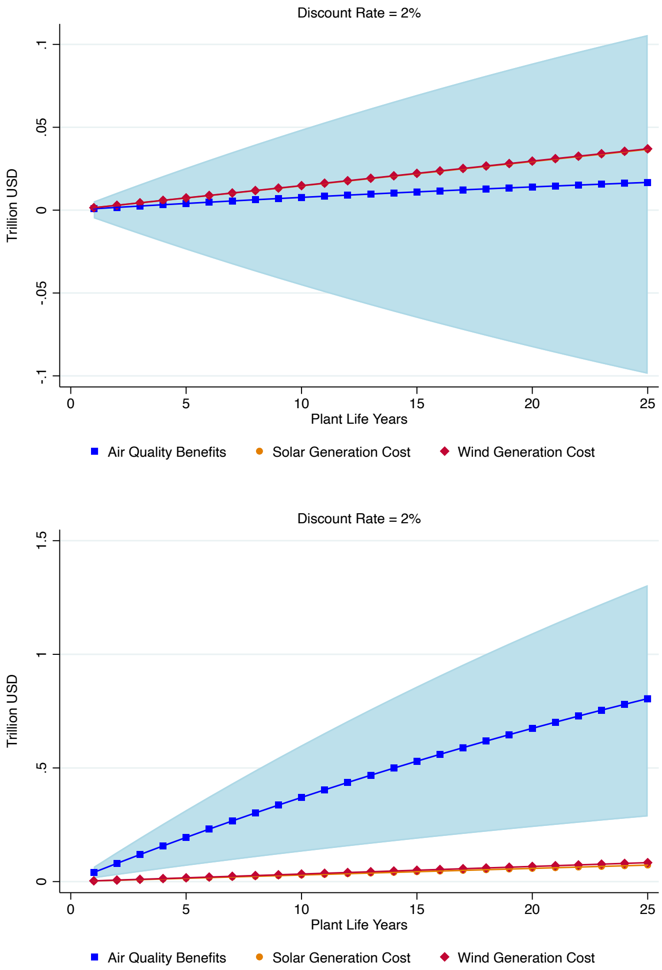
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants in India and China. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. 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 2 notes for details on other variables.

Table 21: **AWTP 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 20 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 15: **Cost-Benefit Analysis Results for India and China**



Notes: Charts show the cost-benefit 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 3 for more details.

Table 22: **Total Benefits of Energy Transition for Different Geographies**

(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 23: **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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

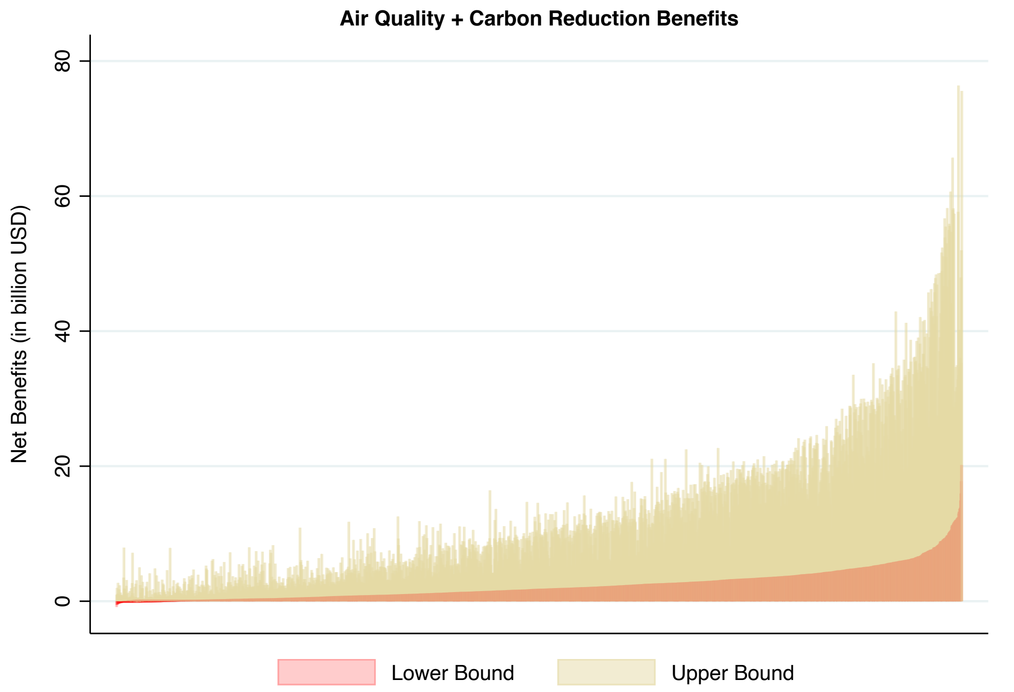
Notes: This table presents estimates using the specification in Equation (9) for operational coal-fired power plants for each education group separately. The sample used in each column is defined by distance band 0-40 km i.e., survey locations that are located within a 40 km distance from the nearest coal power plant. Table 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 2 notes for details on other variables.

Table 24: **WTP Results for 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 23 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 16: **Plant-level Overall Net 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 two shaded regions in both plots represent upper and lower bounds of the benefits estimates. Air quality benefits include the immediate benefits that the exposed population, i.e. households located within a 40 km distance from an operational coal plant, derive from improvement in their ambient air quality due to lower pollution. Carbon reduction benefits are more long-term benefits that realise after some period due to lower concentration of carbon in the atmosphere. 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 excess energy demand because of shutting down respective coal plants.

Table 25: **Country-level Employment Statistics for Different Sources of Energy**

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 section.

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