Equilibrium Particulate Exposure

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Abstract: We assemble global spatially disaggregated panel data describing ambient particulate levels and transport, population, and economic and polluting activities. These data indicate the importance of country level determinants of pollution, of the equilibrium process that separates or brings together people and particulates, of urbanization, and of the composition of economic activity and energy production. We then develop an Integrated Assessment Model describing particulate emissions, economic activity and particulate dispersion. We quantify the model for 31 countries representing more than 60% of world population. Model results indicate the importance of general equilibrium adjustments to particulates policy. For example, restrictions on agricultural burning increase equilibrium pollution exposure in the majority of countries by shifting labor to more polluting industries and locations. The model also indicates important cross-country heterogeneity in the effects of particulates policies.

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1. Introduction

We describe patterns of exposure to airborne particulates, investigate the relationship between equilibrium exposure and levels of various polluting activities, and develop and calibrate an integrated assessment model with which to evaluate the relationship between restrictions on polluting activities, exposure, and welfare. To accomplish this, we first assemble spatially disaggregated global panel data describing 'Aerosol Optical Depth' (AOD), a remotely-sensed measure of particulate concentration. We merge these data with a global panel of gridded population data. These data allow us to measure exposure, the coincidence of people and particulates. We next assemble data describing various possible emissions producing activities, such as fossil fuel consumption and agricultural burning, and estimate relationships between these 'likely suspects' and particulate exposure. Finally, we develop a macroeconomic model of equilibrium exposure and calibrate the model to fit a subset of the the world's countries. This model allows us to evaluate the equilibrium relationship between the cost of polluting activities, exposure, and welfare.

It is hard to overstate the importance of particulates policy. According to the Global Burden of Disease Project (Brauer et al., 2015), airborne particulates kill about 3m people per year. The value of a statistical life for a person living in a country where per capita GDP is 17,000 USD2010, about the median for the sample of countries for which we calibrate out model, is about 3m USD2010.[1] The product of these two numbers is 9 trillion dollars. This is more than 10% of world annual GDP. This estimate can be too large by one or two orders of magnitude and still illustrate our point: particulates are poisonous and managing exposure is an important problem.

It is natural to suspect that the regulation of particulates will have unintended consequences for exposure and welfare. Regulating particulates makes certain industrial process more costly and we expect people to adjust to such policies by reducing the newly costly activity, but also by shifting to unregulated sectors or moving to less regulated locations.[2] For example, farmers in Indonesia may respond to a restriction on agricultural burning by migrating to the city. Thus, this restriction may reduce exposure in the countryside, but increase the population living more polluted cities. If regulation takes the form of revenue generating Pigovian taxes, the way the resulting revenue is used may also be important. For example, if revenue transfers incentivize our Indonesian farmers to remain in the countryside despite newly less productive agriculture, their exposure to pollution may be reduced by the policy.

We provide three types of evidence that these sorts of unintended consequences are economically important. First, we show that the existing literature suggests the presence of these types

[1] From Viscusi and Aldy (2003), we take 6m USD as the value of statistical life (VSL) in the US, and the income elasticity of VSL as 0.6. Given US income per capita of about 55,000 USD2010, we have $(6 \times 10^6)(\frac{17{,}000}{55{,}000})^{0.6} \approx 3 \times 10^6$.

[2] We note that this description implicitly assumes second-best policies. In theory, a comprehensive system of Pigouvian taxes imposed on particulate emissions from all sectors and sources could implement the first-best allocation without unintended consequences. In reality, such a system is unlikely to be feasible, as discussed in Section 8.

of adjustments to particulates regulation. Second, we show reduced form evidence indicating the importance of changes in the geography of particulates as a determinant of exposure. Third, our model will indicate that unintended responses to particulates policy are important in many countries.

Finally, our reduced form results provide a basis for deciding which particulate producing activities make the greatest contribution to particulate exposure in an average country. Our model, on the other hand, provides a basis for evaluating counterfactual particulates policy impacts on exposure and welfare for each of the 31 countries for which we calibrate it. We describe the literature and context of these contributions in section 3, but first define some key terminology and provide additional motivation for our study.

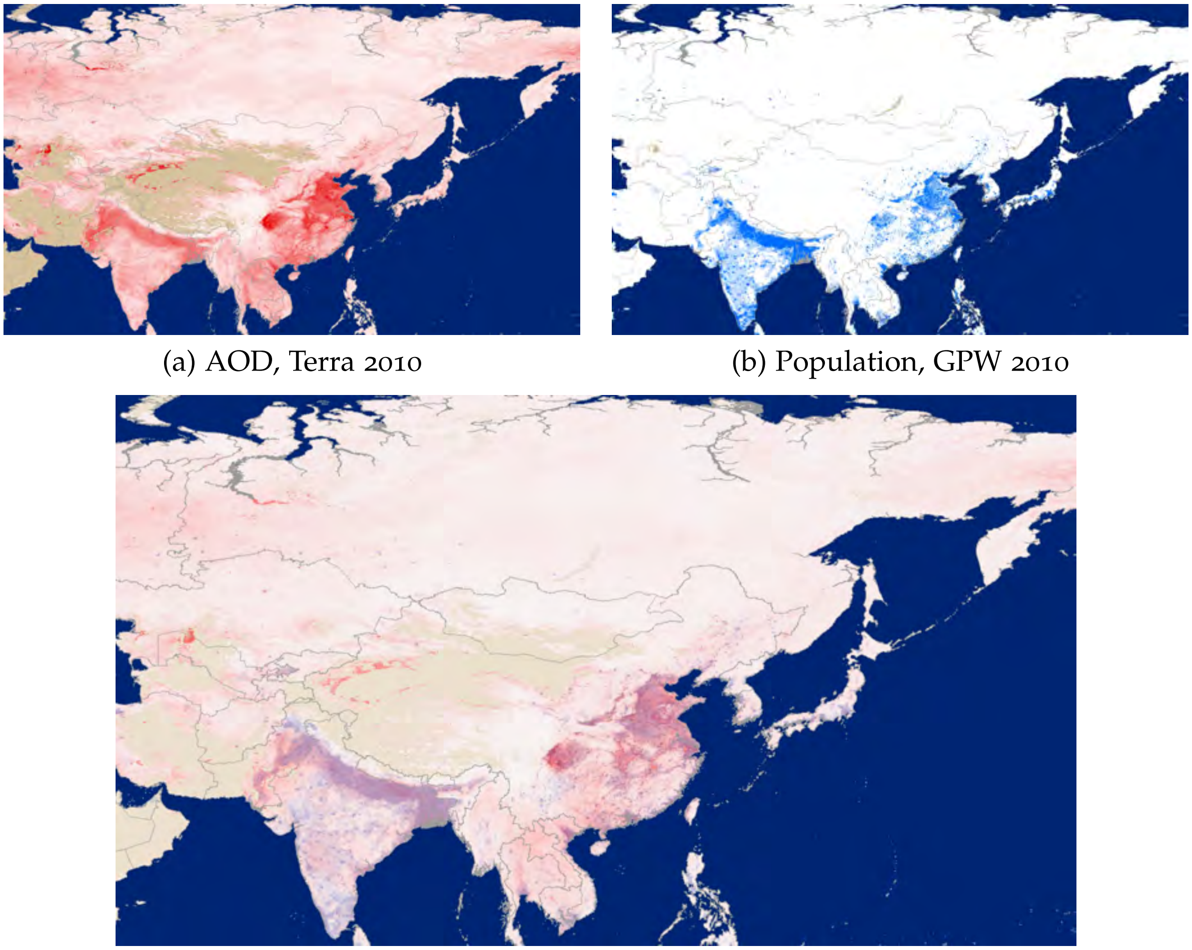
2. The geography of particulate exposure

It will be useful to be explicit about the language we use to discuss particulates. Particulates end up in the air as a consequence of emissions. Emissions, from whatever source, are measured in units of mass. Point source regulation is generally concerned with regulating the mass of emissions. We will generally measure emissions in megatonnes (MT) and occasionally in kilotonnes (KT). Once in the air, particulates disperse. This leads to a certain mass per volume of particulates. This is the concentration of particulates. The units of concentration are mass per unit volume, and this is what is measured by most instruments. We will generally measure concentration in kg/km^3 (or equivalently, μg/m^3). We are primarily concerned with exposure. For our purposes, this will be the person weighted mean of concentration, and its units are AOD points per person. This definition is tractable and transparent, but assumes that exposure is linear in concentration. This may be controversial, but we postpone a discussion of this to section 3.

With this language in place, we turn to a description of concentration and exposure. Figure 1 presents three maps of Asia that show China, India and Russia, among other countries. Panel (a) shows the distribution of AOD in 2010. Darker red indicates higher mean annual particulate levels. Pink and white indicate areas with lower levels. Tan indicates missing data. Unsurprisingly, China is highly polluted, particularly in the central region and the Northeast. India is also highly polluted, particularly in Ganges river valley, although we also see high levels of pollution throughout the subcontinent. Russia is generally less polluted, and much of the pollution occurs in the West, possibly blown in from Europe.

Panel (b) shows population density, also in 2010. China is densely populated except for provinces on its Western frontier. Population is particularly dense in the central region around Chongqing and in the Northeast. Even away from these areas, population appears to be highly concentrated into cities. Population density in India is also high, especially along the Ganges, although even away from this region, population density is almost uniformly high. Russia,

Figure 1: Population, particulates and exposure



(a) AOD, Terra 2010

(b) Population, GPW 2010

(c) Exposure, 2010

in contrast, appears almost unpopulated, although on close inspection, small cities are visible, mostly in the Southern part of the country.

Panel (c) superimposes a partly transparent panel (a) on panel (b). The interpretation of colors follows by taking convex combinations of their meanings in panels (a) and (b). White indicates areas with low population and low pollution. Pink and red indicate areas with high pollution and low population. Blue indicates regions with high population density and low pollution. Purple indicates regions with high pollution and high population density. That is, purple indicates regions where many people are exposed to high concentrations of particulates.

Panel (c) illustrates three features of our data that will recur throughout our analysis. First, exposure is substantially determined by country of residence. Imagine being asked to participate in a lottery where, conditional on your choice of country, you would be assigned to a blue dot in that country at random. If all you care about is your ultimate exposure to particulates, this choice would be relatively easy. Russia is best. China and India are more difficult to distinguish, but India is probably better.

Second, the geography of pollution matters. In Russia, what pollution there is occurs away from population centers and few people experience high levels of particulates. In India and China concentration and population coincide. Close inspection of panel (c), however, suggests that China and India are somewhat different. India is more 'blue', while China is more 'pink'. In India, highly populated and polluted places are surrounded by places that are highly populated, but not as polluted. China is the opposite. Highly populated and polluted places are surrounded by places that highly polluted, but not as densely populated. Moving out of the densest cities looks like a better response to particulates in India than in China.

Third, the geography of exposure is clearly different across countries. Russia couples low concentrations with the separation of population and concentration. China crowds its people into its most polluted places. India is crowded everywhere, including its most polluted places.

Table 1: Levels and changes in concentration and exposure for several countries

	AOD 2000	Mean exposure 2000	%Δ AOD 2000-10	%Δ Mean exposure 2000-10	$\frac{\%\Delta\text{AOD}}{\%\Delta\text{Exposure}}$
Indonesia	0.20	0.27	-15.71	-1.83	8.58
Brazil	0.13	0.12	65.55	28.18	2.33
US	0.14	0.20	-20.48	-11.89	1.72
India	0.28	0.36	30.58	29.03	1.05
Russia	0.12	0.17	52.21	72.66	0.72
China	0.31	0.53	13.58	22.96	0.59
Poland	0.20	0.22	-4.46	-8.39	0.53

Table 1 reinforces and refines these observations. The first column presents an area weighted mean of AOD in 2010 for each of the countries listed. The second column presents our exposure measure, population weighted mean AOD.

Exposure is 0.27 in Indonesia, while AOD is 0.20. This means that an average resident of Indonesia lives in a part of the country that is more polluted than average. Looking down the first two columns of table 1 the smallest country level mean is about 0.12, while the largest is 0.31, Russia and China respectively. The range in exposure is larger, from 0.12 in Brazil to 0.53 in China. Brazil is alone in having its population in places that are less polluted than average. China and India have about the same levels of AOD on average, but exposure in China is much higher. In sum, the first two columns of table 1 confirm what we see in figure 1. Countries matter, as do within country geography of population and concentration.

The next two columns report percentage changes in AOD and in exposure between 2000 and 2010. Indonesia saw AOD fall by about 16%, but exposure fall by only 1.8%. Thus, Indonesia accomplished a dramatic reduction in concentration, but this reduction did not occur in places where people lived (or people migrated to more polluted places). Column 5 gives the ratio of these two changes, Indonesia reduced concentration by about 8.5% for each 1% reduction in exposure.

Looking down the rows of columns 3 to 5, we see that India's increase in concentration matched its increase in exposure closely. China, on the other hand, saw exposure increase almost twice as fast as concentration. Poland decreased exposure more than twice as fast as it decreased concentration.

Table 1 and figure 1 suggest the importance of equilibrium responses to changes in the costs and benefits of particulate emissions. Differences in the geography of particulates mean that in 2000, the average Chinese has about 50% higher exposure than the average Indian, despite almost identical average levels of AOD. Table 1 and figure 1 also suggest the importance of country level factors in determining pollution and exposure.

3. Literature

Our analysis relates to several areas of the literature. First, our setup is motivated by extensive empirical evidence for the importance of general equilibrium adjustments to (incomplete) regulation of particulate emissions, mainly based on studies of the US Clean Air Act. The Clean Air Act is a collection of regulations that impose restrictions on emissions in regions of the US that fail to attain mandated standards for air quality, including levels of particulates. The effects of the Clean Air Act have been studied intensively.

Chay and Greenstone (2005) find that areas subject to regulation under the Clean Air Act saw Total Suspended Particulates (TSP) decline from 90 to 30 $\mu g/m^3$[3] Chay and Greenstone (2005) also find that this decreases in particulates cause an increase in the prices and a 10% decrease in TSP causes an increase in house prices of between 2% and 3.5%. Greenstone (2002) finds that non-attainment regions saw employment decrease by about 600,000 as a consequence of regulation between 1972 and 1987. This is on the order of 1% of total US employment during this time. Walker (2013) finds that workers in non-attainment areas are displaced to clean industries and to attainment areas. Becker and Henderson (2000) find that dirty industries tend to migrate to attainment areas. Finally, Gibson (2019) shows that regulated plants may substitute from air to water pollutants, and that air emissions increase at unregulated plants relative to regulated plants within the same firm.

[3]TSP is a now archaic measure of of particulate concentration. It describes the concentration of particulates of all sizes. In contrast, contemporary measures are PM10 or PM2.5, the concentration of particulates with radius less than 10 and 2.5 μm. Converting from TSP to PM10 or 2.5 is problematic. World Bank Group and United Nations Industrial Development Organization (1999) suggests PM10= 0.55×TSP.

In short, these studies establish the existence of the sorts of general equilibrium effects with which we are concerned for the case of a particular US regulation. More specifically, they establish that regulation of particulates can lead to the migration of workers across sectors and regions in response to both the costs of regulation and the benefits of clean air, and to the migration of firms across regions and sectors. With this said, it is hard to guess from these results whether, for example, the general equilibrium responses to restrictions on agricultural burning in Pakistan or coal taxes in Russia are likely to be important. This is the type of question we hope to address with our analysis.

Second, there is a large literature examining the effect of particulates on health. These papers (e.g. Chay and Greenstone (2005), Arceo, Hanna, and Oliva (2016), Chen, Ebenstein, Greenstone, and Li (2013), Knittel, Miller, and Sanders (2016)) estimate the effect of a marginal unit of particulates, applied to a treated population by a quasi-random process, on a health outcome of interest. Apart from the fact that particulates are surprisingly poisonous, two findings from this literature are relevant.

On the one hand, each of the papers listed above finds that IV estimates of the health effect of particulates is between 3 and 20 times as large as the OLS estimates. If we accept the validity of the various research designs, we can restate the this finding as follows, a unit of particulates applied to a location at random is much more harmful than is a typical unit of particulates in equilibrium. That is to say, in equilibrium people are able to make adjustments that substantially reduce the harmfulness of particulates concentration. Studies of the Clean Air Act demonstrate the possibility of general equilibrium responses to particulates regulation. These papers suggest that such responses might actually be important determinants of equilibrium exposure.

On the other hand, Arceo et al. (2016) in particular, observes that the response of child mortality to marginal increases in particulates is about the same in San Francisco as in Mexico city, despite the large difference in the level of particulates. This fact motivates our simple measure of exposure, the population weighted mean AOD. Implicitly, this measure assumes the linearity in the dose-response function that Arceo et al. (2016) observe. With this said, this assumption is also made in part for tractability. Calculating exposure using the sort non-linear dose-response function used in Brauer et al. (2015) would complicate our analysis dramatically. Importantly, however, we do allow for convex disutility over AOD concentrations in our structural analysis and welfare calculations.

Third, our analysis builds on a rich tradition of integrated assessment models (IAMs), which incorporate environmental processes into economic models. Nordhaus (1975) pioneered the integration of the global carbon cycle into a global energy markets model, and developed the seminal DICE and multi-regional RICE climate-economy IAMs over the ensuing decades (see, e.g., Nordhaus (1994), Nordhaus and Yang (1996), or Barrage (2019a) for a history of these frameworks). This literature now spans a broad diversity of IAMs (see Nordhaus (2013) for a recent review), several of which - including DICE - are used to inform policy decisions across numerous states and countries (see, e.g., Greenstone, Kopits, and Wolverton (2013), Nordhaus (2014), Barrage (2019a)).

Within this broad literature, our analysis aligns more specifically with recent efforts to analyze environmental processes in a general equilibrium context. Much of this work has focused on climate change (Golosov, Hassler, Krusell, and Tsyvinski (2014), Hassler, Krusell, and Smith Jr. (2016)), where an increasing number of studies have demonstrated the importance of general equilibrium interactions with, e.g., trade policy (Hemous (2016)) and fiscal policy (see review by Bovenberg and Goulder (2002), Barrage (2019b)). Many studies in this context also consider the effects of unilateral policies and the potential for emissions "leakage" across countries (e.g., Babiker (2005), Hassler and Krusell (2012)). A separate literature studies greenhouse gas emissions leakage also within countries (e.g., Fowlie (2009)) and in dedicated models (e.g., Fowlie and Reguant (2020)). Given that our model seeks to capture population movement between urban and rural areas, we also relate to a new frontier in IAMs of introducing migration of people and economic activity (e.g., Desmet and Rossi-Hansberg (2015), Desmet, Kopp, Kulp, Nagy, Oppenheimer, Rossi-Hansberg, and Strauss (2018)). Considerably less work in this tradition has studied particulate matter pollution. Carbone and Smith (2008) evaluate the implications of non-separability between household preferences over particulate matter and leisure. They develop a single-region, multi-sector general equilibrium model of the U.S. economy and show that the welfare costs of energy and transportation taxes may be significantly over- or under-estimated by partial equilibrium approaches.

Several modeling groups have developed rich partial equilibrium IAMs that account for particulate matter pollution. Nick Muller and co-authors have developed the AP2 (formerly APEEP) model, which tracks emissions, concentrations, and damages for several local pollutants, including $PM_{2.5}$, across U.S. counties. This model allows an evaluation of spatial heterogeneity in marginal damages from air pollution and its implications for various US environmental policies (Muller and Mendelsohn (2007), (Muller and Mendelsohn (2009), Holland, Mansur, Muller, and Yates (2016)). Though it is extremely rich and spatially detailed, the AP2 model takes the location of people and firms as given, and thus has limited ability to teach us about equilibrium exposure when people and firms have many margins of adjustment to changes in the costs and benefits of particulate emissions.

Perhaps the most extensive multi-country, multi-pollutant IAM has been developed by the International Institute for Applied Systems Analysis (IIASA). The GAINS ("Greenhouse gas - Air pollution Interactions and Synergies") model features an extremely detailed representation of emissions-causing processes, accounting for details such as the distributions of boiler types and livestock species across countries, which affect both baseline emissions and mitigation costs. While the GAINS model is thus extraordinarily rich in its foundations, it is not a competitive equilibrium-based economic model. That is, the GAINS framework does not consider the kinds of behavioral responses to pollution regulation that are the focus of our analysis. We nonetheless build on GAINS for the quantification of our model, as other scholars have done (e.g., Parry, Heine, Lis, and Li (2014)).

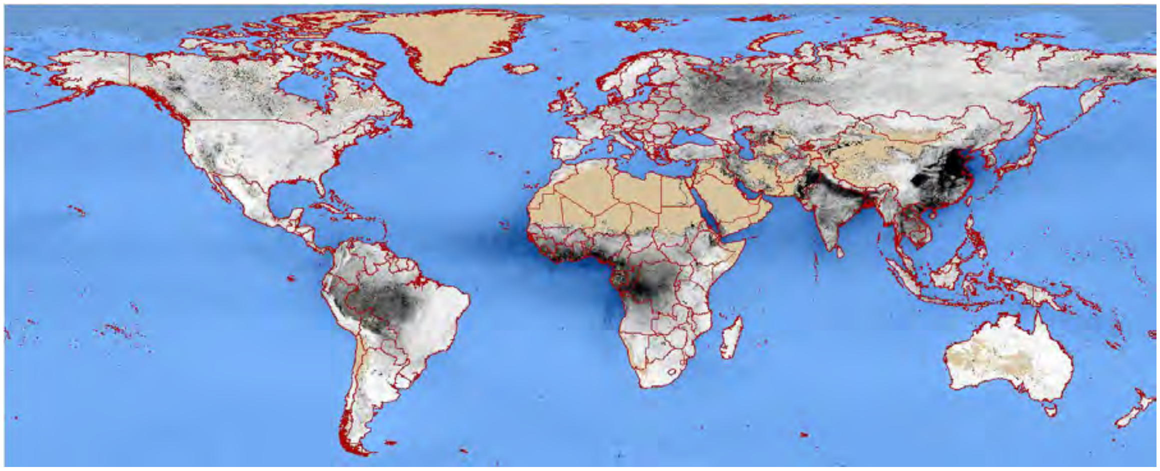
4. Data

The objects of this project are to describe patterns of exposure, to investigate the relationship between equilibrium levels of various polluting activities, and to develop and calibrate an integrated assessment model with which to evaluate the relationship between restrictions on polluting activities and exposure and welfare.

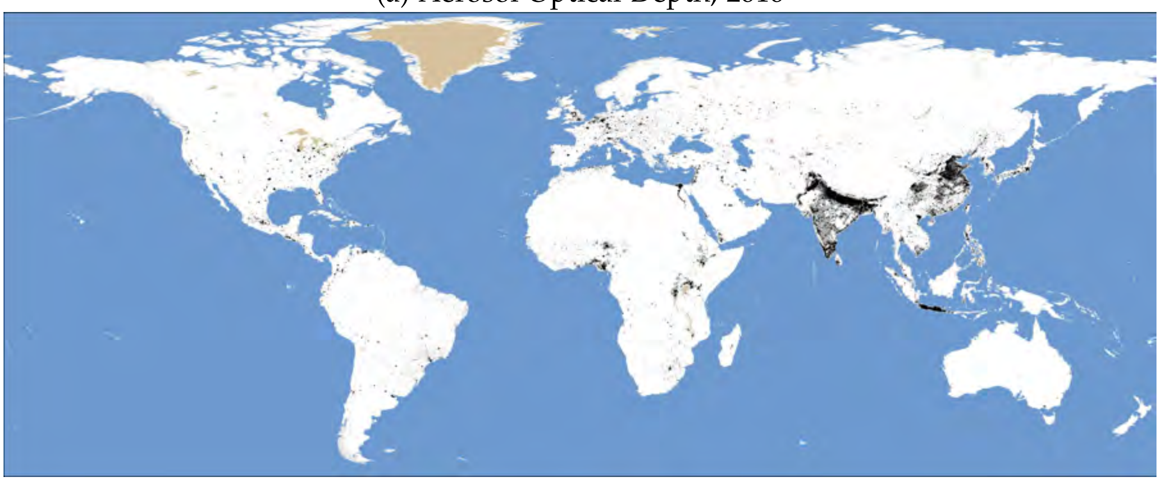
We require four primary types of data. An aggregate measure of exposure must rest on a description of the locations of people and pollution. Consequently, our data set is organized around gridded panel data describing concentration and exposure. We also require a description of polluting activities. In practice, these will be a mix of gridded panel data, e.g., urbanization, and country level data, e.g., fuel use. Finally, we require a description of aspects of the physical environment that affect the deposition, dispersion or natural sources of particulates, e.g., climate, wind and land cover. These data are primarily gridded, remotely-sensed panel data.

In this section we briefly describe each of these four classes of data, relegating more technical details to an appendix. We will also require estimates of particular structural parameters in order to calibrate our model, but postpone this discussion until after we present the model.

Figure 2: World maps of AOD and population in 2010



(a) Aerosol Optical Depth, 2010



(b) Gridded Population of the World, 2010

A *AOD and population*

Table 2: Descriptive statistics

	2000	2010
Whole sample, 233 countries:		
AOD	0.17	0.20
Exposure	0.35	0.40
Pop (000,000)	5,663	6,380
Area (00km^2)	954,970	954,970
Pixels	1,511,863	1,511,863
Main sample, 64 countries:		
AOD	0.15	0.19
Exposure	0.33	0.38
Pop (000,000)	4,392	4,856
Area (00km^2)	606,683	639,751
Pixels	1,036,316	1,106,468
Whole sample excluding India, China, Russia, 230 countries		
AOD	0.17	0.19
Exposure	0.35	0.40
Pop (000,000)	3,390	3,773
Area (00km^2)	704,650	704,650
Pixels	987,242	987,242

We rely on a remotely-sensed measure of particulate concentration, Aerosol Optical Depth, provided by the NASA Terra satellite using the Moderate Resolution Imaging Spectroradiometer (Levy, Hsu, and al., 2015a). MODIS records the intensity of the light reflected into space from the surface of the Earth. Comparing this measured intensity with a reference value allows an estimate of the share of light that is dispersed in the air column. Heuristically, the inverse of this share is AOD. A little more formally,

$$\text{AOD} = -\ln\left(\frac{\text{light arriving at ground}}{\text{light arriving at top of atmosphere}}\right).$$

That is, AOD is a positive, monotone transformation of the fraction of light arriving at the top of the atmosphere that reaches the ground (Jacob, 1999a, p. 141). The nominal scale of AOD reported by MODIS is $0 - 5000$. Following the convention in the literature, we rescale to $0 - 5$. The MODIS Terra data are available from February 2000 until the present, with a lag for processing.[4]

The spatial resolution of the MODIS AOD data is about 3km square and they are available about daily. To ease computation, we reprocess all of our gridded data, including MODIS AOD, to a standard grid with a resolution of 0.0833 arc minutes. This is about 10 kilometers at the equator, becoming finer with movement towards the poles. This results in a grid of cells 4320×1740, with a North-South range from 85 degrees North to 60 degrees South. After reprocessing each daily

[4]A second MODIS satellite, Aqua, began operations in 2002 and also continues to operate (Levy, Hsu, and al., 2015b). Gendron-Carrier, Gonzalez-Navarro, Polloni, and Turner (2018) shows that the correlation between AOD measures from Terra and Aqua are very high so we do not use the Aqua data.

image into this grid, we average over days within each year. Figure 2 (a) presents an image of the resulting AOD map for 2010.

Table 2 provides further description of our AOD data. In 2000, world average concentration was 0.17 and this increased to 0.20 by 2010. Exposure was higher and increased faster, 0.35 in 2000 increasing to 0.40 by 2010. People tend to concentrate in more polluted places.These statistics describe 233 countries, about 6.4b people in 2010, and about 1.5m of our 0.0083 degree pixels. In much of our work the availability of emissions data will lead us to consider a subset of about 60 2010 countries, the exact number varies slightly by year. This will be our 'main sample', and is described in the second panel of table 2. Mean concentration and exposure levels are close to those for the whole sample, and this sample of countries accounts for more than 2/3 of all pixels in the larger sample. China, India and Russia are all outliers. India and China are populous and polluted, while Russia is large and unpolluted. It is natural wonder the extent to which global means reflect these three countries. The third panel of table 2 echos the first, but excludes China, India and Russia. World means change only slightly when we exclude these countries.

We are interested in the concentration of particulates in the air, mass per unit volume. Thus, in order for AOD to be useful for our exercise, we must be able to convert it into units of concentration. We use the conversion factor $\rho = 100\mu\text{g}/\text{m}^3$ PM10 suggested by Gendron-Carrier et al. (2018). Thus, an AOD measure of 1 in one of our nominally 10km^2 pixels maps to an annual average concentration of $100\mu\text{g}/\text{m}^3$ PM10. We will typically measure concentration in units of kg/km^3. As it happens, this scaling of units does not change the value of our conversion factor.

Particulates cause health problems when people come into contact with them, while MODIS measures AOD throughout the whole air column. Ideally, we would measure particulate concentration at ground level. See Hidy et al. (2009) for a discussion of these issues. Related to this, Brauer et al. (2015) use the MODIS together with population and other data in an effort to arrive at more precise estimates of ground level particulates. While the resulting data is likely superior to our raw MODIS data as a measure of ground level particulates, this improvement is accomplished by confounding particulates data with population density. For our purposes, this leads to difficulties in the interpretation of correlations that do not arise with the raw MODIS AOD data. Moreover, the ability of MODIS data to predict ground based particulates is well established, e.g. Gendron-Carrier et al. (2018), Foster, Gutierrez, and Kumar (2009) or Kumar, Chu, and Foster (2007). Given this, we base our analysis on the relatively straightforward MODIS data.

We measure population using version 4 of 'gridded population of the world' (CIESIN, 2016), for 2000, 2005, 2010, and 2015. These data are based exclusively on administrative data describing population. They are constructed by assigning population to about 1 km square cells (0.0083 degrees) and interpolating to provide cell based population estimates in modulo five years. We reprocess these data by consolidating cells into 10×10 groups. The resulting 0.083 degree grid is the basis for our gridded data. Figure 2 (b) presents a map of our population data for 2010.

B *Climate*

Climate is important for our analysis for three reasons. First, relative to ground based instruments, remotely-sensed measures of AOD are less able to distinguish water vapor, particles of water, from the dust and soot that is our main concern. Consequently, controlling for local measures of water vapor may be important in regression analysis, particularly if we are concerned emissions may also be correlated with climate. Second, MODIS is only able to operate on cloud-free days, and so climate has a direct impact on the selection of days and pixels where we measure AOD. Third, climate may have an impact on the deposition rate for particulates as rainfall contributes to wet deposition of particulates (Wu, Liu, Zhai, Cong, Wang, Ma, Zhang, and Li (2018)).

We rely on Jones and Harris (2013) for monthly gridded measures of climate. These data are available monthly with a spatial resolution of 0.5 degrees. We reprocess them to our finer grid and average over months to create annual measures. In particular, we calculate annual means of, days of cloud cover, mean daily precipitation, mean daily vapor pressure, mean daily temperature, and days with frost. We will sometimes use these variables as controls in our regressions.

C *Emissions*

We measure several potential sources of emissions at the country level, cross-border flows, fossil fuel use and economic activity. We measure other potential sources of particulates at the pixel level, urbanization, land cover and fires.

Fossil and organic fuels: Combustion is a major source of particulate emissions. We focus on two kinds of economically important combustion: energy production and biomass burning.

Most production uses energy, and most energy is generated by burning fossil fuels. Some of the burned mass transfers to the air, where it remains suspended as particulate matter. We observe consumption of three main fuel groups, by country, year, and economic sector. The groups are, as defined by the International Energy Agency (IEA): coal, peat, and oil shale (from here on, coal); crude oil, oil products, natural gas liquids, and refinery feedstocks (from here on, oil); and natural gas along with other clean energy sources, including solar, nuclear, geothermal, and wind (from here on, gas/green). To facilitate aggregation across fuels, all energy consumption is measured in million tonnes of oil equivalent (Mtoe).

We observe organic fuel (also called biomass) consumed for about 60 countries (the actual number varies slightly by fuel and year), as reported by the International Institute of Applied Systems Analysis (IIASA). Biomass consumption is measured in petajoules (PJ) and includes household use of organic fuels like wood, dung, and agricultural byproducts burned for energy generation. Agricultural waste burned for clearing and other non-energy purposes is tracked separately. It is related to the use and management of agricultural and undeveloped land. Given that our remotely-sensed data layers are approximately global, the availability of data on organic fuel imposes the most important restriction on the spatial extent of our sample.

GDP sector shares and GDP: Both the level and composition of economic activity are important potential determinants of particulate emissions. Non-combustion processes such as steel production and fertilizer usage can contribute to particulate emissions both directly and via precursors (Fuzzi, Baltensperger, Carslaw, Decesari, Denier van der Gon, Facchini, Fowler, Koren, Langford, Lohmann, et al. (2015)). We thus obtain country-year level data on the GDP shares of agriculture, industry, and services from the World Bank (World Bank Development Indicators), and data on non-combustion particulate emissions from industry, services (i.e., road travel), and agriculture from IIASA.

Urban vs rural: An inspection of figure 1 or 2 suggests that urban areas are more polluted than rural areas. This suggests the importance of distinguishing urban or rural status for exposure.[5] To accomplish this, we rely on two sources of information. The first is our gridded population data, which gives us population density. The second is World Bank (2018), which reports the fraction of each country's population that is urban. Using both data sources, for each country, we assign the smallest possible number of pixels to the urban class, subject to reaching the urban population share reported in World Bank (2018). Figure 4 (a) shows the resulting partition of the world into rural and urban.

Our model will ultimately describe 'small open economies' that consist of rural and urban regions. Calibrations of this model will rely on the geography illustrated in figure 4 (a).

Land cover: In some of our regressions we investigate the relationship between land cover and particulates. We rely on MODIS land cover and fire data, (Channan, Collins, and Emanuel (2014) and Giglio and Justice (2015)). Channan et al. (2014) is annual gridded data with about 5 km^2 resolution. Each cell it reports one of several land cover classifications, among them, crops and barren. We reprocess these data into our standard grid.[6] MODIS fire data are more complicated. MODIS reports measures of fires at approximately two week intervals for 250m^2 cells. To aggregate to our larger cells and longer periods, we calculate the share of 250m^2 pixel days of fire occur in each of our larger and less frequently observed cells. This is our MODIS fire index.

[5] Classification of urban versus rural use in gridded data is a difficult problem and is the subject of active research, e.g. de Bellefon, Coombs, Duranton, and Gobillion (2018). We do not seek to contribute to this literature, but do require a classification of our grid cells into rural and urban.

[6] The MODIS land cover data also report an 'urban' land use code. We experimented with using this code to indicate urban areas. We found that it was less related to population density than our current method. We also investigated changes in the MODIS urban code to track construction, a likely source of particulates. We concluded that the data are too noisy to be informative about new building.

Table 3: Explanatory power of country and year indicators

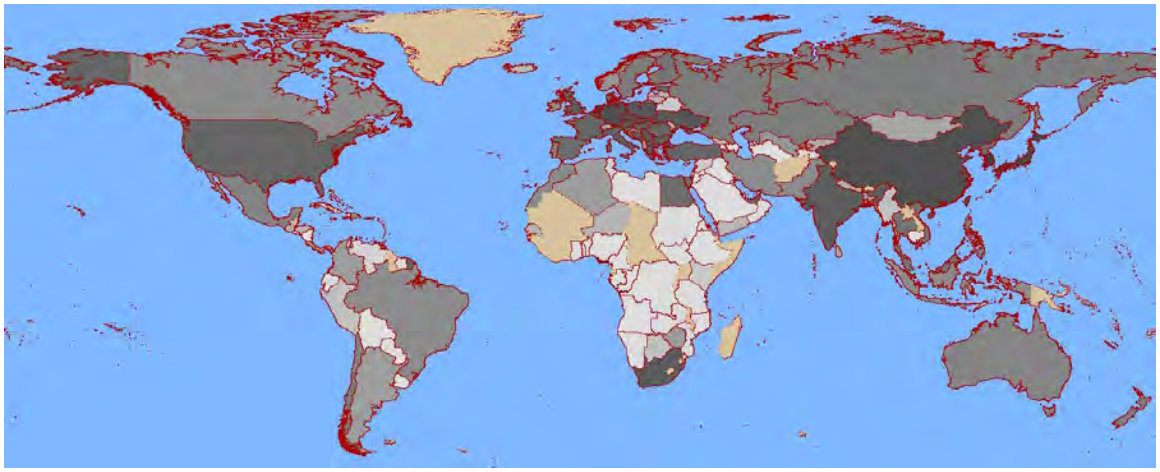
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country FE	Y	.	.	.	Y	.	.
Year FE	.	Y	.	.	.	Y	.
Country × Year FE	.	.	Y	.	.	.	Y
Climate	.	.	.	Y	Y	Y	Y
233 countries:							
N	604809	604809	604809	604012	604012	604012	604012
R^2(Area weighted)	0.388	0.009	0.428	0.178	0.475	0.186	0.512
R^2(Population weighted)	0.485	0.009	0.523	0.131	0.562	0.137	0.595
63 countries:							
N	422377	422377	422377	421860	421860	421860	421860
R^2(Area weighted)	0.298	0.011	0.342	0.115	0.407	0.125	0.447
R^2(Population weighted)	0.467	0.013	0.506	.121	0.553	0.129	0.585

Cross-border flows: It is also natural to suspect that cross-border flows are, at least sometimes, important sources or sinks for particulates. To measure such flows, at the country-year level, we must measure pixel level mean annual wind. To accomplish this, we rely on Wentz, Scott, Hoffman, Leidner, Atlas, and Ardizzone (2015). These are monthly data describing mean wind speed for a 0.25 degree grid. We aggregate to years and reprocess to match our somewhat finer analysis grid. We are left with two grids describing wind speed. One gives mean wind velocity North to South, and the other East to West. Flows to the North and East are positive, and conversely. This together with our AOD data allows us to calculate the aggregate flow across any border in our data (kt/year). The details of this calculation are left for an appendix.

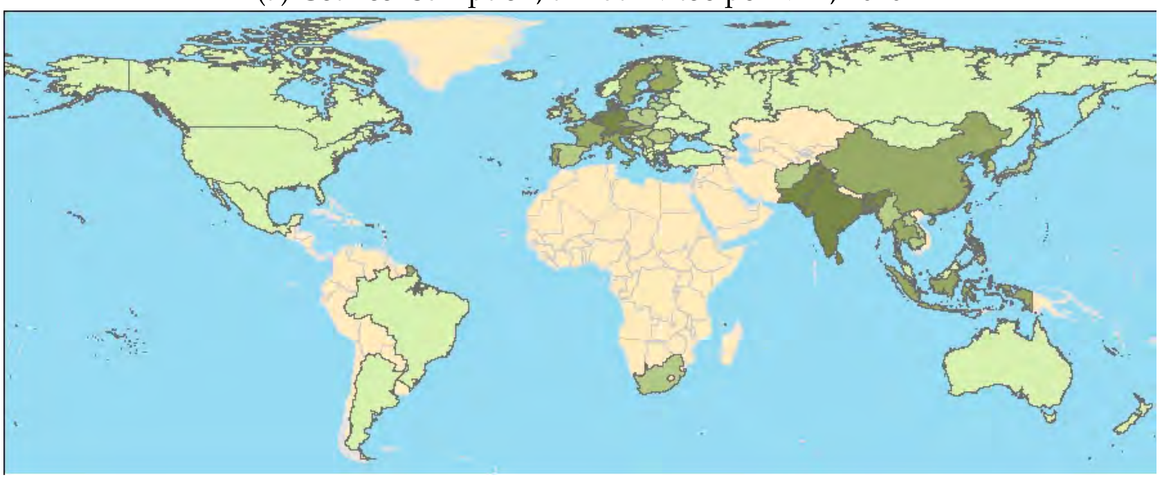
Using our definition of urban and rural areas, we calculate all cross-border flows at the level of the country-region. Figure 4 (b) illustrates these flows for 2010. We represent cross-border flows, not by their total mass, but by their capacity to contribute to concentration. That is, we divide by the volume air in which they disperse, the country-region's area times its mixing height. We can find no systematic evidence about cross country or region differences in mean annual mixing height and so we fix this quantity across countries.

In figure 4 (b), bright red to white country-regions are net exporters of airborne particulates, light to dark gray country-regions are net importers. Most countries, particularly those with long seacoasts, are net exporters. Central Africa is known for both dust storms and agricultural burning, and a handful of these countries are importers. China's southern neighbors are net importers, as are Brazil's southern neighbors. Looking closely at the figure suggests that many European cities export pollution to the surrounding regions.

Figure 3: Coal and organic fuel use per square km, 2010



(a) Coal consumption, annual Mtoe per km^2, 2010



(b) Organic fuel consumption, annual PJ per km^3, 2010

5. Descriptive and reduced form results

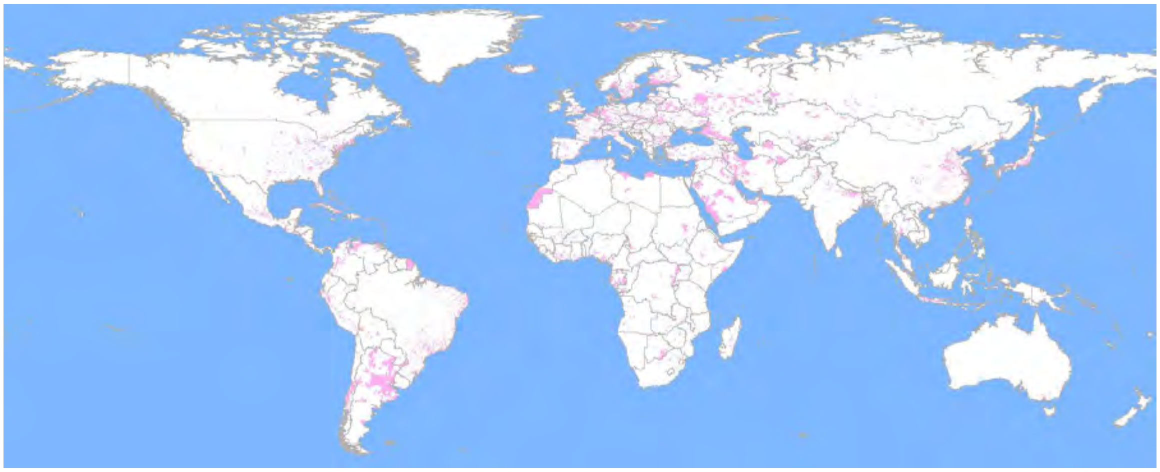
We now turn attention to the equilibrium relationship between concentration, exposure, and sources of particulates. We begin by investigating the importance of country and year level variation in our four year panel of pixels. Table 3 presents the results of a series of regressions of pixel-year level regressions on various indicators and climate controls.

Column 1 of this table presents the results of four regressions of pixel level AOD on Country fixed effects in a 10% sample of pixels. Moving down the column, we first report the number of cell-years in a sample of 233 countries. The is the largest sample we can easily use for our analysis, and reflects all countries that are 'large enough' that they are visible in our 10km^2 grid.[7]

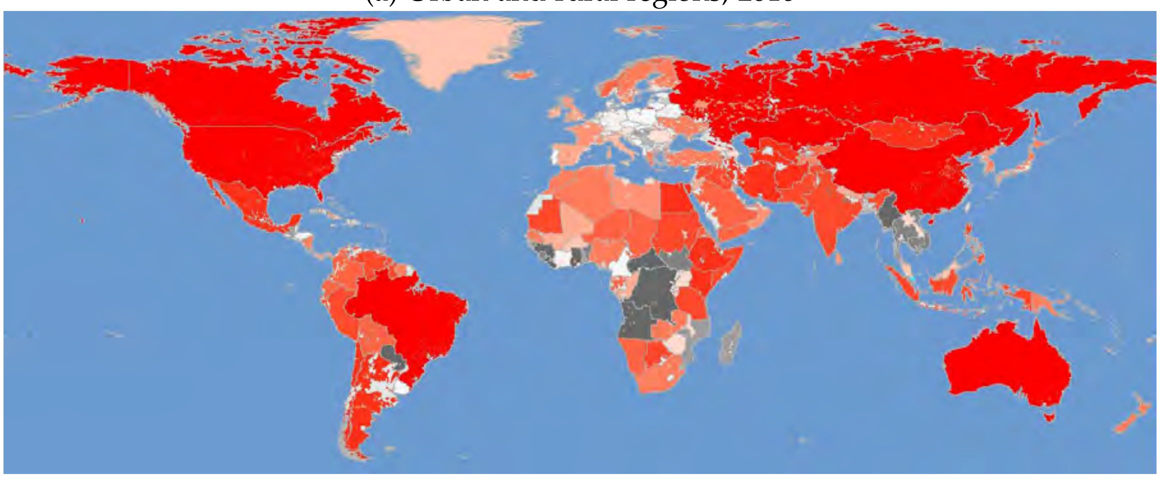
In the next row, we report the R^2 of this regression, 0.39. That is, by including only country level indicators variables, we explain 39% of total variation in pixel level AOD over 2000, 2005,

[7]Strictly, a country drops out of our data set if it does not contain the centroid of one of our 10km^2 cells. In this case, the country drops out of our data set. This occurs to the Vatican, for example.

Figure 4: Urban regions and cross-border flows per sq km, 2010



(a) Urban and rural regions, 2010



(b) Net Flows, annual KT per km^3, 2010

2010 and 2015. At first glance, this seems surprising. Very small particles aside, particulates fall out of the air in days to weeks, and consequently tend not to travel very far. There is a large literature reporting the rate at which particulate concentrations decay as a function of meters from a source, e.g., Cho, Tong, McGee, Baldauf, Krantz, and Gilmour (2009) . Given this prior, the fact that country level variation has so much ability to predict concentration is unexpected. However, reviewing figure 2 (a), it is much less surprising. There are obvious differences in the particulates concentration across Russia, India and China. Our fixed effect regression simply confirms the generality of this phenomena.

The next row of column 1 reports the R^2 of the same regression where cells are weighted by their population rather than their area. Thus, we are explaining the exposure of an average person rather than an average pixel. We explain 47% of the variation in exposure in this regression. That is, knowing only country of residence, it is possible to reduce mean square prediction error for individual exposure almost in half. This is slightly better than is possible predicting concentration. We suspect that this reflects the fact that people are concentrated in a small fraction

Table 4: Population weighted regressions of AOD on pixel-year level sources, country-year indicators and climate. 63 countries, 2000, 2005, 2010, 2015.

	(1)	(2)	(3)	(4)	(5)	(6)
Density	0.00000709***					0.00000771***
	(0.00000139)					(0.00000141)
Urban		0.0925***				0.0772***
		(0.00352)				(0.00356)
Crops			0.000248***			0.000374***
			(0.0000158)			(0.0000100)
Barren				0.00127***		0.00176***
				(0.000215)		(0.000214)
Fire					0.000469	0.000426
					(0.000243)	(0.000256)
N	421741	421860	421860	421860	421860	421741
R^2	0.596	0.613	0.601	0.588	0.585	0.648

Standard errors in parentheses
Controls for country-year fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of the area, and so there is less overall variation in exposure than in concentration.

Moving down column 1, we restrict attention to the sample of countries for which we will ultimately be able to calibrate our model. This sample consists of about 2/3 as many pixels as the full sample. The next two rows present the R^2 of area weighted and population weighted regressions of pixel level AOD on country indicators. As we saw in the full sample, the R^2s are high and are somewhat higher when predicting exposure than when predicting concentration.

Column 2 parallels column 1, but estimates the effect of indicators for the four panel years, 2000, 05, 10, 15. These have relatively little ability to predict either concentration or exposure. However, like the country indicators, they are a little better at predicting exposure than concentration. Column 3 includes indicator variables for each country-year pair. These regressions have only marginally more predictive power than country variables alone. Columns 1-3 suggest that country level factors are important for determining exposure.

Given the importance of climate in the measurement and physics of particulate concentration, we would like to establish that this does not simply reflect country specific climate. Column 7 of table 3 reports a regression, like those in columns 1-3, but where the control variables are our four pixel-year level climate variables. We see that the R^2s in these regressions are about 0.2, across the two specifications and samples. Climate is important.

Columns 4-6 of table 3 replicate columns 1-3, but add our four pixel-year level climate controls. We see that these regressions have higher R^2s than either the corresponding regressions without climate controls. They also have dramatically higher R^2s than the climate only specification in column 7. Thus, climate is important, but country level factors are important independent of climate, and indeed, country level indicators have greater ability to explain variation in

Table 5: Population weighted regressions of AOD on country-year level sources, *without* country-year indicators or climate. 63 countries, 2000, 2005, 2010, 2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Green/km^3	-127***										166***
	(7.3)										(23)
Coal/km^3		296***									300***
		(10)									(14)
Oil/km^3			-42***								-111***
			(2.9)								(9.4)
Ag burn/km^3				3042***							586***
				(106)							(113)
Biomass/km^3					50***						.15
					(1.1)						(1.7)
Urb. share						-.005***					-.002***
						(8.2e-05)					(1.9e-04)
Srv GDP/km^3							-.008***				-.02***
							(3.7e-04)				(.002)
Ind GDP/km^3								.01***			38***
								(.0011)			(.0062)
Ag GDP/km^3									.52***		.24***
									(.008)		(.01)
Flow-/km^3										-178***	-3.9
										(6.7)	(10)
Flow+/km^3										160***	4.3
										(5.9)	(9.9)
R^2	0.01	0.11	0.01	0.19	0.14	0.19	0.02	0.00	0.26	0.04	0.40

Notes: Col (1-5) $N = 422377$, Col (6-13) $N = 422345$. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

concentration and exposure that do climate measures that vary at the pixel-year level.

In sum, these results suggest that world trends are not a first order driver for understanding particulates over the course of our sample period, that country level variation is surprisingly important for understanding concentration, and even more so for exposure. Finally, country effects are fairly stable across the four periods of our data and do not simply reflect country level climate.

We see in table 3 that country level variation can explain close to half of all variation in exposure. We now investigate the extent to which additional pixel level variation is important for exposure.

Table 4 repeats variants of the population weighted regression of column 6 of table 3 on the main sample, where we add pixel-year level covariates. Sample sizes in table 4 are slightly smaller than in table 3 because of missing values for pixel level variables.

Column 1 estimates the effect of pixel-year population density on exposure. Unsurprisingly, people who live in denser places experience higher particulate exposure. Increasing the population of a 10km^2 cell by 100,000 people increases expected exposure by about 0.7 AOD points. Converting to PM10, this is about 70 μg/m^2, the difference between a clean coastal city in the developed world and a large Chinese city. While this response seems large, it improves our ability to predict exposure only slightly. The R^2 in this regression is only marginally higher than column 6 of table 3.

The second column of table 3 includes our pixel level urban indicator (illustrated in figure 4) instead of density. On average people living in urban pixels are exposed to about 0.1 extra AOD points, about 10μg/m^2 PM10. This indicator variable is also highly significant.

Unsurprisingly, like population density, urban status does little to improve our ability to predict exposure. However, the indicator variable reduces our prediction error by more than does the linear term in density. As a first approximation, the step function in density implied by the indicator variable is a better predictor of AOD than a linear term. The geography of our model is partly motivated by this finding. In our model, each country is divided into rural and urban regions.

Columns 3 and 4 include remotely-sensed measures of land cover, share in crops and share barren. Both are sources of dust, and unsurprisingly, contribute to exposure. These results indicate the importance of natural sources to exposure. Exposure is not purely anthropogenic. Physical geography plays a role.

Finally, column 5 includes our remotely-sensed measure of fire intensity in the pixel. This coefficient is not measurably different from zero. This is explained by the physical geography of smoke dispersion. The smoke plume from wildfires and agricultural burning most often spreads out over much larger areas than one of our 10km^2 pixels (Miller, Molitor, and Zou, 2017).

Table 4 column 6 replicates the regression of table 3 column 6, but includes all five of our pixel year level variables. Individual variable coefficients are qualitatively unchanged. Most interestingly, the R^2 of this regression is only 0.65, versus about 0.59 for the regression including only country-year indicators and climate variables. That is, even high quality, spatially disaggregated measures of particulate sources have little ability to improve our ability to predict exposure, once we know country of residence.

We next ask the extent to which country-year level variation in exposure can be attributed to country-year level variation in economic fundamentals. In table 5, we present pixel level regressions of AOD on variables that vary only at the level of the country-year. These regressions are population weighted, and so measure the ability of particular country-year level variables to predict exposure.

Columns 1-3 include measures of fossil fuel use; natural gas and renewables, coal, and petroleum per square kilometer of country area. Holding mixing height constant these variables will be proportional to consumption per unit of country mixing volume. Since the physical process that determines concentration depends on contributions to particulate mass per unit volume, not country level particulate mass, these normalized variables are more relevant to an investigation of concentration and exposure than are country level aggregates.

That the sign on gas is negative points to an inference problem that helps to motivate our model. While natural gas and renewable power generation may cause essentially zero particulate emissions, all else equal, they do not reduce concentration. More likely, countries that rely more heavily on gas and renewables also rely less heavily on dirtier power sources. That is, this regression describes an equilibrium relationship, not a narrowly causal one. Isolating causal relationships requires either a research design that isolates variation in, e.g., natural gas and renewable power reliance, or the development of model in which the importance of different sorts of linkages and adjustment mechanisms can be assessed.

Column 2 estimates the relationship between coal and exposure. Remarkably, county-year level coal consumption has an R^2 of 0.21. Country-year level oil consumption is positively related to equilibrium exposure, but like clean power, it has little predictive ability.

Columns 4 and 5 look at the effect of organic fuel consumption and agricultural burning per square km. These variables have the expected positive signs and even more ability to predict exposure than coal consumption.

Column 6 estimates the effect of the share of a country's area that is urban on particulate exposure. Consistent with what we saw in figure 1, urbanization is strongly predictive of exposure. This variable alone has an R^2 higher than that of coal. However, the sign on this variable is negative, contrary to what we saw in table 4. Taken together, this result and that of table 4 strongly suggest the importance of urbanization as a determinant of equilibrium levels of exposure, but also suggest the importance of a model or quasi-random variation in urbanization to an estimate of a causal relationship.

Columns 7-9 examine the role of GDP in services, industry and agriculture, also per unit of area, on exposure. Production in services has little ability to predict exposure. Countries that produce more agricultural and industrial products have greater particulate exposure, although only agricultural GDP has much ability to predict exposure.

Column 10 estimates the effect of mass per square kilometer of cross-border flows in an out of each country. As expected, flows in increase exposure and conversely for flows out. These two variables have an R^2 of 0.04.

Finally, column 11 conducts a regression including all of these country-year level regressors. Two features of this regressions are noteworthy. First is the relative stability of coefficient estimates. With the exception of natural gas and green power generation, none of the coefficients change signs relative to the regression where the relevant regressor appears alone. Second, the R^2 of this regression is 0.40. In contrast, the R^2 in column 3 of table 3 (the comparable specification) is

0.51. That is, this relatively short list of likely suspects explains most of the variation in exposure that can be explained by factors that vary at the country-year level.

Our results so far suggest the following stylized facts about equilibrium exposure.

1. Exposure is substantially determined by country level factors. The importance of these factors is stable over time and substantially independent of climate.

2. Variation in exposure that is not explained by country-year factors is also not explained by a number of likely candidates that we measure at the pixel-year level. That is, given our data, variation not determined by country-year level factors is essentially random, and in particular, is not explained by spatially disaggregated economic fundamentals.

3. Nearly all country-year level variation in exposure can be explained by a short list of economic fundamentals that vary at the country-year level.

These results contradict our prior that patterns of exposure would be dominated by fine scale spatial variation in emissions and concentration. We conjecture that our results reflects the fact that we consider annual averages over large areas. Particulates move with the wind, and so a local spike in daily concentration may look quite smooth in a yearly average over 10km^2 square cells. These results also indicate the importance of national level particulates policy.

Our results clearly describe equilibrium behavior, not causal comparative statics. Countries that rely more heavily on natural gas and renewables, all else equal, probably do not have cleaner air. More likely, countries that rely on cleaner sources of power also rely less on dirtier sources and take other actions to reduce emissions. In addition, the geography of exposure matters. India's exposure is dramatically lower than China's despite similar mean concentrations. A more thorough understanding of equilibrium exposure requires either a research design that isolates variation in, e.g., natural gas and renewable power reliance, or the construction of a model in which the importance of different sorts of linkages and adjustment mechanisms can be assessed. While both approaches have merit, we here pursue the second approach.

Our primary goal for our model is to evaluate two classes of comparative statics: those that relate particulates policies to outcomes of immediate interest, exposure and welfare; and those that relate particulates policies to unintended consequences such as migration across regions or sectors. Both are of intrinsic and policy interest. Our investigation of unintended consequence should also inform future research on particulates policy. If the primary mechanism for adjusting to particulates policy is migration, then the implications of purely econometric studies of particulates policy are quite different than if adjustment to particulates policy is primarily through goods and factor prices.

6. Model

This section presents the structure of our *Spatial Equilibrium Particulates Integrated Assessment* (SEPIA) model. The model treats each country as a small, open economy inhabited by a continuum of households. For legibility, our exposition omits both country and year subscripts. Each country contains two regions, urban (indexed by u) and rural (indexed by a). There are four sectors of production, as summarized in Table 6. The remainder of this section proceeds by

Table 6: SEPIA Sectors

Sector	Location(s)	Tradeable?	Inputs
Industry (I)	Urban and Rural	Yes	Capital, Labor, Energy
Services (S)	Urban	No	Capital, Labor, Energy
Agriculture (M)	Rural	Yes	Capital, Labor, Energy
Energy Services ($J^j \in I,S,M$)	Urban and Rural	No	Coal, Oil, Gas/Green

describing (i) production, (ii) households, (iii) government, (iv) the pollution model, and, finally (v) competitive equilibrium.

A *Production*

Industry

Industrial output $Y^{I,k}$ in each location $k \in \{u,a\}$ is produced using capital $K^{I,k}$, labor $L^{I,k}$, and composite energy $J^{I,k}$. This energy good, in turn, is produced using coal $E_c^{I,k}$, petroleum $E_p^{I,k}$ and clean (chiefly natural gas) $E_g^{I,k}$ resource inputs. Our benchmark setup adopts standard technology specifications (following, e.g., Golosov et al. (2014)):

$$Y^{I,k} = A^{I,k}(K^{I,k})^{\alpha}(L^{I,k})^{1-\alpha-v^I}\left(J^{I,k}\right)^{v^I} \tag{1}$$

$$J^{I,k} \equiv \left(\kappa_c^I(E_c^{I,k})^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_p^I(E_p)^{I,k})^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_g^I(E_g^{I,k})^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{2}$$

Competitive producers rent capital from international markets at price R^*, hire labor at their respective local wage w^k, and purchase energy services at price $p^{I,k}$. The energy producers, in turn, import fuels at given prices (p_c^*, p_p^*, p_g^*). Fuels may further be subject to sector- and/or region-specific excise taxes $\tau_c^{I,k}$, $\tau_p^{I,k}$, and $\tau_g^{I,k}$. Industrial output serves as the numeraire good.

Services

Production of services Y^S is analogous to industry, although we allow several of the production parameters to vary across sectors. This flexibility allows the model to reflect, for example, the relatively higher importance of petroleum in services (e.g., transportation) and coal in industry.

$$Y^S = A^S(K^S)^{\alpha}(L^S)^{1-\alpha-v^S}\left(J^S\right)^{v^S} \tag{3}$$

$$J^S \equiv \left(\kappa_c^S(E_c^S)^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_p^S(E_p^S)^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_g^S(E_g^S)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{4}$$

Services are not tradable and their price p^S is thus domestically determined.

Agriculture

Agricultural production Y^M differs from the other sectors in two key respects. First, we assume decreasing returns to scale to reflect unmodeled land inputs. Second, we explicitly model agricultural waste burning B and the additional labor cost θ_B required to avoid fires:

$$Y^M = A^M [L^M (1 - \theta_B)]^{\rho_L^M} (K^M)^{\rho_K^M} (J^M)^{\rho_J^M} \tag{5}$$

with $\rho_L^M + \rho_K^M + \rho_J^M < 1$. As is common, we assume that agricultural land rents $\pi^M \equiv ((1 - \rho_L^M - \rho_K^M - \rho_J^M) p^{M^*} Y^M)$ are paid to absentee landlords abroad. Letting ζ denote the country's baseline agricultural burning intensity, agricultural burning B net of abatement is then given by:

$$B = \zeta \cdot Y^M \cdot (1 - (\nu_1 \theta_B)^{\nu_2}) \tag{6}$$

Farmers may be subject to an excise tax τ_B on burning. Otherwise, the sector is analogous to services and industry: Competitive producers hire workers in the rural labor market, rent capital from abroad, and obtain energy services based on an aggregator:

$$J^M \equiv \left(\kappa_c^M (E_c^M)^{\frac{\varepsilon - 1}{\varepsilon}} + \kappa_p^M (E_p^M)^{\frac{\varepsilon - 1}{\varepsilon}} + \kappa_g^M (E_g^M)^{\frac{\varepsilon - 1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon - 1}} \tag{7}$$

where agricultural energy inputs may be subject to excise taxes (τ_c^M, τ_p^M, and τ_g^M). Agricultural output is tradeable at international price p^{M^*}. As is conventional, we denote exogenous world prices with at '$*$' superscript.

Emissions

Each of the sectors in the model economy can produce particulate emissions from several sources. Let ξ^m denote the particulate emissions intensity of activity m. Industrial particulate emissions in each location $k \in \{s,r\}$ stem from three sources: (i) coal combustion $\xi^c E_c^{I,k}$, (ii) petroleum combustion $\xi^p E_p^{I,k}$, and (iii) process emissions (e.g., such as from iron and steel production) which we model as a by-product via $\xi^I Y^{I,k}$. Analogously, the services sector may contribute to urban particulate emissions through (i) coal combustion $\xi^c E_c^S$, (ii) petroleum combustion $\xi^p E_p^S$, and (iii) process emissions $\xi^S Y_S$, which here reflect non-exhaust transport emissions (e.g., road dust suspension). Finally, there are four sources of particulate emissions in the agricultural sector: (i) coal combustion $\xi^c E_c^M$, (ii) petroleum combustion $\xi^p E_p^M$, (iii) waste burning $\xi^B B$, and process emissions $\xi^M Y^M$, which reflect sources such as fertilizer usage.

Total endogenous particulate emissions $Emiss_k$ in each region are thus as follows:

$$Emiss^u \equiv \xi^c [E_c^S + E_c^{I,u}] + \xi^p [E_p^S + E_p^{I,u}] + \xi^S Y^S + \xi^I Y^{I,u} \tag{8}$$

$$Emiss^a \equiv \xi^c [E_c^M + E_c^{I,a}] + \xi^p [E_p^M + E_p^{I,a}] + \xi^M Y^M + \xi^I Y^{I,a} + \xi^B B \tag{9}$$

B *Households*

The economy is populated by a continuum of households indexed by i. Households choose where to live and work based on their preferences over consumption, pollution (AOD), and an idiosyncratic net amenity value of living in the rural area ϵ_i. Intuitively, this value reflects unobserved factors such as rural risk sharing networks. Our benchmark specification models ϵ_i as following a generalized extreme value distribution, in line with standard approaches (e.g., Heblich, Redding, and Sturm (2018)). Letting c^j denote urban and x^j rural consumption of goods $j = I,S,M$, respectively, utility is CES over the aggregate consumption bundle, which, in turn, is a Cobb-Douglas composite of the different consumption goods:

$$V^a(x^I,x^M,x^s,AOD^a,\epsilon_i) \;=\; \frac{\widetilde{x}^{1-\sigma}}{1-\sigma} - \chi_1(AOD^a)^{\chi_2} + \epsilon_i \tag{10}$$

$$\widetilde{x} \;\equiv\; (x^I)^{\theta^I}(x^S)^{\theta_S}(x^M)^{1-\theta^I-\theta^S} \tag{11}$$

$$V^u(c^I,c^M,c^S,AOD^u) \;=\; \frac{\widetilde{c}^{1-\sigma}}{1-\sigma} - \chi_1(AOD^u)^{\chi_2} \tag{12}$$

$$\widetilde{c} \;\equiv\; (c^S)^{\theta^S}(c^I)^{\theta_I}(c^M)^{1-\theta^I-\theta^S} \tag{13}$$

Agents supply one unit of labor inelastically wherever they live, earning w^u in the urban area or w^a in the rural area. In addition, households may receive lump-sum transfers T from the government. We abstract from consumers' savings and investment decisions. The annual budget constraints for households in each region are thus respectively given by:

$$c^I + p^S c^S + p^{M^*} c^M \leq w^u + T \tag{14}$$

$$x^I + p^S x^S + p^{M^*} x^M \leq w^a + T \tag{15}$$

Since the manufactured good is the numeraire in both regions, we are implicitly assuming that trade in this good across the two regions is costless.

Free mobility implies that a marginal agent will be just indifferent between living in the urban or rural area. Their cutoff amenity value ϵ^* is thus defined by the condition:

$$\epsilon^* = \{\frac{\widetilde{c}^{1-\sigma}}{1-\sigma} - \chi_1(AOD^u)^{\chi_2}\} - \{\frac{\widetilde{x}^{1-\sigma}}{1-\sigma} - \chi_1(AOD^a)^{\chi_2}\} \tag{16}$$

C *Government*

Our benchmark analysis considers the equilibrium impacts of a select set of policy instruments: energy input taxes and agricultural burning taxes. Government revenues from these levies G is either discarded or re-distributed to households via lump-sum transfers T. We thus abstract from broader fiscal policy and posit a simple public budget constraint:

$$G = \tau_B B + \sum_j\sum_k \tau_c^{j,k} E_c^{i,k} + \sum_j\sum_k \tau_p^{j,k} E_p^{i,k} + \sum_j\sum_k \tau_g^{j,k} E_g^{i,k},\ j \in \{I,S,M\},\ k \in \{u,a\} \tag{17}$$

$$T \leq G$$

D *Pollution Model*

In order to describe the way that particulates are transported across boundaries, we present a 'two box diffusion model', a slight generalization of one of the most elementary particulate transport models.[8] We note that detailed pollution dispersion models have been developed for both regulatory and research purposes (e.g., EPA (2017)). However, these models are typically designed for the analysis of specific sources' impacts at fine spatial and temporal scales. The goals of this paper, in contrast, are (i) to study pollution movement and concentration changes over large spatial (two regions per country) and temporal (annual) scales, and (ii) to integrate a representation of these processes with a macroeconomic model. These considerations favor our approach. We further note that such stylized box-diffusion models are commonly used in the integrated assessment literature to describe, e.g., the global carbon cycle (e.g., Nordhaus (2017)).

In our model, there are three regions, a box for the rural region, a box for the urban region, and the rest of the world. Particulates in the rest of the world are taken as exogenous and constant. The model's four main assumptions are: particulates are uniformly dispersed within each box; the mass of particulates is conserved; the system is in steady state; and finally, the deposition rate of particulates in each box is proportional to the total mass in the box.[9]

Up until now, we have partitioned the world into 'rural', 'urban' and 'the rest of the world'. For the purpose of describing particulate transport this is not helpful. Instead, we consider a sending region and a receiving region, where the sending region is a net exporter of particulates to the receiver, and the rest of the world. Index these regions by $k \in \{s,r,w\}$. Later, we assign either the rural or the urban region to the sender role and the other to the receiver role in each country, as described in Section 7.

Figure 5 illustrates the main features of the model. Each region $k \in \{s,r\}$ contains emissions sources that produce mass F^{kk} of particulates per unit of time (e.g., kg per year). Each region also receives a flow of particulates from the world, F^{wk}, and sends a flow of particulates to the rest of the world, F^{kw}. The sending region also sends F^{sr} to the receiver. Deposition, or 'flow into the ground', occurs in each region and is denoted D^k.

In any steady state, the conservation of mass requires that the following two conditions hold,

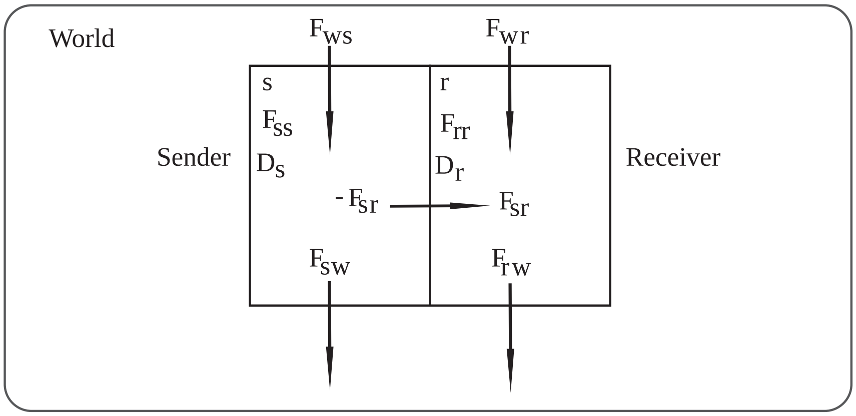
$$
\begin{aligned}
0 &= F^{ss} - D^s + F^{ws} - F^{sw} - F^{sr} \\
0 &= F^{rr} - D^r + F^{wr} - F^{rw} + F^{sr}.
\end{aligned} \tag{18}
$$

The first of these two equations gives a mass balance condition for the sending region, and the second for the receiving region. The two conditions are symmetric except for the treatment of

[8] For example, Jacob (1999b).

[9] Perfect dispersion within each box is a simplifying assumption and without this assumption the problem rapidly becomes intractable. The conservation of the mass of particulates is a basic physical principle and requires that particulates in each box reflect the net of sources, flows in, deposition, and flows out. Our focus on steady state equilibrium is also a simplifying assumption, but one that appears well grounded. We are interested in annual averages, while the deposition, flow and production of particulates operates over much shorter time scales.

Figure 5: A Two-Box model of particulate concentration



Note:

flows from s to r. In steady state, the sum of flows in and internal sources must equal the sum of deposition and flows out.

We next describe each of the elements in (18) and use these conditions to derive expressions for steady-state AOD concentrations in each region as a function of emissions. To proceed, for $k,k' \in \{s,r,w\}$, we introduce the following notation,

$$\begin{aligned}
l^{kk'} &\sim \text{length of border over which wind blows from } k \text{ to } k' \text{ (km) for } k,k' \in \{s,r,w\} \\
v^{kk'} &\sim \text{mean annual wind velocity across-border between } k \text{ and } k' \text{ (km/year) for } k,k' \in \{s,r,w\} \\
\text{AOD}_k &\sim \text{AOD in region } k \text{ for } k,k' \in \{s,r,w\} \\
A^k &\sim \text{Area of region } k \in \{s,r\} (\text{km}^2) \\
Emiss^k &\sim \text{particulate emissions in region } k \in \{s,r\} \text{ (kg/year) from modeled economic activities} \\
Emiss^k_{EX} &\sim \text{particulate emissions in region } k \in \{s,r\} \text{ (kg/year) from unobserved sources such as dust} \\
\lambda &\sim \text{mixing height (km)} \\
\rho &\sim \text{AOD to PM10 conversion factor (kg/km}^3 \text{ per AOD unit)}
\end{aligned}$$

We note that $Emiss^k$ are, in fact, exactly the quantities defined in equations 9 and 9. However, we here index anthropogenic emissions by their sender/receiver status when we earlier indexed them by whether they described rural or urban regions. In fact, we are describing two distinct economic models, one in which the sending region is urban and another in which it is rural. In our calibrations, we will choose between these two models on the basis of the case that obtains for each particular country.

Given this notation, we can describe the elements in (18) as follows. First, the flow into and out of each region $F_{kk'}$ is the product of the concentration of particulates in the source region times the volume of air that crosses from the source into the sink region. For $k,k' \in \{w,s,r\}$ and

$k \neq k'$, we have

$$F^{kk'} = v^{kk'}\lambda l^{kk'}\rho \text{AOD}^k. \tag{19}$$

The first three terms calculate the volume of air crossing the kk' border, and the last two terms give the upwind concentration of PM10. The product of volume and concentration is the mass of particulates transported from k to k'.

Next, given area, A_k, the AOD to PM10 conversion factor, ρ, and the deposition velocity, v^D, deposition is given by:

$$D^k = v_D^k A^k \rho \text{AOD}^k, \tag{20}$$

for $k \in \{s,r\}$. This expression resembles the expression for flow across a border, except that it describes flow into the ground. The difference is that flow across the border reflects flow across the area λl^{kw} at velocity v^{kw}, while deposition reflects flow into land area A^k at velocity v_D.

Finally, approximate emissions in each region are given by:

$$\begin{aligned} F^{ss} &= Emiss^s + Emiss^s_{EX} \\ F^{rr} &= Emiss^r + Emiss^r_{EX} \end{aligned} \tag{21}$$

Finally, substituting (19)-(21) into (18) and rearranging yields intuitive expressions for equilibrium AOD concentrations in each region:

$$\begin{aligned} AOD^s(Emiss^s) &= \frac{v^{ws}\lambda l^{ws}\rho AOD^w + Emiss^s_{EX}}{\rho\left[v^s_D A^s + \lambda(v^{sw}l^{sw} + v^{sr}l^{sr})\right]} + \frac{Emiss^s}{\rho\left[v^s_D A^s + \lambda(v^{sw}l^{sw} + v^{sr}l^{sr})\right]} \\ AOD^r(Emiss^s,Emiss^r) &= \frac{v^{wr}\lambda l^{wr}\rho AOD^w + Emiss^r_{EX}}{\rho(v^r_D A^r + v^{rw}\lambda l^{rw})} + \frac{Emiss^r}{\rho(v^r_D A^r + v^{rw}\lambda l^{rw})} \\ &\quad + \frac{v^{sr}\lambda l^{sr}}{v^r_D A^r + v^{rw}\lambda l^{rw}} AOD^s(Emiss^s). \end{aligned} \tag{22}$$

E *Competitive Equilibrium*

Competitive equilibrium in each time period consists of an allocation $\{L^{I,u},L^{I,a},L^S,L^M;\ K^{I,u},K^{I,a},K^S,K^M;\ J^{I,u},J^{I,a},J^S,J^M;\ E^{I,u}_c,E^{I,u}_p,E^{I,u}_g,\ E^{I,a}_c,E^{I,a}_p,E^{I,a}_g,\ E^S_c,E^S_p,E^S_g,\ E^M_c,E^M_p,E^M_g;\ x^I,x^M,x^S;\ c^I,c^M,c^S;\ B,\theta_B,AOD^u,AOD^a\}$ a set of prices $\{p^S,p^{I,u}_J,p^{I,a}_J,p^S_J,p^M_J;\ w^u,w^a\}$ and policies $\{\tau^{j,k}_c,\tau^{j,k}_p,\tau^{j,k}_g,\tau_B,T$ for $j \in \{I,S,M\}$, $k \in \{u,a\}\}$ such that:

1. Profits are maximized in each sector given prices and policies;

2. Household utility is maximized in each location given prices and policies;

3. Markets clear in the domestic services sector:

$$Y^S = L^u \cdot c^S + L^a \cdot x^S \tag{23}$$

4. The national budget constraint is satisfied:

$$L^a(x^I + p^{M^*}x^M) + L^u(c^I + p^{M^*}c^M) + p_c^*\sum_j\{E_c^j\} + p_p^*\sum_j\{E_p^j\} + p_g^*\sum_j\{E_g^j\}$$
$$+ R^*(K^{I,u} + K^{I,a} + K^S + K^M) + \pi^M + (G - T) \leq Y^{I,u} + Y^{I,a} + p^{M^*}Y^M \quad (24)$$

5. AOD concentrations obey the laws of nature (22).

A detailed listing of the underlying optimality and equilibrium conditions is provided in the Appendix.

7. Calibration

The calibration proceeds in three steps. First, we set certain parameters based on the literature or standard assumptions at common values for all countries ("Directly Calibrated"). Second, we back out certain parameter values directly from data for each country ("Directly from Data"). Third, we select the remaining model parameters to jointly minimize the sum of squared differences between equilibrium moments as observed in the data and our model ("Matching Moments"). Here we provide an intuitive overview of the key data sources and moments, and delve into details only for some of the more challenging and interesting model parameters. The remaining details of the calibration are presented in the Appendix.

Production and Energy: For each country-year, we observe sectoral output values. Using a tilde to distinguish between values and real quantities, we have ($\widetilde{Y^I} \equiv Y^I$, $\widetilde{Y^M} \equiv p^{M^*}Y^M$, $\widetilde{Y^S} \equiv p^S Y^S$) directly from the World Bank, the initial distribution of labor across urban and rural areas from GPW, and obtain energy inputs at the fuel-sector level (e.g., petroleum used in agriculture E_p^M) from the International Energy Agency (IEA). For energy production, the fuel share parameters in each sector (e.g., κ_p^M) can then be inferred directly from optimality conditions (28)-(29) given data on fuel prices (which we obtain from the British Petroleum Company (2016)) and substitution elasticities (ε) (calibrated based on prior literature, see Appendix for details). For sectoral production, backing out productivity parameters requires us to solve for the full initial equilibrium so as to obtain unobserved prices (such as rural and urban wages) and infer the initial distribution of industrial production in urban and rural areas. Intuitively, we use the initial observed distribution of the population across regions, along with observed regional AOD concentrations, aggregate data moments (e.g., total industrial output), and our model equilibrium conditions to infer this distribution via joint matching of moments (see Appendix for details).

Households: Preferences over consumption goods are country specific and are estimated from both World Bank data on sectoral household expenditures (2010) and services sector output shares. The calibration of preferences over AOD and rural living is more challenging. The benchmark calibration sets pollution disutility level parameter χ_1 to match novel estimates of household willingness to pay (WTP) for particulates pollution reductions by Ito and Zhang (2019). They estimate a mean WTP of USD 5.46 per $\mu g/m^3$ PM10 reduction for households in China with an annual income of $2,253 who experience mean winter PM10 concentrations of 115 $\mu g/m^3$. We assume a quadratic pollution disutility curvature (χ_2=2) and set χ_1 to match this WTP estimate given each country's relevant preference and price parameters.[10]

Given these preference parameters, we can then infer rural amenity value ϵ^* for the marginal agent in equilibrium by using the free mobility condition (16). Our generalized extreme value distribution assumption necessitates the selection of a shape and scale parameter.[11] Where possible, we take advantage of the panel nature of our data and select these parameters to jointly match the observed population distributions of multiple years (e.g., 2010 and 2005), given observed AOD levels and our estimates of the equilibrium consumption and wage distributions in each of those years, respectively. Alternatively, we select these parameters to fit only the base year distribution of the population given relative wages and pollution levels and an assumed migration elasticity (e.g., a 50% increase in urban wages increases urban population by 10%, ceteris paribus).[12]

Pollution: The baseline PM10 pollution intensities of different fuels and activities (e.g., ζ^c,ζ^M, etc.) can differ markedly across countries and time. In order to quantify these parameters, we take advantage of the comprehensive collection of country- and activity-specific particulate pollution intensity estimates from the IIASA GAINS model. IIASA collects and processes detailed data on countries' fuel input mixes (e.g., ash content of coal), technologies (e.g., the distribution of boiler types), and considers baseline environmental policy and mandated abatement levels to construct country-, year- and activity-specific estimates of emissions factors. The IIASA estimates are careful and comprehensive and have previously been used produce cross-country comparisons of emissions and impacts, such as Parry et al. (2014).

For the pollution dispersion model, we observe area, boundary, and wind information directly in our geographical and meteorological data, as described in Section 4. For deposition velocities, we obtain estimates specific to rural versus urban environments from the EPA's ASPEN (Assessment System for Population Exposure Nationwide) model (EPA (2000)), a detailed pollution dispersion framework developed by the US EPA. [13] Average mixing height λ is estimated based on data from the EPA's Support Center for Atmospheric Modeling, and we set the AOD-PM10 conversion parameter ρ at 100 $\mu g/m^3$ based on Gendron-Carrier et al. (2018). Finally, we set

[10]Ito and Zhang's estimates represent a 5-year aggregate. We convert this figure into an annualized equivalent assuming a personal discount rate of 3% per year.

[11]We set the location parameter loc via $CDF^{-1}(loc) = exp(-1)$.

[12]For example, in some city-year-pairs we observe higher urban-wage ratios in a comparison year with a lower urban population share. This pattern cannot be reconciled with our specification of ϵ being drawn from the same distribution across years. Consequently, in these cases, we calibrate the ϵ distribution using only the base year of data.

[13]The ASPEN model considers annual averages of pollution dispersion, as relevant for our framework.

exogenous emissions $Emiss_{EX}$ in each country-region-year as the residual to match observed AOD levels from our data.

There are 31 countries for which we are able to assemble all of the data required for calibration and counterfactual policy evaluation. These countries are home to about 64% of the world's population. The results of counterfactual policy experiments for these 31 countries are described in the next section.

8. Counterfactual policy evaluation

Our benchmark analysis compares the impacts of three empirically relevant policy interventions: (1) A national tax on petroleum inputs (equivalent to a 15% ad-valorem tax),(2) a national tax on coal (equivalent to a 15% ad-valorem tax), and (3) an agricultural burning tax ($300/MT). This burning tax serves as wedge representation of different policies that may be adopted in practice. For example, in India, farmers can be fined for crop residue burning,[14] and Indonesia has banned certain types of burning in 2014 (see Rohadi (2017)).

Our initial analysis assumes that no revenues are collected, or equivalently, that revenues are used for non-productive purposes. Appendix tables 13-15 present the results of this analysis for each of the 31 countries for which we calibrate our model. We later consider the possibility that revenues are fully collected and rebated lump-sum to consumers. Appendix tables 16-18 present the results of this analysis for each of the 31 countries for which we calibrate our model.

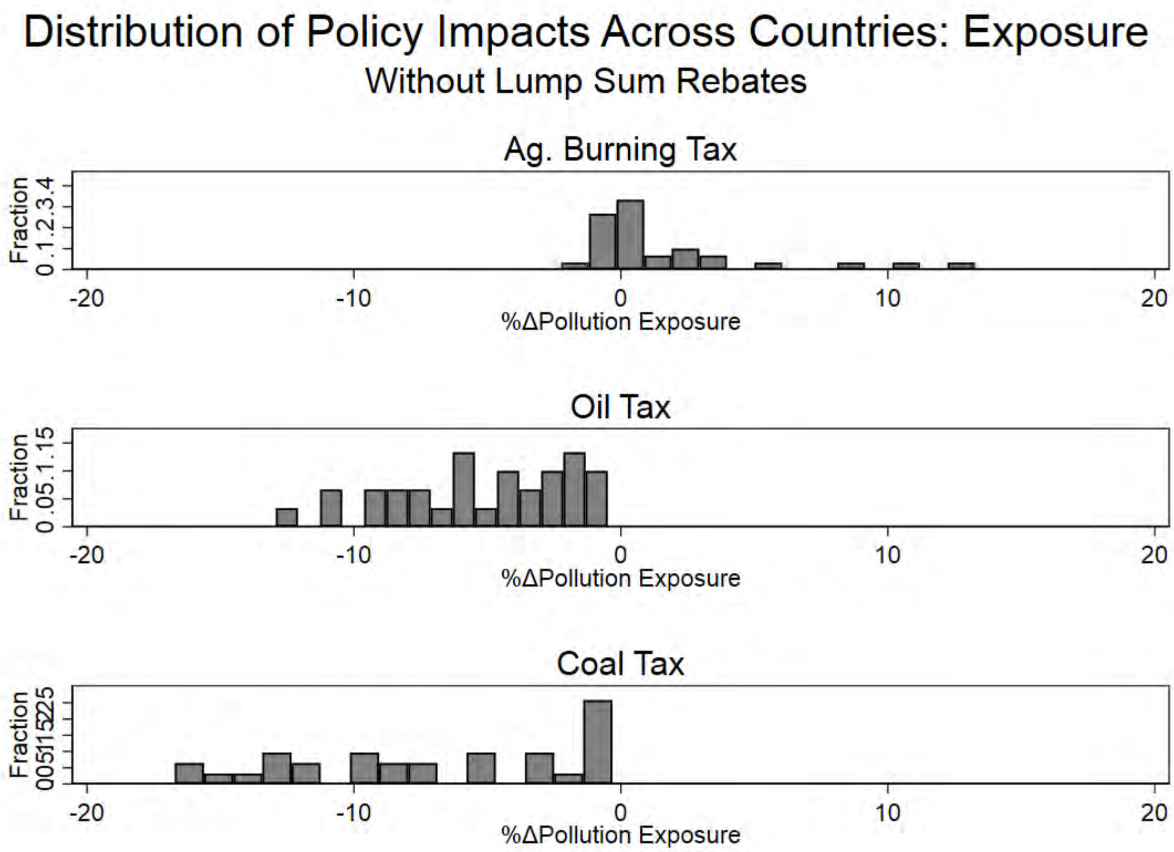
Figure 6 presents the first set of results. It displays the distribution of estimated policy impacts on equilibrium aggregate pollution exposure across countries. For agricultural burning taxes (top panel) the estimated changes in exposure are *positive* in the majority (60%) of countries, but range from -2.2% (in Bangladesh) to +13% (in Ukraine). Below we explore the drivers of these impacts through more detailed case studies. For the oil tax (middle panel), the estimated impacts on equilibrium pollution exposure are negative in all countries, but vary by more than an order of magnitude, ranging from -13% (in Portugal) to only -0.5% (in Bosnia and Herzegovina). For the coal tax (bottom panel), the impacts on exposure are similarly negative but range from -17% (in China) to -0.3% (in Pakistan).

Of course one might expect specific fuel tax impacts to vary across countries due to heterogeneity in baseline fuel mixes. In order to further gauge whether the results in Figure 6 are surprising, for seven countries we compare these predicted changes in pollution *exposure* to a stylized partial equilibrium measure of the predicted change in *emissions*.

Specifically, for each policy targeting activity $j \in \{AgBurn, Coal, Oil\}$, this measure corresponds to observed changes in emissions from the targeted activity weighted by its baseline share of total emissions. For example, if the coal tax decreased coal emissions by 20%, and if coal

[14]India Times, Nov. 17, 2018 "Despite Ban and Penalties, Stubble Burning Has Only Increased This Year"

Figure 6: Exposure Impacts across Countries



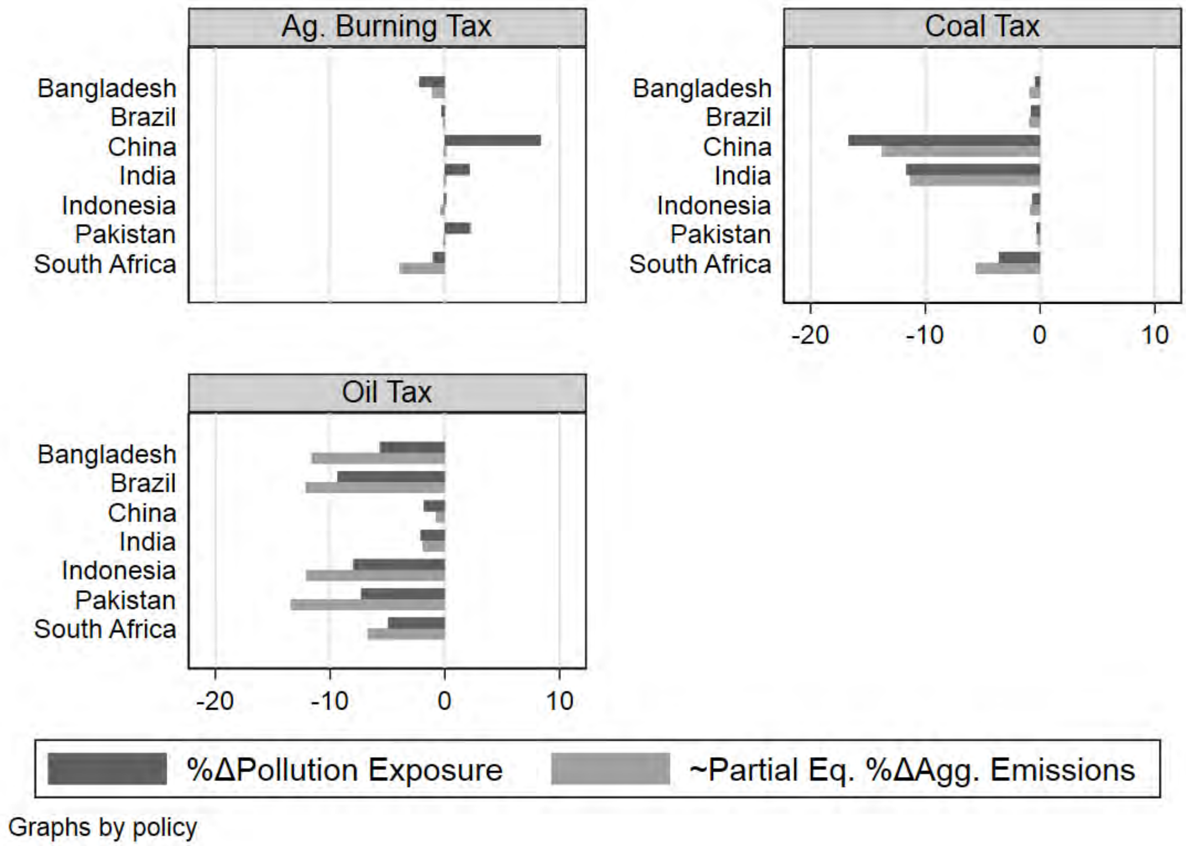
accounted for 50% of total emissions in the baseline, we might naively expect the tax to achieve a 20% · 50% = 10% reduction in aggregate emissions.

$$\text{Partial Eq. } \%\Delta\text{Agg. Emissions}_j \equiv \%\Delta\text{Emissions}_j \cdot \text{EmissionsShare}_{j,Baseline}$$

Figure 7 presents this comparison for seven countries. The results showcase the potential importance of both general equilibrium effects and cross-country heterogeneity: For benchmark parameter values, we find that policies which decrease agricultural burning *emissions* are predicted to increase aggregate pollution exposure in China, India, and Pakistan. In contrast, in Bangladesh, agricultural burning taxes reducing emissions and have a larger negative effect in on particulates in general equilibrium.

Consequently, even when using the same model structure to compare outcomes across countries, both the estimated policy impacts and the bias associated with partial equilibrium measures differs in magnitude and in *sign*. This holds true for fossil fuel taxes as well, where the partial equilibrium emissions change measure significantly over-estimates exposure reduction in some cases, but considerably under-estimates exposure reductions in others. For example, the partial

Figure 7: Partial vs. General Equilibrium Impact Measures



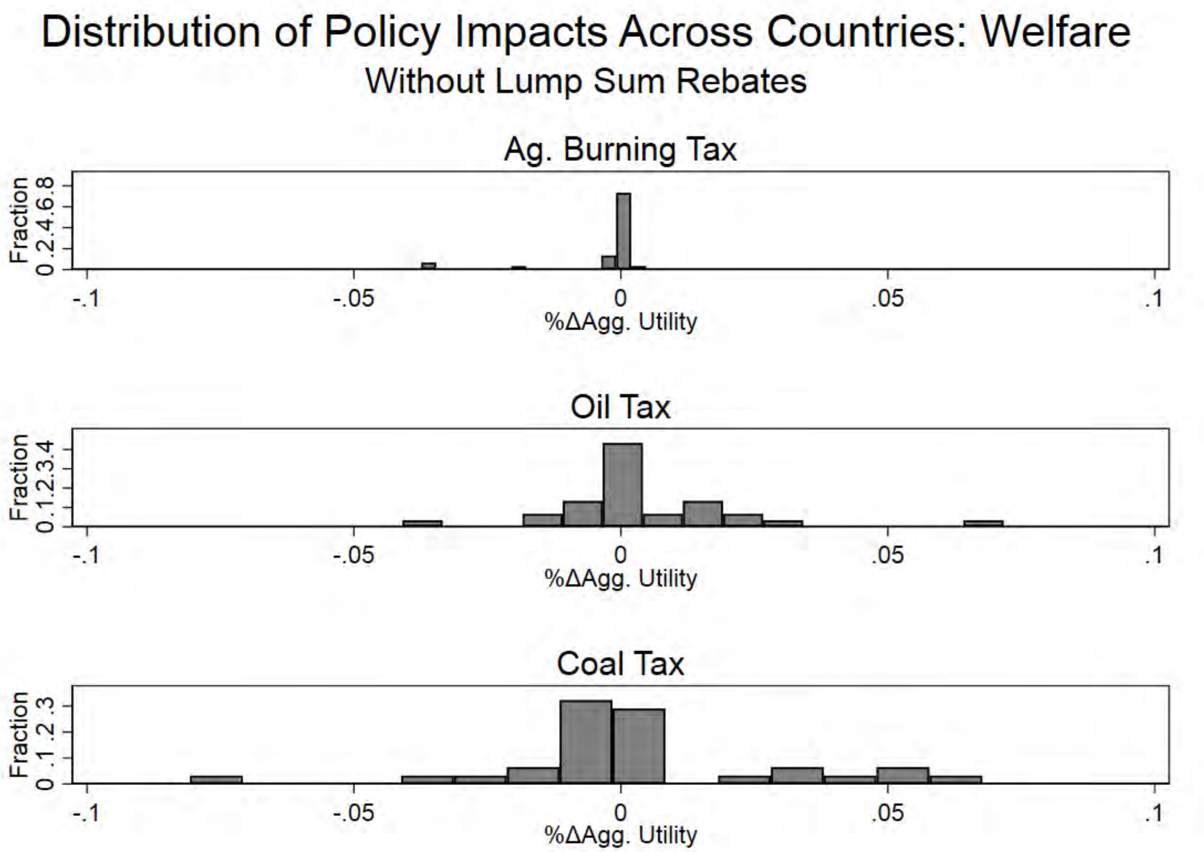
equilibrium emissions measure over-estimates oil tax impact on exposure by more than a factor of two for Bangladesh, while under-estimating impacts by more than a factor of two for China.

The discussion thus far has focused on policy impacts on pollution exposure. We now consider changes in welfare. Figure 8 presents the distribution of each policy's welfare effects across countries, measured as aggregate utility percentage change. The results once again showcase a wide range of possible outcomes, with the same taxes having significant negative welfare effects in some countries, and similarly sized positive impacts in others.

One important point to consider here is the effect of policy revenue management. The results presented thus far assume that our policy wedges collect no usable revenues, or, equivalently, that revenues are spent on non-productive purposes. Assuming that full revenues are collected and rebated lump-sum to households leads to a similarly wide range of estimated policy impacts on pollution exposure (see Appendix Figure 11), but shifts the distribution of welfare effects to the right, as shown in Figure 9.

The importance of both fiscal management and cross-country heterogeneity is further illustrated by Table 7, which compares policies' welfare-rankings across the same seven countries. That is, we compare policies' impacts on aggregate utility in each country, and rank them from

Figure 8: Welfare Impacts across Countries



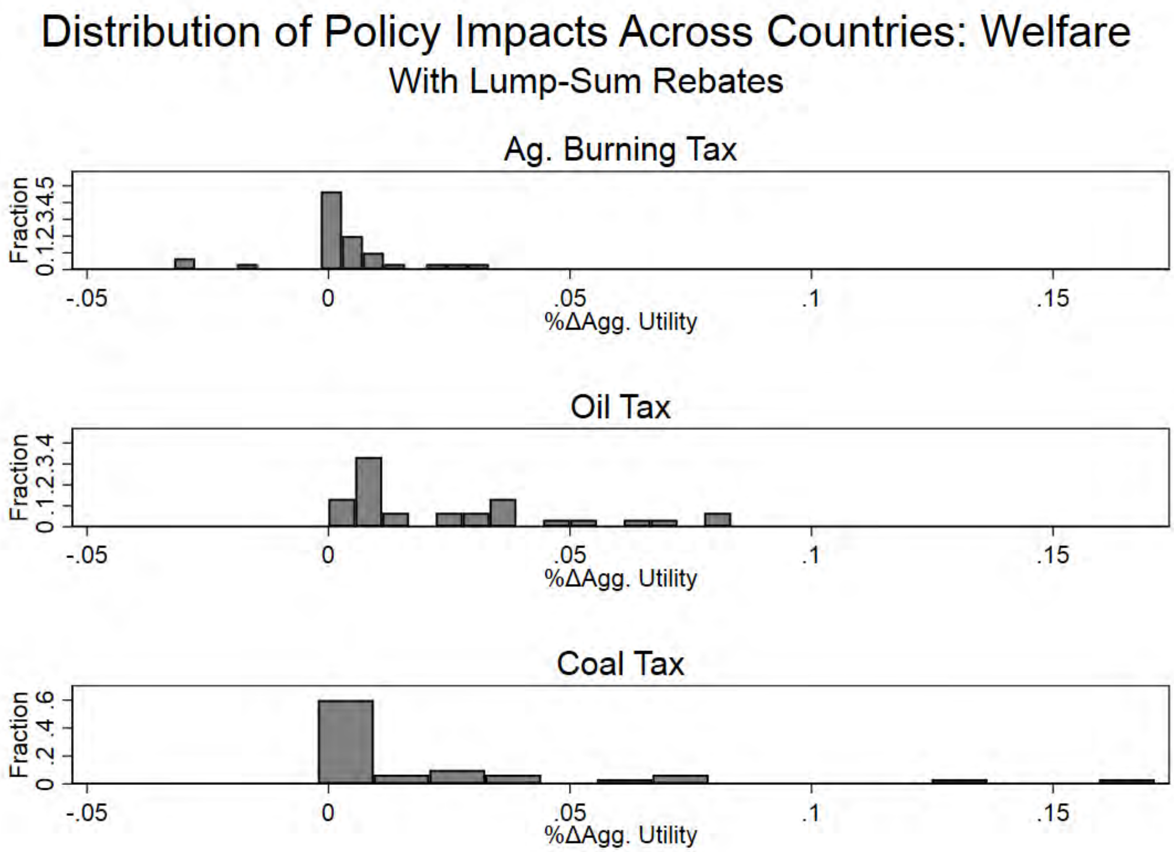
best (rank 1) to worst (rank 3). Two features of Table 7 stand out. First, each policy ranks highly in some countries but poorly in others. Second, each country's rankings may depend strongly on revenue management. For example, in Brazil, the petroleum tax ranks worst (3) when revenues are discarded, but ranks best (1) when revenues are collected and rebated lump-sum.

Table 7: Policy Welfare Rankings across Countries

	No Rebate			Lump-Sum Rebate		
	Ag. Burning	Coal	Oil	Ag. Burning	Coal	Oil
Brazil	1	2	3	2	3	1
China	1	3	2	2	3	1
India	1	3	2	3	1	2
Pakistan	1	2	3	1	3	2
Bangladesh	2	1	3	1	3	2
Indonesia	2	3	1	1	3	2
South Africa	2	3	1	3	2	1

To better understand why policies' impacts differ so markedly across countries and impact

Figure 9: Welfare Impacts across Countries - Revenue Rebates



measures, we examine China and Bangladesh in more detail. Table 8 presents more detailed simulation results for China. The agricultural burning tax is predicted to *increase* aggregate pollution exposure by over 8% in this setting. Table 8 panel B confirms that this increase occurs despite the fact that this tax successfully reduces agricultural burning by over 30%. Importantly, Table 8 panel B also reveals that the tax decreases agricultural output and employment. These displaced agricultural workers are predicted to move mainly into rural industry. This labor supply shock, in turn, leads to a substantial (>30%) increase in rural industrial output, and thus also an increase in rural fossil fuels consumption. Jointly, these changes drive the predicted 25% increase in rural pollution exposure in response to the agricultural burning tax. In China, the model suggests limited movement into the cities as a result of the agricultural burning tax. In other countries, however, urban migration in response to a tax on agricultural burning may make an important contribution to equilibrium changes in pollution exposure that result from the tax.

These types of general equilibrium effects do not always undo the benefits of an agricultural burning tax. In Bangladesh, for example, the burning tax is five times more effective at reducing pollution exposure than the coal tax. As shown in Table 9, the burning tax is effective despite the fact that it pushes agricultural workers into rural industry. One important difference is

Table 8: Counterfactual results for China in base year 2010 with policy revenue discarded.

Panel A: Aggregate effects									
							Welfare		
	Agg. Exposure (AOD/bil.)	Agg. Exposure $\%\Delta$	Urban Emiss. (MT/yr)	Urban Exposure $\%\Delta$	Rural Emiss. (MT/yr)	Rural Exposure $\%\Delta$	Agg. $\%\Delta$	Avg. Urban $\%\Delta$	Avg. Rural $\%\Delta$
Baseline	0.693	-	4776.0	-	963.6	-	-	-	-
Oil Tax	0.682	-1.56	4714.2	-1.17	941.5	-2.41	-.0091	-.0015	1.3917
Burning Tax	0.724	4.56	4777.4	0.05	1100.8	14.21	-.0007	-.0000	1.3936
Coal Tax	0.587	-15.17	4165.5	-11.8	756.9	-22.24	-.0769	-.0130	1.3762
Panel B: Rural Impacts									
	Industry Output ($bil.)	Industry Empl. (bil.)	Ag. Output ($bil.)	Ag. Empl. (bil.)	Ag. Burning (MT)	Coal Use (ktoe)	Oil Use (ktoe)	AOD	
Baseline	1168.9	0.3462	5918.9	0.3256	131.4	469.2	51.7	0.328	
Oil Tax	1145.7	0.3408	5975.0	0.3301	132.7	460.6	44.7	0.321	
Burning Tax	1384.1	0.4099	4901.7	0.2617	98.87	538.0	55.7	0.375	
Coal Tax	1022.3	0.3092	6331.6	0.3557	140.6	365.2	47.8	0.258	
Panel C: Urban Impacts									
Policy	Industry Output ($bil.)	Industry Empl. (bil.)	Services Output (tril.units)	Services Empl. (bil.)		Coal Use (ktoe)	Oil Use (ktoe)	AOD	
Baseline	4495.5	0.2736	52.01	0.3779	.	2274.8	421.6	0.724	
Oil Tax	4483.6	0.2741	51.76	0.3782	.	2263.9	367.0	0.715	
Burning Tax	4497.0	0.2737	52.02	0.3779	.	2275.4	421.7	0.724	
Coal Tax	4469.9	0.2779	51.75	0.3805	.	1965.9	415.2	0.631	

that industry in Bangladesh is significantly less coal-intensive than in China. In particular, coal's energy share parameter in Chinese industry is $\kappa_c^I = 0.8353$, compared to $\kappa_c^I = 0.1010$ in Bangladesh. These differences reflect factors such as heterogeneity in the composition of industry (e.g., garments versus steel).

As a final point of comparison, Table 10 presents results for China that are analogous to Table 8, but with lump-sum revenue redistribution for each policy.[15] At first glance, all policies appear more effective at reducing aggregate pollution exposure with revenue rebates.

Upon further inspection, comparing Table 8 with Table 10 reveals that urban exposure decreases at the expense of rural exposure, which decreases by less (or increases by more) with rebates. The core cause is that lump-sum rebates increase rural incomes by relatively more than urban ones, thus drawing urban residents with high rural amenity values away from the cities. These changes are reflected in the higher rural industry employment figures in Table 10 panel B compared to Table 8 panel B. As urban areas in China are more polluted than rural ones, this movement decreases aggregate exposure, ceteris paribus.

In sum, two main insights emerge from the quantitative analysis. First, the results demonstrate the importance of heterogeneity and national context for the assessment of a given policy. We find that, even under an apples-to-apples comparison based on the same analytic framework, the

[15] Slight differences in the baseline scenario across Tables 10 and 8 arise as we assume a very small burning tax in the baseline scenario for numerical reasons, resulting in a non-zero difference with revenue rebating.

Table 9: Counterfactual results for Bangladesh in base year 2010 with policy revenue discarded.

Panel A: Aggregate effects

	Agg. Exposure (AOD/bil.)	Agg. Exposure %Δ	Urban Emiss. (MT/yr)	Urban Exposure %Δ	Rural Emiss. (MT/yr)	Rural Exposure %Δ	Welfare Agg. %Δ	Welfare Avg. Urban %Δ	Welfare Avg. Rural %Δ
Baseline	0.083	-	2.78	-	1.03	-	-	-	-
Oil Tax	0.079	-5.67	2.45	-11.72	0.92	-3.00	0.00	-0.03	0.02
Burning Tax	0.081	-2.23	2.78	-0.01	0.91	-3.21	0.00	0.00	-0.00
Coal Tax	0.083	-0.44	2.75	-0.99	1.03	-0.19	0.00	-0.03	0.02

Panel B: Rural Impacts

	Industry Output ($bil.)	Industry Empl. (bil.)	Ag. Output ($bil.)	Ag. Empl. (bil.)	Ag. Burning (MT)	Coal Use (ktoe)	Oil Use (ktoe)	AOD
Baseline	23.1	0.0310	476.4	0.0662	13.9	0.2	1.1	0.595
Oil Tax	23.2	0.0312	474.6	0.0660	13.8	0.2	0.9	0.577
Burning Tax	39.6	0.0531	335.5	0.0441	7.9	0.3	0.9	0.576
Coal Tax	23.0	0.0309	477.1	0.0663	13.9	0.2	1.1	0.594

Panel C: Urban Impacts

Policy	Industry Output ($bil.)	Industry Empl. (bil.)	Services Output (tril.units)	Services Empl. (bil.)		Coal Use (ktoe)	Oil Use (ktoe)	AOD
Baseline	83.9	0.0134	8.22	0.0292	.	0.8	3.1	0.598
Oil Tax	83.9	0.0134	8.22	0.0292	.	0.8	2.7	0.528
Burning Tax	83.9	0.0134	8.22	0.0292	.	0.8	3.1	0.598
Coal Tax	84.0	0.0134	8.23	0.0292	.	0.7	3.1	0.592

same policy can have *qualitatively* different impacts on both pollution exposure and welfare both across and within countries. Second, the results highlight the importance of general equilibrium effects for particulate policy assessments. While agricultural burning taxes may reduce particulate emissions from waste burning, our results suggest that their general equilibrium effects may push workers into more polluting activities or regions, thus potentially increasing pollution exposure. Importantly, however, we also find examples where partial equilibrium estimates would *underestimate* the extent to which a given policy reduces pollution exposure in equilibrium.

9. Conclusion

Particulates exposure is poisonous while policies to reduce particulate emissions involve the regulation of fossil fuel consumption and agriculture, both fundamentally important activities. Thus, balancing the costs and benefits of particulate regulation is an economic problem of the first order. With few exceptions, analyses of particulate exposure and regulation do not consider the full range of potential responses to particulates policies; firms may choose more expensive and cleaner production processes, workers and firms may shift to less regulated activities, people and firms may move to less regulated regions, or to regions with a comparative advantage in less polluting activities.

We assemble data describing particulate exposure throughout the world. These data suggest the following conclusions. First, cross country heterogeneity is important: China, India and

Table 10: Counterfactual results for China in base year 2010 with lump sum rebates.

Panel A: Aggregate effects									
							Welfare		
	Agg. Exposure (AOD/bil.)	Agg. Exposure %Δ	Urban Emiss. (MT/yr)	Urban Exposure %Δ	Rural Emiss. (MT/yr)	Rural Exposure %Δ	Agg. %Δ	Avg. Urban %Δ	Avg. Rural %Δ
Baseline	0.695	-	5212.8	-	535.5	-	-	-	-
Oil Tax	0.677	-2.56	5060.0	-3.99	532.5	0.49	3.34	0.03	1.38
Burning Tax	0.750	7.86	5142.7	-2.30	687.5	29.57	3.32	0.14	1.53
Coal Tax	0.568	-18.30	4379.3	-17.26	419.6	-20.50	1.90	-0.79	-0.33
Panel B: Rural Impacts									
	Industry Output ($bil.)	Industry Empl. (bil.)	Ag. Output ($bil.)	Ag. Empl. (bil.)	Ag. Burning (MT)	Coal Use (ktoe)	Oil Use (ktoe)	AOD	
Baseline	575.8	0.2310	1828.3	0.4410	131.5	258.2	33.2	0.330	
Oil Tax	575.6	0.2329	1845.6	0.4472	132.7	258.1	29.1	0.328	
Burning Tax	807.2	0.3238	1514.1	0.3545	98.9	334.3	37.8	0.423	
Coal Tax	488.3	0.2001	1955.8	0.4818	140.6	199.6	31.2	0.258	
Panel C: Urban Impacts									
Policy	Industry Output ($bil.)	Industry Empl. (bil.)	Services Output (tril.units)	Services Empl. (bil.)		Coal Use (ktoe)	Oil Use (ktoe)	AOD	
Baseline	5089.6	0.2935	50.21	0.3580	.	2490.2	440.7	0.727	
Oil Tax	4964.7	0.2875	49.76	0.3568	.	2435.4	379.5	0.706	
Burning Tax	5000.7	0.2883	50.05	0.3568	.	2455.9	436.9	0.717	
Coal Tax	4816.2	0.2836	49.61	0.3580	.	2071.4	424.3	0.611	

Russia are different in their production of emissions and in the extent to which emissions lead to exposure. Second, the economic geography of exposure is important. China and India both saw about the same increase in average concentration between 2000 and 2010, but exposure in China increased by much more. Third, about half of all variation in exposure is determined by country-year level factors. Fourth, most country-year level variation in exposure is explained by the levels of a handful of country-year economic variables; urbanization, coal consumption, agricultural GDP, organic fuel consumption, and cross-border particulate flows. Perhaps more surprising, the half of variation in exposure that is not explained by country-year level quantities, is also not explained by the available disaggregated data. For our purposes, within country variation in exposure across our 10km^2 pixels looks random, or more precisely, is largely unexplained by our spatially disaggregated economic variables; population density, land cover and fires.

Our econometric analysis should be regarded as largely descriptive. While it suggests the importance of various factors for equilibrium exposure, ultimately, we are estimating equilibrium relationships. For policy purposes, we would like evaluate the casual effect of particular interventions. To accomplish this, we develop a the SEPIA model. This model provides a logically coherent description of the way that a small open economy responds to particulates policy. Calibrating this model to each of the 31 countries for which we have sufficient data allows us to evaluate the effects of policies restricting the combustion of petroleum, coal, and agricultural waste on a country-by-country basis.

In addition to providing a logically coherent macro-economic description of how particulate emissions and regulation affect production and consumption, the SEPIA model integrates an economic model with a model of particulate dispersion. While the theoretical integration of physical and biological processes into economic models is a long tradition, SEPIA adds to the literature by integrating particulate dispersion into a macroeconomic model that allows equilibrium adjustment margins observed in prior empirical studies. In addition to improving our ability to describe the economics of equilibrium particulates exposure, the comparative statics implied by the model provide can answer fundamental questions about particulates policy: Should particulates policy target coal, petroleum or agricultural waste burning? Which of these policies, if any, is welfare improving? What are the unintended consequence of such policies?

A good deal of research remains to be done. First, our primary unit of analysis is an annual average over a 10km^2 cell. In contrast, much of the research on particulates considers much smaller spatial scales and shorter time frames. That there is a lot of variance over these smaller, shorter scales, means that our relatively aggregated measure is smoothing out variation in particulate exposure that may be economically important. Providing insight into these issues is probably important and is certainly beyond the reach of our data.

Second, our finding that pixel level variation in population density and land cover has little ability to explain variation in pixel level concentration and exposure is surprising and deserves further attention. Given the importance of aggregate economic quantities to exposure, it is natural to suspect that the finer scale processes that determine exposure are also determined by an economic equilibrium, even if the features of this equilibrium are invisible in our data.

Third, our object was to develop a model that would allow us to evaluate policy relevant comparative statics across countries. This requires that we satisfy ourselves with a stylized description of each county's economy that ignores country level idiosyncrasies. It is clearly feasible to develop country specific models that provide a more accurate and detailed description of equilibrium particulate exposure. We hope that our work precipitates this line of research.

Finally, our evaluation of the comparative statics of equilibrium particulate exposure relies entirely on our model. An alternative approach would rely on quasi-experimental variation, e.g., in coal prices, to evaluate similar comparative statics. This appears to be a challenging agenda. However, the development of such a literature would complement our inquiry and, hopefully, increase its credibility.

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10. Appendix

A *Competitive Equilibrium*

This section elaborates details of the competitive equilibrium not already provided in Section 6.

Production: First, sectoral outputs $\{Y^{I,u},Y^{I,a},Y^S,Y^M,J^{I,u},J^{I,a},J^S,J^M\}$ are produced acccording to the production technologies (2)-(7). Second, profit-maximizing input demands equate marginal products to factor prices for each type of producer. For industry and services, these conditions are given by:

$$
\begin{aligned}
\frac{(1-\alpha-v^m)Y^m}{L^m} &= w^k && (25)\\
\frac{\alpha Y^m}{K^m} &= R^* && (26)\\
\frac{v^m Y^m}{J^m} &= p^{J,m} && (27)\\
m &\in \{I,u;I,a;S\}\\
k &= \begin{cases} u & \text{if } m \in \{I,u;s\} \\ a & \text{if } m \in \{I,a\} \end{cases}
\end{aligned}
$$

For energy producers, the corresponding fuel input demands are:

$$
\begin{aligned}
\frac{E_c^m}{E_p^m} &= \left(\frac{\kappa_c^m}{\kappa_p^m}\left(\frac{p_p^*+\tau_p^m}{p_c^*+\tau_c^m}\right)\right)^{\varepsilon} && (28)\\
\frac{E_c^m}{E_g^m} &= \left(\frac{\kappa_c^m}{\kappa_g^m}\left(\frac{p_g^*+\tau_g^m}{p_c^*+\tau_c^m}\right)\right)^{\varepsilon} && (29)\\
m &\in \{I,u;I,a;S,M\}
\end{aligned}
$$

Finally, in agriculture, the profit-maximizing conditions for input demands and burning abatement θ_B are given by:

$$
\begin{aligned}
\rho_L^M \frac{Y^M}{L^M}\left[p^{M^*}-\tau_B\left(1-(\nu_1\theta_B)^{\nu_2}\right)\xi^B\right] &= w^a && (30)\\
\rho_K^M \frac{Y^M}{K^M}\left[p^{M^*}-\tau_B\left(1-(\nu_1\theta_B)^{\nu_2}\right)\xi^B\right] &= R^* && (31)\\
\rho_J^M \frac{Y^M}{J^M}\left[p^{M^*}-\tau_B\left(1-(\nu_1\theta_B)^{\nu_2}\right)\xi^B\right] &= p_J^M && (32)\\
\frac{\rho_L^M Y^M}{(1-\theta_B)}\left[p^{M^*}-\tau_B\left(1-(\nu_1\theta^B)^{\nu_2}\right)\xi^B\right] &= \tau_B\left[(\nu_1)^{v_2}(\nu_2)(\theta_B)^{\nu_2-1}\xi^B Y^M\right] && (33)
\end{aligned}
$$

Households: The optimal consumption bundle for urban households maximizing their utility (12) subject to budget constraint (14) satisfy optimality conditions:

$$
\begin{aligned}
\frac{(1-\theta^I-\theta^S)}{\theta^I}\frac{c^I}{c^M} &= p^{M^*} && (34)\\
\frac{\theta^S}{\theta^I}\frac{c^I}{c^S} &= p^S && (35)
\end{aligned}
$$

Analogously, for rural households, consumption bundles satisfy the budget constraint (15) and:

$$
\begin{aligned}
\frac{(1-\theta^I-\theta^S)}{\theta^I}\frac{x^I}{x^M} &= p^{M^*} && (36)\\
\frac{\theta^S}{\theta^I}\frac{x^I}{x^S} &= p^S && (37)
\end{aligned}
$$

Household $i's$ optimal choice of location k^* is given by:

$$k^* = \left\{ \begin{pmatrix} u & \text{if } \frac{\widetilde{c}^{*1-\sigma}}{1-\sigma} - \chi_1(AOD^u)^{\chi_2} > \frac{\widetilde{x}^{*1-\sigma}}{1-\sigma} - \chi_1(AOD^a)^{\chi_2} + \epsilon_i \\ a & \text{o.w.} \end{pmatrix} \right.$$

Letting $F(\epsilon)$ denote the cumulative distribution function of idiosyncratic amenity values ϵ, and with the marginal agent's value ϵ^* defined by (16), the aggregate share of the population living in the urban area must thus satisfy:

$$\frac{L^{I,u} + L^S}{\overline{L}} = F\left(\frac{\widetilde{c}^{*1-\sigma}}{1-\sigma} - \chi_1(AOD^u)^{\chi_2} - \frac{\widetilde{x}^{*1-\sigma}}{1-\sigma} + \chi_1(AOD^a)^{\chi_2}\right) \tag{38}$$

Aggregate Conditions: Finally, competitive equilibrium requires that the domestic market for services clears (23), the government's budget constraint is satisfied (17), the national budget constraint holds (24), and that the country's labor market clears:

$$\overline{L} = L^M + L^S + L^{I,u} + L^{I,a}$$

B *Calibration*

The calibration proceeds in three steps. First, we set certain parameters based on the literature or standard assumptions at common values for all countries ("Directly Calibrated"). Second, we back out certain parameter values directly from data for each country ("Directly based on Data"). Third, we select the remaining model parameters to jointly minimize the sum of squared differences between equilibrium moments as observed in the data and our model ("Matching Moments").

Directly Calibrated: Table 11 summarizes the parameters calibrated based on the literature.

Table 11: Benchmark Parameters - Directly Calibrated

Parameter	Value(s)	Sources and Notes
α	0.33	Standard
ρ_L^M	0.52	Combine Fuglie (2010) cross-country estimates,
ρ_K^M, ρ_J^M	0.32, 0.05	Gollin, Lagakos, and Waugh (2013), and modeler's judgement
ε	0.95	GHKT (2014)
ν_1,ν_2	2, 0.5	Norgrove and Hauser (2015) estimates, modeler's judgement
σ	1.5	Nordhaus (2008)
R^*	0.15	Real return of 5%/year plus 10% depreciation
ρ	$100\frac{\mu g}{m^3}$	Gendron-Carrier et al. (2018)

The agricultural production parameters warrant further discussion. Fuglie (2010) reviews empirical estimates of agricultural input elasticities across countries, and computes weighted global average values over the categories given in table 12:

We assign "Land & Structures" equally between land and capital, split ""Machinery & Energy" equally between capital and energy, and attribute the remaining materials inputs proportionally

Table 12: Fuglie (2010): Agricultural Factor Share Estimates (Weighted Global Avg.)

Labor	Land & Structures	Livestock & Feed	Machinery & Energy	Chemicals & Seed
0.35	0.21	0.23	0.10	0.10

to labor and capital. Reassuringly, the resulting labor share estimate of $\rho_L^M = 0.52$ matches Gollin, Lagakos, and Waugh's (2013) insight that empirical evidence on agriultural cost shares from share tenancy arrangements suggest that 50-50 splits between labor and other factors are common across countries and time, including in modern-day U.S. agriculture.

The burning abatement cost function parameters are more challenging to calibrate as they lack the empirical foundations underlying the general agricultural production function. There are, however, some studies and data points. Norgrove and Hauser (2015) estimate that "fire exclusion led to an approximately 50% increase in labor requirements for planting, weeding, and harvesting both in the maize and plantain systems" in the Congo Basin. In surveys, Indonesian farmers have reported that clearing peatland manually requires one to two months time for what could be accomplished by fire in a few day (Rohadi (2017)). In India, it is commonly reported that the labor cost for manual harvesting - which avoids the stubble that otherwise needs to be burned - is currently around Rs 3,000 - 4,000 per acre, whereas the cost of renting a combine machine (which does not clear the stubble) is Rs 1,500-2,000, suggesting a doubling of harvesting costs for full fire abatement.[16] As a benchmark, we posit an abatement cost function in the spirit of the seminal DICE model (Nordhaus (2017)). Specifically, letting μ denote the fraction of burning avoided, specification (6) implies that:

$$\theta_B = \frac{1}{\nu_1}(\mu)^{\frac{1}{\nu_2}} \tag{39}$$

We select parameters ν_1 and ν_2 to match the following moments: (1) Eliminating burning by 100% increases labor costs by 35%, and (2) reducing burning by 50% increases labor costs by 8.75%.

Directly based on Data: The following list describes the parameters and initial equilibrium values of allocations and prices based directly on data.

Economic Model:

- Base year fuel input usage across sectors (E_c^m, E_p^m, E_g^m for $m \in I; S,M$) are set based on data from the International Energy Agency (OECD//IEA (2018)). We map the data into our model's sectors via the following assumed classification:

[16]"Delhi chokes on smoke from neighbouring states", Soumya Pillai and Vishal Rambani, Hindustan Times, October 24, 2016. URL: [http://www.hindustantimes.com/delhi-news/delhi-chokes-on-smoke-from-neighbouring-states/story-zAkXkflle5MoUXLNYfZaoH.html]

IEA Sector	Model Sector
Agriculture and Forestry	Agriculture
Commercial and public services	Services
Fishing	Agriculture
Industry	Industry
Residential	Services
Transport	Services

- Energy resource prices are based on data from BP (British Petroleum Company (2016)). We average across global commodity prices for each fuel to compute annual values of p_c^*, p_p^*, and p_g^* (calibrated based on natural gas prices) and then adjust by the energy content of the fuel to arrive at prices per Mtoe.

- Based on these prices and quantities, we can then directly back out each sector's energy production κ's for each country via (28)-(29) given the following additional assumption for each $m \in I; S{,}M$:

$$1 = \kappa_c^m + \kappa_p^m + \kappa_g^m$$

- With values for fuel inputs and energy production parameters in hand, we can infer each sector's energy aggregate production $J^I \equiv J^{I,u} + J^{I,a}$, J^S, and J^M in the country-year via (2, 4, 7).

- We can then infer each country's base year aggregate energy input prices for each sector p_J^I, p_J^S, and p_J^M from the relevant fuel price indexes

$$p_J^m = \left((\kappa_c^m)^\varepsilon (p_c^* + \tau_c^m)^{1-\epsilon} + (\kappa_p^m)^\varepsilon (p_p^* + \tau_p^m)^{1-\epsilon} + (\kappa_g^m)^\varepsilon (p_g^* + \tau_{g,m})^{1-\epsilon} \right)^{\frac{1}{1-\varepsilon}},$$

for $m \in \{I{,}a; I{,}u; S{,}M\}$. Note that we must also account for pre-existing taxes. As a benchmark we set those to zero for individual fuels, but we allow for and back out from the data a rural industry energy services tax wedge τ^{Ja} (isomorphic to certain fuel tax combinations) as described in the "Matching Moments" section below.

- For each country, we then set energy expenditure shares (ν^I, ν^S, ρ_J^M) based on the observed base year share. For example (and analogously for other sectors):

$$\nu^I = \frac{p_J^I \cdot J^I}{Y^I}$$

- The emissions coefficients for each fuel type (ξ^c, ξ^p, ξ^g) are based on IIASA GAINS model data described in Section 7. The specifics are as follows. First, we obtain IIASA's estimates of each country's total PM10 *emissions* by fuel/activity for all available years of our sample (2000, 2005, 2010, 2015).[17] Second, we obtain IIASA's estimates of each country's energy use by key fuel type (coal, liquid fuel, natural gas, etc.). Finally, we divide emission from

[17]We specifically consider the ECLIPSE_v5a_CLE_base scenario which reflects current law.

each fuel by fuel quantity to derive *emissions coefficients* (KT of PM10 per PJ) for each fuel type-country-year.[18]

- The emissions coefficient for industrial output (ξ^I) is derived by dividing non-combustion industrial emissions totals for each country-year (from IIASA) by industry output in the relevant country-year.

- The emissions coefficient for services (ξ^S) is similarly derived by deriving IIASA's estimates of total non-exhaust road emissions by services output in the relevant country-year.

- The emissions coefficient for agricultural *output* combines IIASA's estimates of (i) non-burning related agricultural emissions (e.g., fertilizer use) and (ii) emissions from general biomass energy inputs. The sum of these terms is then divided by agricultural output in the relevant country-year.

- The emissions coefficient for agricultural *burning* (ξ^B) is obtained directly from IIASA's detailed emissions factor listings ("Emissions factors and related parameters for PM (TSP) and CO2"), specifically as the PM10 emissions coefficient for the "WASTE_AGR" variable.

- For consumer preference parameters, we consult World Bank data on sectoral household expenditure estimates across countries from 2010. First, we map the reported categories into our model's basic sectors as follows:

World Bank Data	**Model**
Clothing and Footwear	Industry
Education	Services
Energy	Industry
Financial Services	Services
Food and Beverages	Agriculture
Health	Services
Housing	Services
ICT	Industry
Others	Industry
Personal Care	Services
Transport	Services
Water Utility	Services

Second, since the data do not cover all of our sample countries, we extrapolate consumption shares for countries with missing data. Letting $D^{Inc}_{j,2010}$ denote the income (GDP per capita) quintile of country j in 2010, we specifically estimate, e.g.:

$$\theta^{I,j,2010} \quad = \quad \beta_0 + \sum_{j=1}^{4} \beta_j D^{Inc}_{j,2010} + \varepsilon_j$$

[18] We note that IIASA also makes publicly available the extremely detailed activity data and fuel coefficient estimates underlying their analysis. These differentiate, for example, coal emissions coefficients of pilverized versus fluidized bed versus grate firing combustion boilers. IIASA's total emissions data reflect their estimates of the distribution of these technologies within each country-year. Our use of these total emissions along with energy inputs data thus yields an appropriately weighted average emissions factor at the fuel level, as relevant for our analysis.

and use predicted shares $\widehat{\theta^{I,j}}$ where needed. Third, given that the model treats the services sector as non-traded, in order to better match service sector output data, we set the service sector consumption share based on observed base year service sector output shares:

$$\theta^S = \tilde{Y^S}/Y$$

where $\tilde{Y^S}$ denotes service sector GDP and Y total GDP. Finally, the remaining good (here agriculture) expenditures share is then set as the residual based on:

$$1 = \theta^I + \theta^S + \theta^M$$

- Finally, based on the structure of the model, we can back out initial equilibrium levels of capital in both services and agriculture:

$$K^S = \alpha \cdot \widetilde{Y^S}/R^*$$
$$K^M = \rho_M^K \cdot \widetilde{Y^M}/R^*$$

where the tilde marks output *values* (i.e., $p \cdot Y$) as observed in sectoral GDP data.

Pollution Model:

- Dry deposition velocities are based on the EPA's ASPEN model (EPA (2000)). Their analysis presents different deposition velocity values depending on (i) urban versus rural areas, (ii) wind speed, and (iii) atmospheric stability. We adopt values relevant to each region (urban or rural), compute weighted (based on border lengths) average wind speeds for each area, and assume neutral atmospheric stability to select the appropriate deposition velocity for a given country-year.
- ASPEN provides dry deposition rates. We adjust for the average prevalence of wet deposition through a proportional increase of +37% based on estimates by Wu et al. (2018).[19]
- Mixing height λ is set to 0.5 km based on data from the EPA's Support Center for Regulatory Atmospheric Modeling (SCRAM). SCRAM previously provided twice daily mixing height observations across the United States at the monitoring station level. The data contain at least one station per state, including coverage in Hawaii and Alaska, thus reflecting a very diverse set of climatic and geographic areas. In the most recent year of observations (1991), the average morning mixing heigh recored is 487 meters.

[19] In countries where the exogenous emissions ($Emiss^s_{EX}$ or $Emiss^r_{EX}$) implied by the benchmark calibration at baseline AOD and emissions levels are negative, we further adjust the deposition rates to the minimum level required to ensure that exogenous emissions are non-negative.

Matching Moments: Given the data and calibrated values described thus far, we select the following remaining unknown parameters and initial equilibrium values to minimize the squared sum of differences betwen the model's equilibrium conditions and the data: Sectoral productivities $A^{I,u}$, $A^{I,a}$, A^{S} A^{M}; industry allocations across urban and rural areas $K^{I,u}$, $K^{I,a}$, $L^{I,u}$, $L^{I,a}$, $J^{I,u}$, $J^{I,a}$, $Y^{I,u}$, $Y^{I,a}$; labor allocations towards the other sectors L^{M}, L^{S}; prices p^{S}, $p^{M^{*}}$, w^{u}, w^{a}; household consumption bundles c^{I}, c^{S}, c^{M}, x^{I}, x^{S}, x^{M}; and a rural industry energy services tax wedge $\tau_{J}^{I,a}$. Initial experimentation suggested that assuming equal marginal products of overall energy services between the rural and urban industry sectors is difficult to match given the data and the rest of the model. We therefore allow for and back out from the data a rural energy services tax wedge defined by:

$$\frac{v^{I}Y^{I,a}}{J^{I,a}} = p_{J}^{a}(1+\tau_{J}^{I,a}) \tag{40}$$

This wedge can be positive or negative depending on whether rural industry energy services have relatively higher or lower marginal products than urban industry for a given country-year.

Another special point to note is that our model assumes that households earn only labor income and that returns to capital are paid abroad. Consequently, the model under-estimates household income levels relative to reality. In order to match the model's implied household demand for services to an empirical moment, we thus use observed services output adjusted by the approximate labor income fraction, specifically:

$$((L^{I,a}+L^{M})x^{S}+(L^{I,u}+L^{S})c^{S})p^{S} = \tilde{Y^{S}}(1-\alpha-max(\nu^{I},\nu^{S},\rho_{J}^{M}))$$

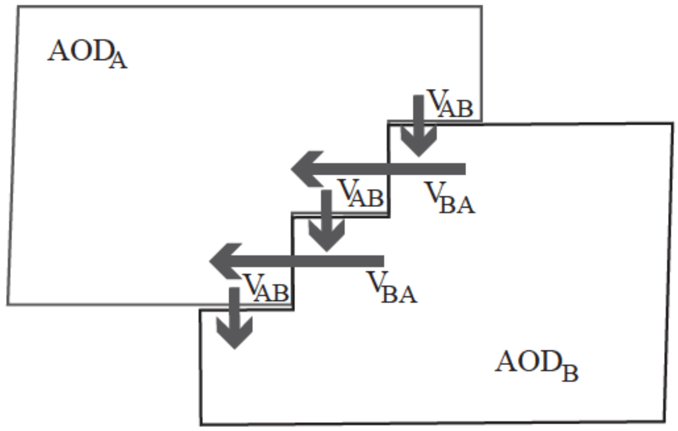
The remainder of the calibration proceeds as follows. Given rural versus urban industry energy demands ($J^{I,u}$, $J^{I,a}$) we can then back out the implied fuel usages in each area ($E_{c}^{I,u}$, $E_{c}^{I,u}$, $E_{c}^{I,u}$, $E_{c}^{I,u}$, $E_{c}^{I,u}$, $E_{c}^{I,u}$) via (28)-(29). Given each country's preference parameters and domestic price levels, we then also set the pollution disutility parameters to match the model's implied marginal willingness to pay (MWTP) to empirical estimates:

$$MWTP_{AOD} = \frac{-MU_{AOD}}{MU_{c_{I}}} = \frac{\chi_{1}(\chi_{2})(AOD^{u})^{\chi_{2}-1}}{\widetilde{c}^{1-\sigma}\theta_{I}(c^{I})^{-1}}$$

We set $\chi_{2} = 2$ and select χ_{1} so that (B) equals 1.16 - Ito and Zhang's (2019) 5-year estimate of \$5.46 per household annualized at a discount rate of 3% per year - when evaluated at the relevant income (\$2,253.5) and AOD levels of 1.15 (corresponding to PM10 levels of 115 $\frac{\mu g}{m^{3}}$).

Finally, and as described in Section 7, we then select the marginal rural amenity value ε^{*} at initial equilibrium is then pinned down by (16), and we select the GEV distribution parameters to match the rural-urban population distribution observed in the data at the initial equilibria for two separate model years (2005 and 2010 in the benchmark calibration), or to match the base year distribution (2010) and a migration-urban wage elasticity of 0.2.

Figure 10: Calculation of cross-boundary flows



Note: Logic for calculating the mass of cross-border particulate flows from gridded AOD and wind data.

C *Calculating cross-border particulate flows*

Figure 10 illustrates the boundary between two hypothetical regions where AOD is constant within each region. The arrows illustrate wind velocity across the border. For the sake of illustration, each instance of V_{BA} has velocity 2 and reflects the East-West wind velocity across the AB boundary. Letting the length of the solid bar at lower center be one unit distance, wind V_{BA} operates across two units of length. Therefore, the East-West transport of particulates is given by the length of the border over which wind travels from B into A, times the velocity of the wind, times mixing height, times the concentration of particulates in region B. Let λ denote mixing height and recall that ρ converts AOD to concentration, transport from region B to A is given by,

$$2 \times \lambda \times V_{BA} \times \rho \times \text{AOD}_B$$

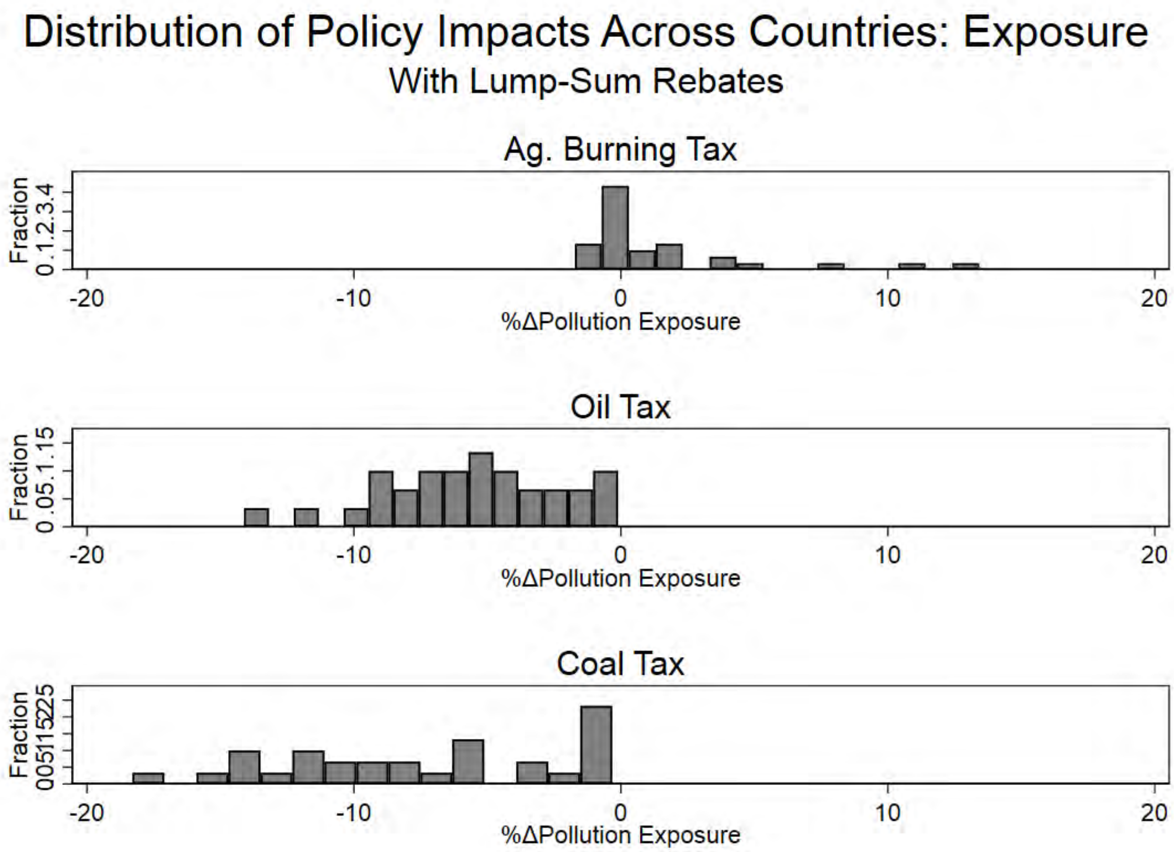
Performing a similar calculation for flows from A to B and summing, we have net flows from A to B

$$F_{BA} = (2 \times \lambda \times V_{BA} \times \rho \times \text{AOD}_B) - (3 \times \lambda \times V_{AB} \times \rho \times \text{AOD}_A)$$

This is exactly the way that we calculate flows in practice, with one exception. Where we have here assumed that there is no pixel level variation in AOD within a region, in practice, the wind operates on whatever AOD we measure in its own cell.

Our model will ultimately require two further structural parameters to describe flows across-borders. The first is border length. This is trivial to compute, and in this case, the border between regions A and B is 5 units long. The second parameter is the velocity of the cross-border wind, $v_{BA} (= -v_{BA})$. This is a complicated quantity because, to summarize cross-border wind, we must describe the direction it travels and the length of the border over which it operates. For the

Figure 11: Policy Impacts across Countries



purpose of the model, wind velocity is defined as the velocity that explains the actual observed transfer of particulate mass across the border. That is, $v_{AB}\rho\lambda\text{AOD}_A \equiv F_{AB}$.

D *Further Calibration Results*

Table 13: Country Results - No Rebate

Country	Policy	Exposure %Δ Agg.	Urban	Rural	Utility %Δ
Australia	Oil Tax	-3.33	-3.72	-0.61	0.00
Australia	Ag. Burning Tax	0.08	0.00	0.64	0.00
Australia	Coal Tax	-8.76	-9.41	-4.26	-0.01
Bangladesh	Oil Tax	-5.67	-11.72	-3.00	0.00
Bangladesh	Ag. Burning Tax	-2.23	-0.01	-3.21	0.00
Bangladesh	Coal Tax	-0.44	-0.99	-0.19	0.00
Bulgaria	Oil Tax	-4.06	-3.50	-5.53	0.02
Bulgaria	Ag. Burning Tax	5.06	6.82	0.35	-0.04
Bulgaria	Coal Tax	-9.49	-8.28	-12.71	0.05
Bosnia and Herzegovina	Oil Tax	-0.50	-1.57	0.41	0.02
Bosnia and Herzegovina	Ag. Burning Tax	1.99	0.00	3.68	-0.00
Bosnia and Herzegovina	Coal Tax	-14.32	-12.35	-16.01	-0.03
Belarus	Oil Tax	-8.88	-10.46	-4.44	-0.00
Belarus	Ag. Burning Tax	0.12	0.00	0.45	0.00
Belarus	Coal Tax	-2.45	-3.10	-0.61	-0.00
Brazil	Oil Tax	-9.36	-12.14	-1.19	-0.00
Brazil	Ag. Burning Tax	-0.32	0.00	-1.26	0.00
Brazil	Coal Tax	-0.82	-1.01	-0.24	-0.00
Canada	Oil Tax	-4.28	-1.05	-18.48	-0.01
Canada	Ag. Burning Tax	7.10	16.61	-34.81	-0.02
Canada	Coal Tax	-3.41	-3.86	-1.42	-0.00
China	Oil Tax	-1.85	-1.05	-3.55	-0.01
China	Ag. Burning Tax	8.37	0.17	25.92	-0.00
China	Coal Tax	-16.71	-11.25	-28.40	-0.08
Croatia	Oil Tax	-7.81	-9.55	-4.87	-0.00
Croatia	Ag. Burning Tax	-0.47	-0.01	-1.26	0.00
Croatia	Coal Tax	-3.07	-3.85	-1.75	-0.00
Czech Republic	Oil Tax	-2.47	-2.57	-2.19	0.01
Czech Republic	Ag. Burning Tax	-0.99	-1.06	-0.79	0.00
Czech Republic	Coal Tax	-10.02	-8.69	-13.80	0.04
Estonia	Oil Tax	-11.11	-12.97	-7.40	0.00
Estonia	Ag. Burning Tax	-0.31	0.00	-0.92	0.00
Estonia	Coal Tax	-1.13	-1.15	-1.10	-0.00
Great Britain	Oil Tax	-4.59	-4.94	-2.91	-0.00
Great Britain	Ag. Burning Tax	-0.02	0.00	-0.11	0.00
Great Britain	Coal Tax	-7.91	-7.79	-8.50	-0.00
Greece	Oil Tax	-4.51	-4.03	-6.06	-0.01
Greece	Ag. Burning Tax	0.58	0.02	2.36	-0.00
Greece	Coal Tax	-9.73	-9.03	-11.99	-0.01

Table 14: Country Results - No Rebate, Ctd.

		Exposure %Δ			
Country	**Policy**	**Agg.**	**Urban**	**Rural**	**Utility %Δ**
Hungary	Oil Tax	-2.29	-2.55	-1.74	0.01
Hungary	Ag. Burning Tax	-0.03	-0.03	-0.02	0.00
Hungary	Coal Tax	-7.19	-7.55	-6.43	0.03
Indonesia	Oil Tax	-7.97	-12.33	-0.57	0.00
Indonesia	Ag. Burning Tax	0.03	0.00	0.07	0.00
Indonesia	Coal Tax	-0.68	-1.02	-0.10	0.00
India	Oil Tax	-2.11	-3.06	-1.34	0.00
India	Ag. Burning Tax	2.17	0.01	3.91	0.00
India	Coal Tax	-11.66	-9.83	-13.14	0.00
Republic of Korea	Oil Tax	-6.12	-5.25	-10.88	-0.01
Republic of Korea	Ag. Burning Tax	0.93	0.00	5.97	-0.00
Republic of Korea	Coal Tax	-8.31	-7.57	-12.30	-0.01
Lithuania	Oil Tax	-5.70	-5.03	-6.65	0.07
Lithuania	Ag. Burning Tax	1.52	2.44	0.23	-0.02
Lithuania	Coal Tax	-5.37	-5.31	-5.44	0.07
Malaysia	Oil Tax	-8.52	-8.80	-7.54	0.03
Malaysia	Ag. Burning Tax	0.03	0.02	0.08	-0.00
Malaysia	Coal Tax	-0.92	-0.87	-1.06	0.00
Pakistan	Oil Tax	-7.29	-12.90	-3.86	-0.01
Pakistan	Ag. Burning Tax	2.22	0.01	3.58	-0.00
Pakistan	Coal Tax	-0.32	-0.25	-0.36	-0.00
Poland	Oil Tax	-1.07	-1.21	-0.88	0.01
Poland	Ag. Burning Tax	-0.06	-0.03	-0.11	0.00
Poland	Coal Tax	-12.68	-13.20	-11.92	0.03
Portugal	Oil Tax	-12.93	-12.45	-14.14	-0.01
Portugal	Ag. Burning Tax	-0.80	0.00	-2.79	0.00
Portugal	Coal Tax	-0.47	-0.38	-0.70	-0.00
Romania	Oil Tax	-3.25	-5.11	-1.10	0.01
Romania	Ag. Burning Tax	0.66	0.10	1.30	-0.00
Romania	Coal Tax	-5.07	-7.60	-2.12	0.00
Russia	Oil Tax	-2.61	-1.41	-7.75	-0.01
Russia	Ag. Burning Tax	3.81	0.00	20.12	-0.00
Russia	Coal Tax	-13.11	-12.25	-16.81	-0.01
Serbia	Oil Tax	-10.89	-2.29	-18.31	-0.04
Serbia	Ag. Burning Tax	10.37	0.40	18.97	-0.00
Serbia	Coal Tax	-15.63	-12.15	-18.64	-0.02
Slovakia	Oil Tax	-1.60	-1.88	-1.25	0.01
Slovakia	Ag. Burning Tax	0.39	0.21	0.61	-0.00
Slovakia	Coal Tax	-11.88	-11.40	-12.50	0.06

Table 15: Country Results - No Rebate, Ctd.

		Exposure %Δ			
Country	**Policy**	**Agg.**	**Urban**	**Rural**	**Utility %Δ**
South Africa	Oil Tax	-4.96	-6.47	-1.54	0.01
South Africa	Ag. Burning Tax	-1.04	-0.31	-2.69	0.002
South Africa	Coal Tax	-3.59	-3.03	-4.86	-0.03
Thailand	Oil Tax	-6.50	-11.57	-1.55	0.00
Thailand	Ag. Burning Tax	-0.40	0.00	-0.78	0.00
Thailand	Coal Tax	-0.96	-1.67	-0.26	-0.00
Turkey	Oil Tax	-0.66	-0.97	0.24	0.00
Turkey	Ag. Burning Tax	3.44	0.02	13.12	-0.00
Turkey	Coal Tax	-12.50	-12.17	-13.44	-0.00
Ukraine	Oil Tax	-1.84	-1.67	-2.18	0.00
Ukraine	Ag. Burning Tax	13.27	10.12	19.63	-0.04
Ukraine	Coal Tax	-14.98	-13.47	-18.04	0.02
USA	Oil Tax	-6.29	-7.20	-1.47	0.00
USA	Ag. Burning Tax	-0.28	0.00	-1.77	0.00
USA	Coal Tax	-5.65	-6.13	-3.09	-0.00

Table 16: Country Results - Lump-Sum Rebate

		Exposure %Δ			
Country	**Policy**	**Agg.**	**Urban**	**Rural**	**Utility %Δ**
Australia	Oil Tax	-4.94	-7.08	9.85	0.01
Australia	Ag. Burning Tax	-0.29	-0.74	2.88	0.00
Australia	Coal Tax	-10.01	-12.12	4.60	-0.00
Bangladesh	Oil Tax	-5.75	-12.57	-2.76	0.00
Bangladesh	Ag. Burning Tax	-3.17	-7.66	-1.20	0.00
Bangladesh	Coal Tax	-0.45	-1.07	-0.17	0.00
Bulgaria	Oil Tax	-4.35	-5.85	-0.32	0.04
Bulgaria	Ag. Burning Tax	4.95	6.08	1.91	-0.03
Bulgaria	Coal Tax	-9.81	-10.83	-7.06	0.07
Bosnia and Herzegovina	Oil Tax	-0.49	-3.95	2.47	0.07
Bosnia and Herzegovina	Ag. Burning Tax	1.99	-0.53	4.14	0.01
Bosnia and Herzegovina	Coal Tax	-14.33	-14.63	-14.09	0.02
Belarus	Oil Tax	-8.93	-12.43	0.93	0.01
Belarus	Ag. Burning Tax	0.07	-0.72	2.30	0.00
Belarus	Coal Tax	-2.45	-3.11	-0.57	0.00
Brazil	Oil Tax	-9.22	-13.56	3.51	0.00
Brazil	Ag. Burning Tax	-0.33	-0.94	1.48	0.00
Brazil	Coal Tax	-0.81	-1.11	0.05	-0.00
China	Oil Tax	-2.56	-3.99	0.49	0.03
China	Ag. Burning Tax	7.86	-2.30	29.57	0.03
China	Coal Tax	-18.30	-17.26	-20.50	0.02
Czech Republic	Oil Tax	-3.47	-9.55	13.88	0.05
Czech Republic	Ag. Burning Tax	-1.18	-2.19	1.67	0.01
Czech Republic	Coal Tax	-11.71	-26.98	31.78	0.13

Table 17: Country Results - Lump-Sum Rebate, Ctd.

		Exposure %Δ			
Country	**Policy**	**Agg.**	**Urban**	**Rural**	**Utility %Δ**
Croatia	Oil Tax	-8.24	-12.34	-1.33	0.03
Croatia	Ag. Burning Tax	-0.60	-0.70	-0.43	0.01
Croatia	Coal Tax	-3.12	-4.18	-1.34	0.00
Estonia	Oil Tax	-12.20	-19.59	2.56	0.08
Estonia	Ag. Burning Tax	-0.38	-0.33	-0.47	0.00
Estonia	Coal Tax	-1.15	-1.22	-1.00	0.00
Great Britain	Oil Tax	-5.49	-9.27	13.12	0.01
Great Britain	Ag. Burning Tax	-0.04	-0.07	0.12	0.00
Great Britain	Coal Tax	-8.34	-9.57	-2.31	0.00
Greece	Oil Tax	-5.22	-8.26	4.50	0.01
Greece	Ag. Burning Tax	0.48	-0.55	3.75	0.00
Greece	Coal Tax	-10.07	-10.86	-7.55	0.00
Hungary	Oil Tax	-2.97	-6.02	3.53	0.03
Hungary	Ag. Burning Tax	-0.09	-0.33	0.42	0.00
Hungary	Coal Tax	-7.50	-9.20	-3.88	0.04
Indonesia	Oil Tax	-8.48	-13.76	0.51	0.01
Indonesia	Ag. Burning Tax	-0.61	-1.68	1.19	0.01
Indonesia	Coal Tax	-0.82	-1.39	0.15	0.00
India	Oil Tax	-2.42	-4.34	-0.88	0.00
India	Ag. Burning Tax	1.52	-2.71	4.92	0.00
India	Coal Tax	-11.98	-11.11	-12.68	0.00
Republic of Korea	Oil Tax	-6.53	-12.48	25.77	0.01
Republic of Korea	Ag. Burning Tax	0.85	-0.93	10.50	0.00
Republic of Korea	Coal Tax	-8.65	-10.97	3.94	0.00
Lithuania	Oil Tax	-5.70	-5.94	-5.36	0.08
Lithuania	Ag. Burning Tax	1.52	2.20	0.57	-0.02
Lithuania	Coal Tax	-5.37	-5.34	-5.40	0.07
Malaysia	Oil Tax	-8.69	-9.47	-5.99	0.03
Malaysia	Ag. Burning Tax	-0.03	-0.21	0.58	0.00
Malaysia	Coal Tax	-0.98	-1.11	-0.53	0.00
Pakistan	Oil Tax	-7.43	-14.42	-3.16	0.01
Pakistan	Ag. Burning Tax	2.02	-1.98	4.47	0.02
Pakistan	Coal Tax	-0.33	-0.34	-0.32	-0.00
Poland	Oil Tax	-0.11	-10.32	14.65	0.06
Poland	Ag. Burning Tax	-0.01	-0.84	1.19	0.01
Poland	Coal Tax	-9.18	-33.00	25.23	0.17
Portugal	Oil Tax	-14.12	-15.84	-9.84	0.01
Portugal	Ag. Burning Tax	-1.00	-0.57	-2.09	0.00
Portugal	Coal Tax	-0.62	-0.79	-0.18	0.00
Romania	Oil Tax	-3.88	-9.47	2.58	0.05
Romania	Ag. Burning Tax	0.19	-2.85	3.72	0.03
Romania	Coal Tax	-5.46	-10.35	0.20	0.03
Russia	Oil Tax	-4.70	-10.29	19.27	0.02
Russia	Ag. Burning Tax	3.67	-0.64	22.15	0.00
Russia	Coal Tax	-14.46	-17.66	-0.74	0.01
Serbia	Oil Tax	-9.98	-9.30	-10.57	0.03
Serbia	Ag. Burning Tax	10.68	-1.25	20.98	0.01
Serbia	Coal Tax	-15.12	-15.73	-14.60	0.02

Table 18: Country Results - Lump-Sum Rebate, Ctd.

Country	Policy	Exposure %Δ Agg.	Urban	Rural	Utility %Δ
Slovakia	Oil Tax	-1.36	-4.12	2.17	0.04
Slovakia	Ag. Burning Tax	0.40	0.09	0.80	-0.00
Slovakia	Coal Tax	-11.80	-12.37	-11.07	0.07
South Africa	Oil Tax	-6.14	-9.30	1.03	0.03
South Africa	Ag. Burning Tax	-0.92	-0.04	-2.91	0.00
South Africa	Coal Tax	-6.25	-9.47	1.04	0.01
Thailand	Oil Tax	-6.66	-12.46	-0.98	0.01
Thailand	Ag. Burning Tax	-0.52	-0.60	-0.44	0.01
Thailand	Coal Tax	-1.02	-2.00	-0.07	0.00
Turkey	Oil Tax	-0.62	-1.71	2.47	0.00
Turkey	Ag. Burning Tax	3.49	-0.58	15.02	0.00
Turkey	Coal Tax	-12.48	-12.68	-11.92	-0.00
Ukraine	Oil Tax	-1.54	-3.15	1.71	0.01
Ukraine	Ag. Burning Tax	13.42	9.08	22.17	-0.03
Ukraine	Coal Tax	-14.59	-15.18	-13.42	0.03
USA	Oil Tax	-7.34	-9.93	6.38	0.01
USA	Ag. Burning Tax	-0.37	-0.21	-1.20	0.00
USA	Coal Tax	-6.22	-7.61	1.10	0.00