Pollution, Productivity, and Place

Anshuman Tiwari*

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Abstract

How do the health benefits of reducing air pollution translate into aggregate income gains? Income gains can differ from health benefits because labor productivity may vary in the places where people experience lower pollution, and because labor reallocation to those places may reinforce agglomeration economies. This paper shows that incorporating two physical features of pollution sources - their location and long-distance dispersion tendency - can alter the importance of labor productivity and reallocation, and lead to very different income gains from pollution control policies that otherwise produce similar population health benefits. To understand these interactions, I develop a spatial equilibrium model that accounts for the movement of both pollution and people across space. I apply this model to study income gains from two archetypal pollution control policies that target non-industrial sources in India and produce similar population exposure reductions, but in very different places. One policy controls agricultural fires in northwestern India that spread pollution across much of north India, and another policy reduces localized emissions from sources such as vehicles within India's 10 largest cities. Accounting only for differential labor productivity in the places experiencing lower pollution, I find that the latter policy leads to a 3 times larger GDP gain relative to the former. Further accounting for labor reallocation and agglomeration economies leads to a 6 times larger GDP gain. These results have important implications for spatial targeting of pollution control, especially in poor-yet-polluted LMICs.

* UC Santa Barbara (email: atiwari@ucsb.edu). Financial support from the Environmental Defense Fund, the Grantham Research Foundation and STICERD is gratefully acknowlegded.

1 Introduction

Improving air quality can produce substantial health benefits. But how do spatially targeted pollution control measures translate into aggregate productivity gains? Health improvements in targeted locations will produce larger income gains if labor productivity, or the real output per worker, in that location is higher. At the same time, changes in relative air quality across space create incentives for labor reallocation. If less productive rural areas are targeted by pollution control, the narrowing rural-urban wage gap can reallocate workers to rural areas, leading to smaller gains from sorting. On the other hand, lower emissions from rural areas may lead to cleaner downwind cities, reallocating workers to those cities and increasing the gains from reallocation since urban areas are more productive. This paper develops a spatial equilibrium framework to account for the movement of both people and pollution across space, and applies it to India to study the productivity implications of spatially targeted pollution control measures.

Almost all of India's population in 2020 experienced annual concentration higher than the WHO limit for particulate matter below 2.5 microns in size, commonly referred to as PM2.5 (Greenstone 2022).[1] Exposure to such pollution is known to cause serious health effects that lower the physical productivity of workers.[2] Lowering pollution would therefore improve health and physical worker productivity, but the income gains from these improvements will be larger if they occurred in places with a larger marginal product of labor. While the location of the emissions source is important for this reason, a key feature of sources is how likely those emissions are to affect people living in distant, downwind places. Sources such as agricultural fires, wildfires, thermal power plants or industrial

[1] The WHO annual average limit is 5 μg/m3. 62% lived above India's own guidelines of 40 μg/m3. Delhi's annual average PM2.5 level was 98.6 μg/m3 in 2019, in comparison with New York city's average of 7 and London's at 11.4.

[2] For instance, Chang et al. (2016) show that higher PM2.5 levels lower the number of pears picked by workers at a factory. In terms of health effects, both short-term and prolonged exposure can cause premature mortality in people with heart or lung diseases, lead to heart attacks, asthma, decreased lung function or cancer, stroke and a variety of other conditions.

smokestacks increase pollution in their vicinity but also disperse pollution to downwind locations that may be hundreds of kilometers away (Singh et al. 2021; Burke et al. 2021). On the other hand, emissions from sources such as vehicle tailpipes typically decay within a short distance, affecting air quality only within the jurisdiction in which they are driven. Depending on this feature of the source, emissions control can leads to better air quality and improved health in places with very different marginal products of labor, and therefore different income gains.

In addition to this partial equilibrium mechanism for income gains, changes in relative air quality also cause the relative wage and amenity differentials across *all* locations to change, generating incentives to migrate in general equilibrium. The dispersion feature of the regulated pollution source can change whether workers reallocate to more productive urban or less productive rural locations: if relatively more workers move to high productivity locations, aggregate gains will be larger due to better spatial allocation of labor. Between 2002 and 2010, PM2.5 increased by an average of 10% across India, with substantial heterogeneity across regions. I provide evidence that a 1% increase in pollution reduced worker migration into Indian districts by 2%. Since pollution, economic activity and migration are jointly determined, I instrument for changes in pollution with exogenous shifts in upwind agricultural fires that are unrelated to patterns of local industrial growth.

This paper studies aggregate income gains from spatially targeted emissions control policies, in other words, policies that are place-based. Reduced form analysis cannot answer this question since any change in pollution levels across space alters the inventive to migrate even in locations where air quality is unaffected by the policy. Instead, I build a worker location choice model that can accommodate migration of workers and dispersion of pollution across fine-grained geographic units in India, while being tractable enough to conduct policy analysis. Specifically, I embed pollution dispersion across locations into a spatial equilibrium framework featuring agents with heterogeneous preferences for locations, and realistic migration costs that restrict mobility (Redding and Rossi-Hansberg

2017). This framework allows for rich counterfactuals to simulate pollution control measures currently being implemented in India. The model also accounts for other mechanisms by which pollution control could affect aggregate productivity: (1) labor reallocation toward cities can affect agglomeration economies (Au and Henderson 2006), and (2) labor reallocation could also have congestion effects, for example on house prices (Bayer et al. 2009).

The migration response away from pollution that I document may be explained by two potential channels. First, the worker productivity effects of pollution may depress incomes (Borgschulte et al. 2022). All else equal, a greater pollution differential between two locations will increase the income differential, lowering the incentive to migrate to the more polluted location (W. A. Lewis 1954; Harris and Todaro 1970). The income elasticity governs how worker migration responds to income differences across locations: a lower elasticity implies that higher incomes need to be paid on average to induce marginal workers to migrate. Second, pollution may lower quality of life and thus have a direct amenity value (Roback 1982). The amenity elasticity governs whether workers respond to pollution by migrating away due to a lower quality of life. Prior work on developing countries argues that this second channel is less important given the low willingness to pay to avoid air pollution damages as a consequence of low income levels (Greenstone et al. 2021; Greenstone and Jack 2015).

I estimate these income and amenity elasticities together in a gravity framework implied by the quantitative model, leveraging data on worker migration across 600 district pairs from the Indian population census along with data on wage and pollution levels. I employ an instrumental variables strategy to deal with endogeneity concerns about unobserved, residual factors that affect migration and are correlated with wage or pollution.[3] Specifically, I construct a shift-share instrument for wages that weights 5-digit industry national average wages by lagged local employment share in those industries (Tombe and Zhu

[3] For example, the quality of housing stock or pre-existing origin-destination migrant networks.

2019). For pollution, I exploit exogenous variation arising from exposure to upwind agricultural fires. I find an income elasticity of 3.45, while the point estimate of -0.15 for the amenity elasticity is not statistically distinguishable from zero. Before I can conduct policy analysis using the model, I also estimate several other parameters that govern spatial equilibrium.

I now turn to evaluating the aggregate productivity gains from two policies that are based on India's recently announced pollution control measures. The first policy simulates a 10% reduction of emissions from crop burning or agricultural fires originating in the two states of Punjab and Haryana in northwestern India that accounted for ~56% of burning events in 2010.[4] Dispersal of smoke from crop residue burning in distant rural areas is an important contributor to pollution in north India, accounting for up to 20% of annual PM2.5 concentrations in Delhi in recent years (Singh et al. 2021). The second policy simulates control of within-city sources such as vehicles and cookstoves in the 10 largest cities of India.[5]

I hold total population-exposure reduction constant between the crop burning and localized urban emissions policies, such that well-established public health-based benefit calculations would judge both policies to be near-identical.[6] Accounting only for place-specific labor productivity differences, the urban emissions policy increases total GDP by 3 times more than the crop buring policy. Accounting also for labor reallocation to cleaned-up places and the resulting agglomeration economies, the urban emissions pol-

[4] This policy is based on the Commission for Air Quality Management Act, 2021 (CAQM) that regulates emissions sources that affect north India, including cities such as Delhi, Agra, Kolkata and Lucknow. This commission was established through an act of parliament, and includes members from most north Indian states. The commission has been empowered to control the practice of burning.

[5] This policy is based on the National Clean Air Program (NCAP) that was launched in 2019 (Ganguly et al. 2020). In the first phase, this program required cities to develop action plans for transport sector interventions and emissions from burning wood for cooking. I rely on a city-level source apportionment study that estimates the share of each district's PM2.5 that comes from local transport and domestic sectors (McDuffie et al. 2021)

[6] The precise calculations depend on the shape of the dose-response function considered. The EPA uses a linear function that would produce identical benefits from these two policies, whereas a concave dose-response would judge the crop burning policy better due to larger marginal health benefits for rural residents who are exposed to relatively lower baseline PM2.5 levels.

icy increases total GDP by 6 times more than the crop burning policy. Labor reallocation accounts for less than 1% of the GDP gains in general equilibrium from the crop burning policy, as opposed to more than half of the gains from the urban emissions policy.

What explains these results? Pollution dispersion and worker migration interact with the location and dispersion features of each source to determine aggregate benefits. Gains from migration are larger when air quality improvements reallocate workers to cities, since workers produce higher economic output in a more productive city compared to a rural area. The control of fires improves air quality along the entire pollution dispersion path that includes some cities, but it improves air quality in rural areas more. As a result, migration is skewed toward rural areas, and productivity gains from migration are smaller. On the other hand, policies to control sources such as vehicle or cookstove emissions improve air quality solely within the city. This reinforces the comparative advantage of cleaned-up cities, leading to higher productivity gains from reallocation to those cities that further reinforces agglomeration economies.

This paper makes several contributions. I provide the first estimates for aggregate productivity gains from pollution control in India, and among the first for anywhere in the world. These results also suggest that air quality regulation that only accounts for health benefits may underestimate benefits from abatement (US EPA 2015; Currie and Walker 2019).[7] This is especially true in rapidly urbanizing economies that also suffer from some of the worst air pollution in the world. Spatial sorting can change both the spatial distribution and magnitude of health benefits that are based on partial equilibrium calculations. Further, a more complete characterization of benefits from pollution control policies under consideration would account both worker migration and pollution dispersion, since income gains from avoided pollution dispersion and from resulting labor reallocation are at least as important as the local health benefits in India.

This paper also contributes to the macro-development literature that has tended to view

[7] Indian air quality regulation is also based on similar standards.

migration toward urban areas as being synonymous with economic growth and development (W. A. Lewis 1954; Gollin 2014). This paper argues that pollution leads to spatial misallocation of labor because unpriced pollution externalities from economic activity reduce worker productivity and wages, thus attracting fewer workers to polluted places. This misallocation is larger when the pollution externality affects cities where the same worker can be relatively more productive. The implication is that tackling air pollution sources within cities is a more promising way of generating economic growth. This mechanism also differs from Khanna et al. (2023) who quantify aggregate productivity losses from high-skilled workers' stronger preferences for clean air that leads them to migrate away from pollution in China. Much of this literature explains the persistence of large spatial productivity gaps within countries Bryan and Morten (2019). This paper relates more closely to the question posed in W. A. Lewis (1954) of whether worker reallocation can increase economic output.

The rest of the paper is structured as follows. Section 2 describes the data used in the paper while section 3 motivates the quantitative model. Section 4 presents the model while section 5 describes the estimation of the parameters governing equilibrium. Section 6 describes the results from policy counterfactuals and section 7 concludes.

2 Data and Measurement

2.1 Air quality

An important consideration for air quality data is complete geographical coverage. Ground-level monitoring station coverage in India is extremely sparse (Greenstone and Hanna 2014). Observations from these stations also may be more susceptible to manipulation (Greenstone et al. 2022; Ghanem and Zhang 2014). On the other hand, satellite imagery-based products provide complete coverage and cannot be manipulated by local actors. The source of remote sensing data on air quality in this paper is Hammer et al. (2020), a gridded reanalysis product of global surface PM2.5 concentrations at a resolution of 0.01°. This product combines satellite imagery data on Aerosol Optical Depth with state-of-the-art chemical transport models, and calibrates the output to global ground-based observations. This product has been used in the literature to measure PM2.5 levels in settings where ground level observations are sparse (Khanna et al. 2023). These data are aggregated up to the district level using spatial averaging for analysis.

2.2 Crop Burning

Crop burning is the practice of setting fire to leftover residue after crop harvest, also referred to as agricultural fires. There are no representative ground-level observations of this phenomenon, but the National Aeronautics and Space Administration (NASA) agency of the United States produces the Fire Information for Resource Management System (FIRMS) product that is widely used to identify such fires. This product provides information on daily, pixel-level fire detection across the world. FIRMS provides a few related products: a Near-Real Time (NRT) fires using the MODIS instrument aboard Terra and Aqua satellites, a quality-controlled standard product from the same instrument but with a 2-3 month lag and another NRT product using the VIIRS instrument from the Suomi-NPP and NOAA-20 satellites. The main difference between the first two and the third is the resolution of the data. MODIS products are at 1 km resolution and are available from 2000 (with higher reliability from 2002 onward when the Aqua satellite was launched) whereas VIIRS products are at 375 m but only available from 2012.

Since the main analysis in this paper relies on data from before 2012, I am unable to use the higher-resolution VIIRS-based product. The primary analysis utilizes the MODIS quality-controlled standard product which differs from the NRT data in that corrections are made to the imprecise location of the Aqua satellite in the NRT data. Imagery data from Aqua and Terra satellites is available at least four times daily for each pixel on Earth and is processed by NASA using a proprietary algorithm to isolate a ground-level fire signal from other signals such as solar flares.[8]

I combine this data with land use data from the European Space Agency Climate Change Initiative's land cover map (version 2.07).[9] This allows the subset of fires that is found on agricultural land to be separated from natural forest fires since this paper is interested in agricultural fires. I aggregate and resample the land cover data which is at a resolution of 300 m to the fire data grid (which is at 1 km resolution); an indicator for agricultural land use is the main output from this process. All fires are then masked based on this indicator variable to find the subset of agricultural fires.

2.3 Migration

The source of data on migration in this paper is the Population Census of India, 2011.[10] For the reduced form effect of pollution on migration, I utilize census table D03 on migrant inflows for each district from other districts within the last 4 years and 5-9 years. I relate changes in these inflows for each district with changes in average pollution within each period, instrumenting for pollution changes with changes in neighboring district fire exposure. Migrant inflow data is broken down by gender and the reason for migration. I use this table to show that the primary reason for female migration in India is for marriage, since the social norm is for newly-married women to move to their husband's town or village. In contrast, the dominant reason for male migration is work-related.

The spatial equilibrium approach has specific data requirements in the form of migration shares from all possible origins to all possible destinations, in order to estimate the amenity and income elasticities of migration. These requirements are satisfied by the ag-

[8] Further information on these products is available at https://firms.modaps.eosdis.nasa.gov

[9] Data is available at https://cds.climate.copernicus.eu/cdsapp/#!/dataset/satellite-land-cover

[10] See https://censusindia.gov.in/census.website/data/census-tables

gregate census data by constructing migration shares from census tabulations of the number of people canvassed in each district by the district of birth. The use of district of birth as the origin and district of enumeration as the destination is an approach the literature has taken before (Bryan and Morten 2019). This measure of migration shares should capture all migrants except for those who were not present in their destination at the time of enumeration for idiosyncratic reasons.

The census provides two separate tabulations of location of birth and location of enumeration (the person's location at the time of interview for the census). First, table D-01 provides data on the number of people enumerated in a given district who were born in districts of the same state. This allows construction of within-state migration shares across districts. Second, table D-11 provides data on the number of people who were enumerated in a given district but were born in a different state of the Union of India. In order to construct the complete data set on migration shares across *all* districts of India, I need to allocate data from table D-11 on the total number of workers who were born in a given state but moved to a district outside that state, to the various districts in the state of origin. This data is not publicly available.

In order to do this, I utilize information on the out-migration tendency of districts from table D-01 by calculating each district's share of out-migrants within the same state. Then I assume that these within-state out-migration shares are the same for out-migration to districts in other states. This allows me to allocate the number of out-migrants to a district outside the state, to each district of the state of origin. To the extent that certain districts send out more migrants, whether within state or outside, this method would capture migration shares from a district in a given state to another district outside that state, with some error. This method also does not use additional information such as distance between districts or relative wages that enter the estimating equation.

2.4 Wages

Wage data are utilized mainly in the estimation of migration elasticities. These come from the National Sample Survey Organization's Employment and Unemployment round 68 for the year 2010-11. The sample provides microdata on individual earnings and work hours within the last 7 days from date of enumeration along with information on 5-digit industry codes; whether the work contract was permanent (salaried) or made on the spot (casual labor); and whether work was done within household, for an employer or on public works. I restrict the sample to individuals aged 18-59, who work for an employer regardless of contract type as the most representative group of people when constructing city-level wage.

2.5 Meteorological data

Wind data are used to construct exposure to agricultural fires for every origin-destination pixel pair. Details of the methodology follow in section 3.3.1 below. These data come from the ERA5 family of global gridded reanalysis datasets produced by the European Center for Medium Range Weather Forecasting (ECMWF).[11] Reanalysis data combine ground-level observations and satellite data with chemical transport models that represent physical and chemical processes in the atmosphere to produce reliable and complete coverage for the world. Since ground-level observations are particularly sparse in developing countries, these reanalysis data are widely used in the literature on climate and air pollution (Auffhammer et al. 2013). Hourly wind speed and direction data are taken from the ERA5-Land hourly dataset which is available at a resolution of 0.1°. These are combined with daily agricultural fires at the pixel level to construct the fire exposure variable, as described in section 3.3.1 below. Finally, I also construct temporal averages for weather variables including rainfall, temperature and relative humidity from this data set to be

[11] Data is available at https://cds.climate.copernicus.eu

used as controls in the regression analysis.

3 Motivation

3.1 Physical Features of Targeted Sources Matter for Income Gains

An important feature of pollution sources for income gains is their physical location: are sources in rural or urban areas? A person living in a rural area who experiences health improvement due to a given pollution reduction would produce more real output they produce as a result of this health improvement. Now imagine another person, similar in most other respects, but who lives in an urban location and is likely to work in a higher marginal product industry. If this urban worker experiences the same health improvement as the rural person, the urban resident is more likely to produce larger real output by virtue of their working in a *place* that is characterized by a higher marginal product. In this way, two pollution control policies that achieve the same population health benefits might lead to very different income gains if the reduction in pollution is targeted at very different places.

A second feature of pollution sources that matters for income gains is whether they disperse pollution to downwind locations hundreds or thousands of kilometers away, sometimes termed "long-distance transport." If a rural source affects urban pollution, the income gains from controlling emissions from this particular rural source may be larger than another rural sources that only affected local pollution (and the other way around for urban sources). Air pollution regulation must target specific sources in order to achieve standards that are set out by legislation. Targeted sources may differ in the two physical dimensions outlined above, and therefore may have distinct consequences for income gains.

3.2 Indian Pollution Control Programs Target Distinct Sources

In this paper, I study two policies that are motivated by real-world policy dilemmas facing Indian policymakers. Urban policymakers are likely to emphasize upwind emissions from mostly rural areas so that they can avoid taking blame for local emissions that also contribute to high pollution levels.[12] At the same time, national policymakers invariably focus on reducing emissions from urban sources first, since the media highlight urban issues more even as urban citizens tend to have a greater voice in the media.

These competing pressures are seen in two recent pollution control programs of the Government of India. The Commission on Air Quality Management Act, 2021 (CAQM) is a recent legislation that aims to curb pollution in north India, an area that includes cities such as Delhi, Lucknow and Agra. CAQM explicitly targets crop residue burning in rural areas of northwestern India that disperse smoke over hundreds of kilometers to cities in north India. At the same time, the National Clean Air Program, 2019 (NCAP) is a recent attempt to clean up pollution in 122 cities that are classified as "non-attainment" cities, or having air pollution above certain thresholds. Phase 1 of NCAP targets sources within cities such as vehicles and cookstove emissions that also tend not to affect downwind areas far away, so-called "localized sources" (Ganguly et al. 2020).

In this paper, I simulate two hypothetical policies that are based on CAQM and NCAP. Due to their differences on the two physical features of emissions sources being controlled, varying importance of economic mechanisms may lead to distinct income consequences of pollution control from these two policies. In order to analyze *how* these economic mechanisms based on the physical features of emissions sources, I hold fixed the *health benefits* from the two policies of interest. These health benefits are determined by environmental regulators using standard methodology that related the change in pollution exposure per person to changes in morbidity and mortality risk (for eg. the risk of death or disabil-

[12] This happens with alarming frequency in the case of seasonal crop residue burning that sharply increases pollution levels during the winter and spring seasons in the city of Delhi.

ity from a stroke) using published epidemiological dose-response functions. Therefore, I hold the total population-exposure fixed between these policies, so that they will be rated as producing similar health benefits.[13]

3.3 Long-distance Pollution Dispersion Matters for Crop Burning

The main determinant of long-distance pollution dispersion from a given source is whether the emissions plume reaches a height where ground-level convective processes are unable to bring the plume down to earth close to the source location. Once captured by upper atmospheric winds, the plume can travel hundreds or even thousands of kilometers (Vallero 1973). Other factors that can impact this process include the decay rate of pollutants, meteorological conditions, and the presence of obstructions like buildings. For example, localized emissions from vehicles can get trapped by buildings due to limited airflow (Wang et al. 2006). Various studies on the decay rates of vehicular pollutants finds that these emissions rarely travel more than a couple of kilometers (Liu et al. 2019). At the same time, emissions from indoor cookstoves that burn polluting fuels like firewood and charcoal can affect ambient concentrations in the vicinity (Chafe et al. 2014). Evidence from India also suggests that air pollution from such sources only affect local air quality (Guttikunda et al. 2023).

On the other hand, crop residue burning in rural areas is a well-known public health issue in distant, downwind cities (Singh et al. 2021). Although air pollution modelers have done work on understanding the contribution of crop residue burning on downwind pollution (Guttikunda et al. 2023), tools to conduct the kind of policy simulation I perform do not exist. Therefore, in the next section, I develop a method that facilitates a spatially explicit yet computationally feasible analysis of where air quality would improve as a result of

[13]: If the dose-response function is linear, these benefits will be identical. For some diseases, this function may be concave in pollution exposure. Slightly larger health gains will therefore be achieved for places that have lower baseline pollution; these are usually rural places. It is rare to find any convex dose-response functions, although ongoing epidemiological research may find one.

controlling crop residue burning.

3.3.1 Modeling Pollution Impact of Crop Residue Burning

First, I briefly cover the causes of crop burning (also referred to as agricultural fires). Crop burning is used to clear agricultural fields of leftover residue after the crop harvesting, before sowing and planting the next crop (Shyamsundar et al. 2019); this differs from slash-and-burn agriculture that is practiced in parts of Africa and Indonesia (Andini et al. 2018). Figure 1 provides a map of where crop burning is most prevalent in India; fires are concentrated in the northwestern states of Punjab and Haryana. It is a common practice in these regions since the rice residue must be removed before the wheat crop can be sowed. The turnaround time between rice harvest and wheat sowing is about 2 weeks, dictated by seasonal patterns. This further incentivizes the use of burning to remove the residue. Appendix section 9.4 provides more detail on the causes behind the burning of agricultural residue.

In the rest of this section, I develop a smoke dispersion model to calculate smoke exposure of any location to all upwind fires. I then estimate the impact on PM2.5 of this smoke exposure. These two objects capture the consequences for pollution reduction of the crop burning policy. I start with the smoke dispersion model. In order to capture the contribution of crop burning emissions E_o in source district o on air quality in receptor district d, I construct a source-receptor smoke dispersal matrix for all pairs of districts. Since agricultural fires are observed at a daily level, I leverage daily variation in wind patterns at the *origin* district to construct this matrix for every year y and $o \neq d$ as follows

$$\omega_{ody} = \left(\sum_{t=Jan-1-y}^{Dec-31-y} \theta_{odt} E_{ot} \right) \tag{1}$$

where

$$\theta_{odt} = \frac{wind_{odt}}{distance_{od}}$$

A schematic for the construction of θ_{odt} is shown in figure 2. The numerator $wind_{odt}$ is the daily average fraction of time that the wind at o blows towards d on day t. In order to calculate $wind_{odt}$, I start by assigning each hourly wind observation in o on day t into one of 36 bins of 10 degree span each, based on the wind direction that hour (true north is 0 degree as in the figure). I then construct the wind speed-weighted fraction of time the wind was blowing in each of these 36 bins by aggregating hourly observations for day t. $wind_{odt}$ is calculated by summing up wind fractions for the bins within th 180-degree cone in the direction of d from o.

Daily smoke exposure from o to d is then calculated by multiplying θ_{od} by daily emissions E_{ot} at origin. Annual smoke exposure from pixel o to d is then the sum of daily smoke exposures. Once I have this source-receptor matrix for each year in hand, I construct total smoke exposure Ω_d for destination d as the sum of exposures ω_{od} from all origins o *plus* the local annual emissions E_d.

$$\Omega_d = (\sum_{o \neq d} \omega_{od}) + E_d \tag{2}$$

The vector Ω summarizes the smoke exposure of any given location to crop burning in *all* other locations, accounting for daily changes in fire activity and wind pattern at those locations. Figure 3 demonstrates visually that this smoke exposure metric positively correlates with PM2.5 across Indian districts.

In order to estimate the causal effect of annual smoke exposure Ω_{dy} on average annual PM2.5 concentration PM_{dy}, I run the following regression at the district-level using panel data from 2002-2016. I estimate various functional forms of g(.); more details is provided in the appendix. Summary statistics for the regression variables are provided in table 7.

$$PM_{dy} = g(\Omega_{dy}) + Y_y + D_d + \epsilon_{dy} \tag{3}$$

The identification assumption is that local pollution levels do not lead to abatement of crop burning, in local or upwind areas. This is likely to be satisfied, given that most regulations on crop burning are not implemented (Jack et al. 2022).

Figure 4 depicts this empirical relationship for a cubic functional form of g(.). Appendix table A.1 shows the estimated functional form for this exercise.

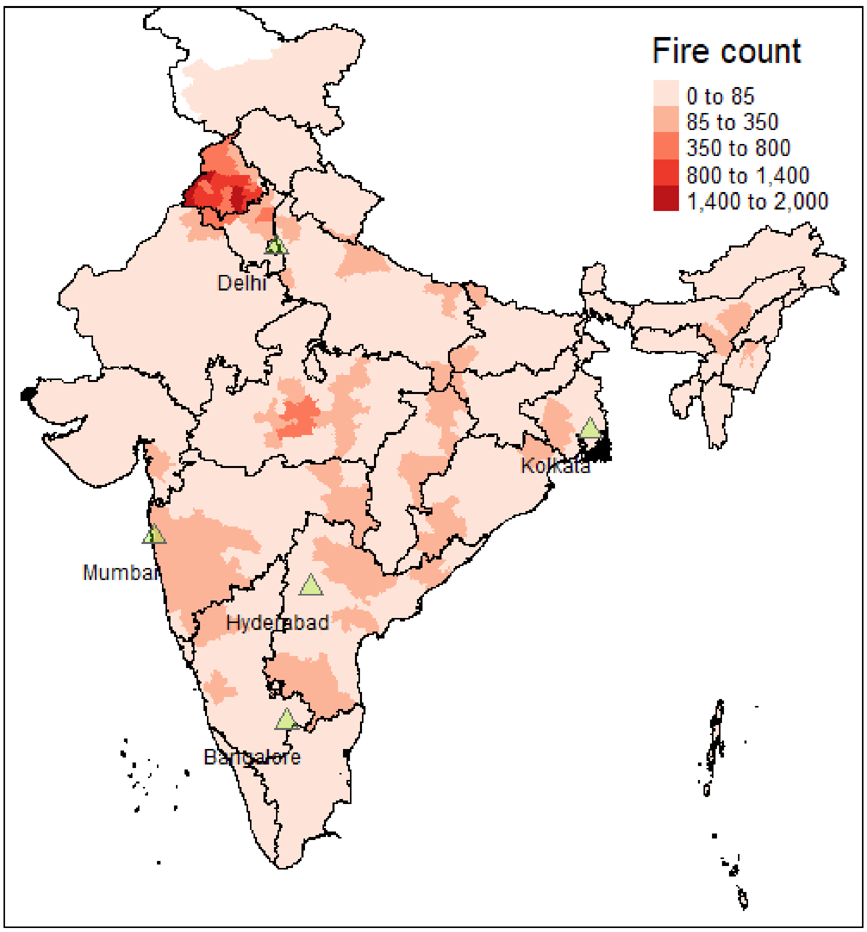
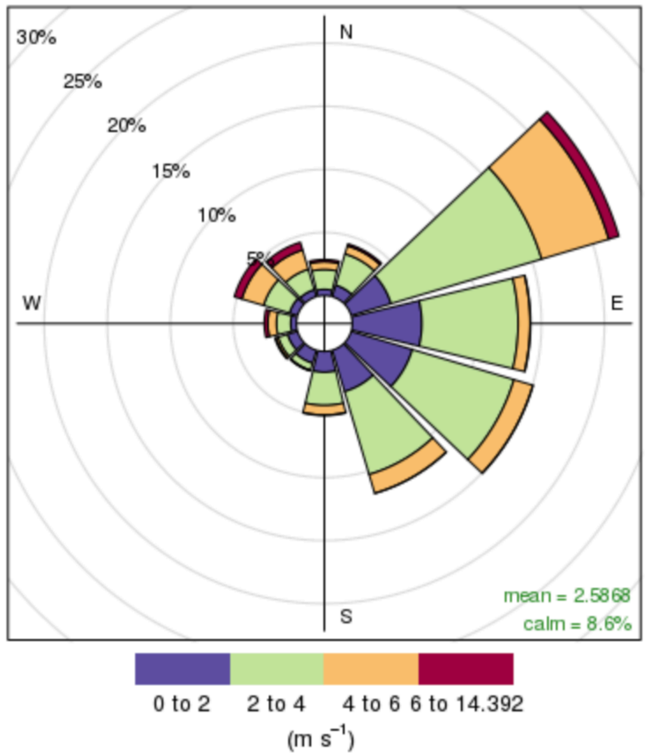


Figure 1: Hotspots of fire activity in India (2010)

(a) Wind direction at origin



(b) Direction from origin to receptor

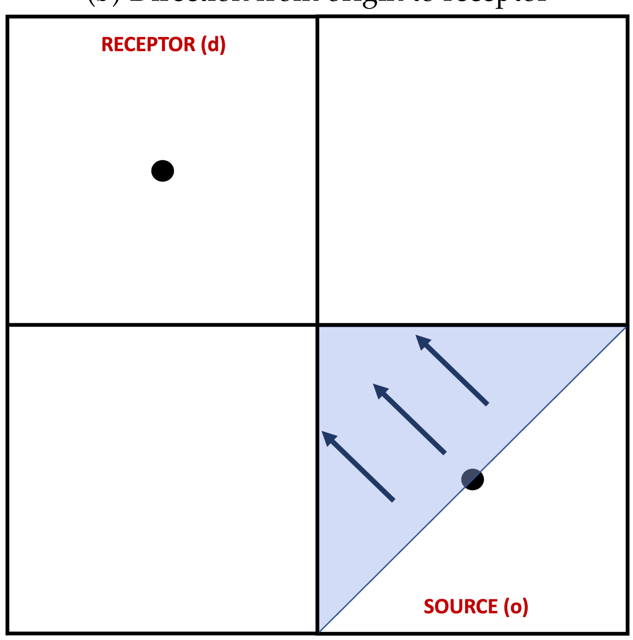
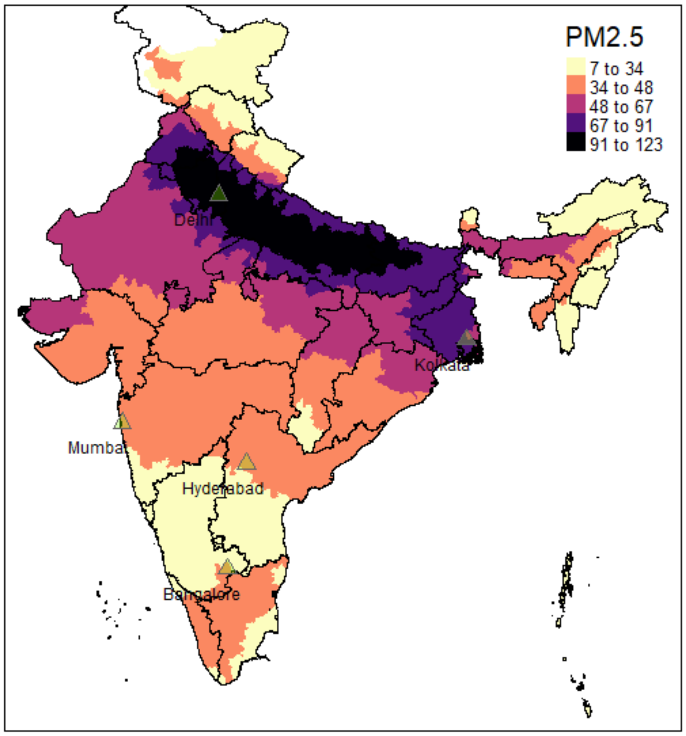


Figure 2: Schematic for construction of smoke exposure for Smoke Dispersion Model. The windrose in panel (a) captures the direction from which the wind blows. ↩

(a) Annual District PM2.5 Concentration (2010)



(b) Annual District Smoke Exposure Ω (2010)

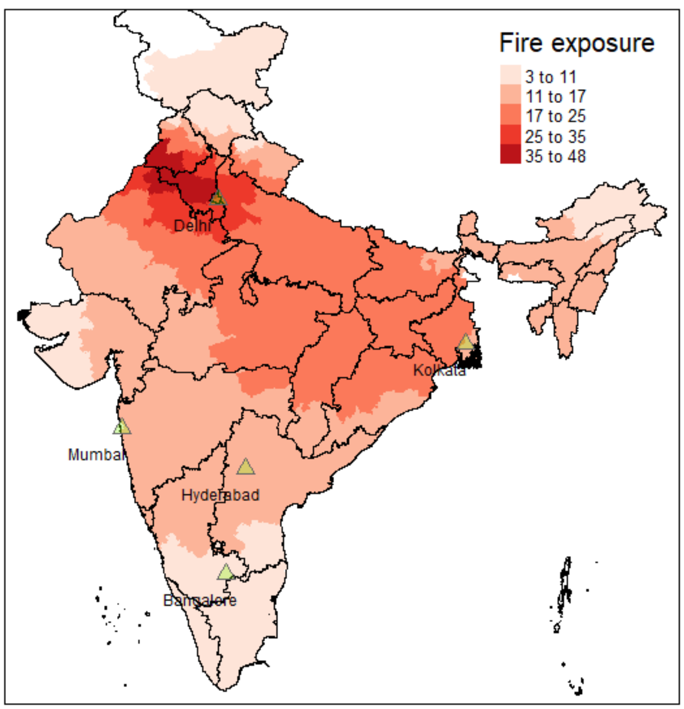


Figure 3: Spatial correlation between district smoke exposure and PM2.5. ↩

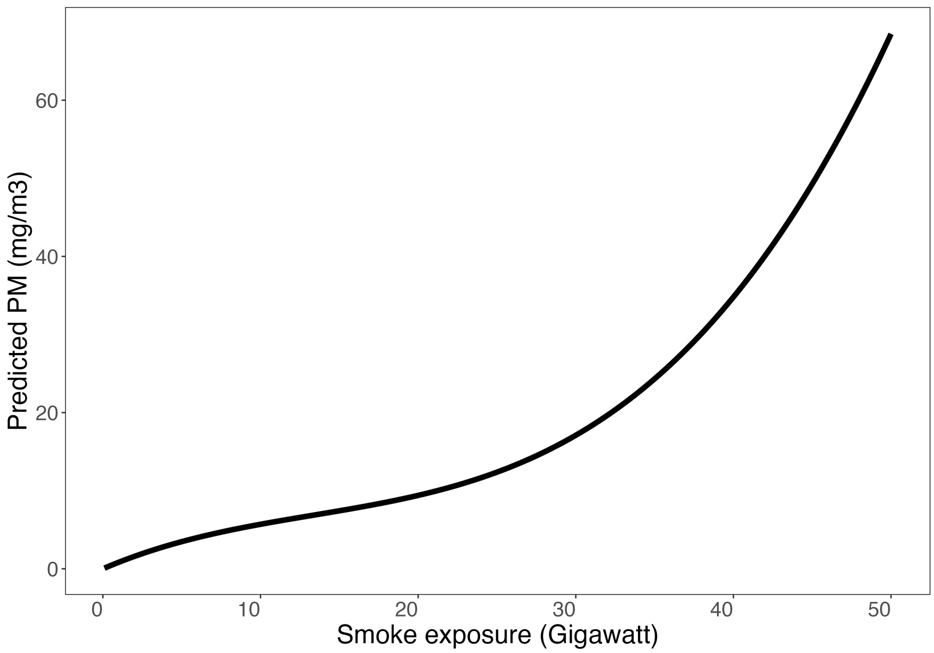


Figure 4: Relationship between District Smoke Exposure and PM2.5

3.4 Pollution Alters Location Choice

Does migration to Indian districts reduce in response to higher pollution from fires? To answer this question, I conduct a reduced form exercise that relates changes in district migrant inflows of workers between 2006-2010 and 2001-2005 to changes in average annual pollution concentrations in those years. Local changes in pollution are likely to be determined by growth patterns that are also positively correlated with migrant inflows. Therefore, the OLS estimate will be biased toward zero, underestimating the true effect of pollution on migrant inflows that we expect to be negative. In order to solve this endogeneity problem, I instrument for change in pollution with change in exposure to distant fire activity in upwind districts. This instrument allows me to isolate changes in pollution in district d that have nothing to do with economic activity in d but instead are due to changes in fire activity in upwind districts. The identifying assumption is that the shift in average 4-year agricultural fire activity in the upwind district s is correlated with changes in migrant inflow in d only through its effect on pollution changes in d.

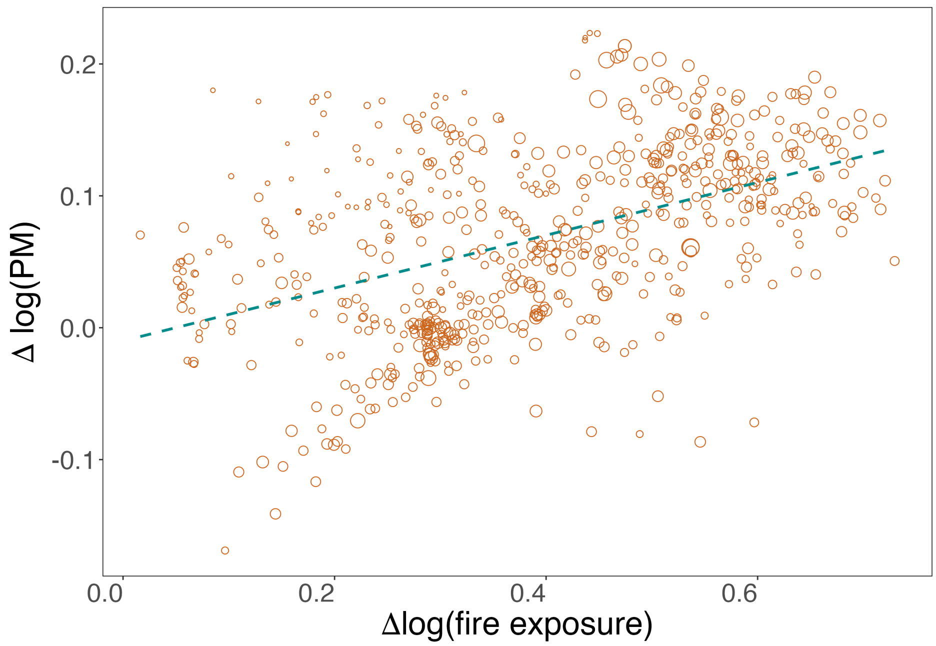


Figure 5: Visualizing the first stage between smoke exposure and pollution

I conduct this analysis on migrant inflows into districts indexed by d, as specified in equation 4. The first differences specification removes any fixed determinants of migrant inflows at the district level that also determine pollution, such as the presence of a coastline. Instrumenting for $\Delta log(PM)$ with $\Delta log(SmokeExposure)$ addresses the concern of joint changes in migration and pollution due to local industrial growth patterns.Figure 5 plots the first stage; there is a very strong correlation between change in smoke exposure and change in pollution. I also allow for separate trends in migration and pollution for districts in the Indo-Gangetic plain (North), peninsular (South) and Himalayan (Far North and North-East) regions since their cultural and geographic distinctiveness makes comparisons within these regions more compelling.

$$\Delta log(Migrant\, inflow_d) = \Delta \beta log(PM_d) + Geographic\_FE_d + \Delta \epsilon_d \tag{4}$$

Table 1 documents the results of this exercise for inflows of migrants who move for work. Column (1) suggest that a 1% change in pollution levels is associated with a 0.96% reduction in migrant inflows, on average. This is likely to be a biased estimate due to omitted variables that determine both pollution and migration. Column (3) documents an elasticity of -1.99 (standard error of 0.86). This implies that a 1% increase in pollution reduces migrant inflows by ~2%. As can be seen in column (4), the smoke exposure instrument is strongly correlated with pollution; since this exposure to distant, upwind fires is exogenous to local economic activity and is unlikely to be a result of local activity, this instrument is both valid and exogenous, and the estimate of -1.99 in column (3) is unbiased. Appendix table **??** finds similar results when not controlling for separate trends by the three regions.

While these results provide evidence for a sorting response to pollution across Indian districts, they do not explain the mechanisms behind this finding. This paper hypothesizes two potential channels through which air pollution can affect migration decisions. The first channel is the well-documented harmful effects on physical worker productivity (Graff Zivin and Neidell 2012; Chang et al. 2019; Fu et al. 2021). While this literature focuses on the intensive margin of reduction in worker output per hour, there also may be an extensive margin reduction in the number of hours worked due to air pollution. The net result of these intensive and extensive margin effects is a reduction in total output since pollution acts like a negative TFP shock, also reducing the marginal product of labor. Firms may adjust to lower output and profits by attempting to lower the wages they pay. This is consistent with recent evidence on the negative effect of air pollution on worker income in the US (Borgschulte et al. 2022). Figure 6 also presents correlations that are consistent with this hypothesis from India: nominal wages are lower in districts with higher pollution.

Secondly, the absence of air pollution can also be thought of as an amenity, generating compensating differentials in wages for locations with higher pollution. This only arises if workers value clean air as an amenity. The literature on air pollution in developing countries suggests that workers have a low willingness to pay for clean air, including for reasonably cost-effective adaptations such as mask-wearing (Greenstone and Jack 2015). These findings are consistent with the notion of clean air as a normal good, so that demand for it is muted in a low-income country like India. But, the findings in this paper that districts with higher pollution receive lower migrants could also arise if workers avoid polluted cities. This second mechanism would be consistent with recent work documenting that the disamenity costs of migration that lead some workers in India to forego gains of up to 35% of income by not migrating to cities may relate to air pollution as well (Imbert and Papp 2020).

The effect of pollution on inflows of migrant workers is consistent with either mechanism. The quantitative model can help guide us toward a solution to the empirical challenge of separating the amenity and income channels through which pollution affects location choice of workers.

Table 1: Effect of Pollution on Migrant Inflows

	Dependent variable			
	Δ log(inflow)			Δ log(PM2.5)
	OLS	Reduced Form	2SLS	First Stage
	(1)	(2)	(3)	(4)
Δ log(PM2.5)	-0.96		-1.99	
	(0.39)		(0.86)	
Δ log(Fire Exposure)		-0.52		0.25
		(0.22)		(0.04)
Observations	627	627	627	627
Geographical Fixed Effect	Y	Y	Y	Y
First stage F-stat				267.8

Notes: Outcome variable is change in log migrant inflow for those who listed their reason for migration as work-related between 2006-2010 and 2001-2005. Standard errors clustered at region level in brackets.

3.5 Migration Costs Affect Location Choice

Spatial productivity gaps may be explained by the presence of large migration costs across space. I document the existence of large migration frictions across Indian districts through the following regression of migration from each origin to destination district on origin and destination fixed effects and three measures of migration costs.[14] These measures are (1) the inverse hyperbolic sine of distance between origin and destination, proxying for difficulty of migration due to travel cost and time as well as distance from home (2)

[14] Estimation is done via Poisson Pseudo Maximum Likelihood estimator of Silva and Tenreyro (2006) since it has many desirable properties over OLS in a gravity-like framework, including the ability to handle zero migration. Section 5.2 justifies the use of PPML based on these properties.

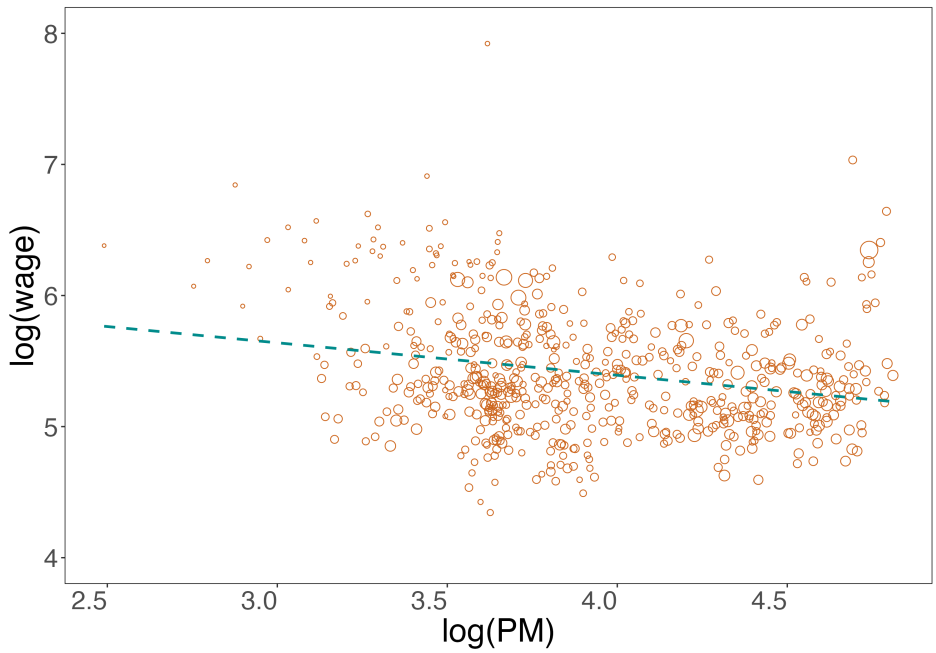


Figure 6: Wages are negatively correlated with pollution in 2010

whether the districts share a cultural affinity, proxied by a different language being spoken in the districts, and (3) whether the districts are in different states, proxying for origin-state biased policy and other state-level determinants of migration patterns.

$$L_{od} = \alpha_1 ihs(dist_{od}) + \alpha_2 \mathbb{1}(lang_{od}) + \alpha_3 \mathbb{1}(state_{od}) + D_o + D_d + \epsilon_{od} \tag{5}$$

As results in table 2 show, all three of these measures of migration costs strongly predict the share of migration across districts.

Table 2: Migration Costs and Labor Reallocation

	Dependent variable
	L_{od}
	(1)
$ihs(distance_{od})$	-1.017
	(0.007)
Different language	-0.344
	0.081
Different state	-1.919
	(0.081)
Observations	360,000
Adj Pseudo R-Sq	0.98
Fixed Effects	Origin + Destination

Notes: Estimation via PPML. SEs clustered at enumeration district. ihs is the inverse hyperbolic sine of distance to account for zero distance. The indicator variables for *language* and *state* turn on when origin and destination districts do not share the main language or are in different states.

4 Spatial Equilibrium Model with Pollution Externalities

This section incorporates air quality spillovers into a canonical quantitative model of economic geography (Redding and Sturm 2008) to investigate how spatial productivity differences and labor reallocation interact with the movement of people and pollution to determine income gains from specific pollution control measures. The reader is referred to Redding and Rossi-Hansberg (2017) for a survey of the economic geography literature on the development of these models.

4.1 Worker Preferences

There are $\overline{L}_o$ workers in location o to begin with. Workers have preferences over a consumption good C_d, amenities B_d and air quality (the inverse of air pollution level PM_d).

$$u_{od} = \epsilon_{od} B_d (PM_d)^{\lambda} C_d M_{od}$$

B_d consists of a fixed component that can include climate and other institutional features, as well as an endogenous component that varies in response to congestion. An example of such a congestion force is the cost of housing that depends on the housing supply elasticity. ϵ_{od} is an idiosyncratic preference shifter that captures preferences for location d. ϵ_{od} is i.i.d across workers and locations, and is drawn from a Frechet distribution given by the CDF $F(\epsilon) = e^{-\epsilon^{-\eta}}$. The parameter η controls the dispersion of these shocks. A small value of η implies that the probability of a large draw for ϵ is larger, implying that the worker is particularly attached to location of birth o and would not move even with large wage differentials or high pollution levels at source. This can captures real world features such as strong local ties, for example. The parameter η can also be interpreted as the income elasticity of migration, something the equilibrium equations of the model will make clear.

PM_d is the level of air pollution in location d. If workers have preferences over clean air, locations will be characterized by compensating differentials for pollution, with elasticity given by λ. If $\lambda < 0$ then pollution does indeed have amenity value for workers.

In this quasi-dynamic model, worker born in location o has made a decision on whether to stay or move to another destination location d when we observe them. But movement across locations is costly. This migration cost M_{od} from origin o to destination d may represent physical costs of migration, salient differences in culture and language, and also policy differences such as access to welfare benefits that are attached to the location of birth. About 80% of migration in India is within the state, an entity that shares a common language and cultural features as well providing access to these benefits

Labor income in location d is given by wage w_d. Workers choose the location where they receive highest utility, subject to moving costs. If the indirect utility function for the worker is represented by V_{od}, then the worker chooses d over d' if V_{od} > $V_{od'}$. Indirect utility function is given by

$$V_{od} = \epsilon_d B_d M_{od} (PM_d)^{\lambda} (\frac{w_d}{P_d})$$

This formulation allows us to write the migration share from o to d, π_{od}, as follows, where we have made use of the properties of the Frechet distribution. A derivation is provided in appendix section

$$\pi_{od} = \frac{L_{od}}{\overline{L}_o} = \frac{[B_d M_{od} (PM_d)^{\lambda} (\frac{w_d}{P_d})]^{\eta}}{\sum_{k=1}^{N} [B_k M_{ok} (PM_k)^{\lambda} (\frac{w_k}{P_k})]^{\eta}} \tag{6}$$

All of the local income is derived from wages and is completely spent on demand for the consumption good. Therefore, total demand D_d is given by

$$D_d = w_d L_d$$

4.2 Production and General Equlibrium

Each location d produces a homogeneous good Y_d using a linear technology with labor L_d and TFP A_d. Each worker supplies one unit of inelastic labor. TFP varies across locations and may be affected by pollution PM_d and agglomeration forces.

$$Y_d = A_d L_d$$

Markets are perfectly competitive. Therefore, the price of each good equals marginal cost.

$$P_d = \frac{w_d}{A_d}$$

All goods are produced and consumed locally so there is no goods trade. Output is then determined purely by demand D_d. Assuming the consumption good to be the numeraire ($P_d = 1$), the wage in each location is pinned down by

$$w_d = A_d$$

Model equilibrium is characterized by the following equation.

$$\pi_{od} = \frac{L_{od}}{\overline{L}_o} = \frac{\left[B_d (PM_d)^{\lambda} w_d M_{od}\right]^{\eta}}{\sum_{k=1}^{N} \left[B_k (PM_k)^{\lambda} w_k M_{ok}\right]^{\eta}} \tag{7}$$

$$L_d = \sum_{o=1}^{N} \pi_{od} \overline{L}_o \tag{8}$$

Productivity A_d, pollution PM_d and amenity B_d endogenously adjust when the population in a location change. The next sections describe the adjustment mechanisms and associated elasticities. The population vector is the variable that adjusts until equilibrium is reached in the model, pinning down the values of all other endogenous variables that depend on it.

4.3 Productivity is Endogenous due to Agglomeration and Pollution

TFP varies by location due to fixed exogenous factors like soil quality, presence of rivers, or availability of raw materials like mineral ores; agglomeration forces; and the effect of pollution on worker productivity. Equation 9 formalizes these ideas. $\overline{A}_d$ is exogenously determined productivity that does not respond to employment.

$$A_d = \overline{A}_d(PM_d)^{\beta}L_d^{\phi} \tag{9}$$

β determines how worker productivity responds to pollution; if $\beta < 0$, productivity is negatively affected by pollution. The strength of agglomeration forces that may arise from any potential non-excludable innovation (Arrow 1962) is captured by ϕ^j.

4.4 Amenity is Endogenous due to Congestion Forces

Amenity value of a location depends on endogenous factors such as housing rental prices. The elasticity ψ captures these factors. As more workers move into a city, congestion forces such as rental rates rise, making the city slightly less desirable for the next migrant.

$$B_d = \overline{B}_d L_d^{\psi} \tag{10}$$

4.5 Pollution from crop burning

Pollution PM_d in location d is modeled as follows

$$PM_d = (\overline{PM}_d)g(\widetilde{\Omega}_d) \tag{11}$$

The fixed component of pollution $\overline{PM}_d$ captures exogenous sources of pollution from within the district. Analogous to the discussion in section 3.3, $\widetilde{\Omega}_d$ is the contribution of total smoke exposure from all sources to pollution in location d. But differing from the empirical exercise described earlier, $\widetilde{\Omega}_d$ is constructed using a source-receptor matrix that depends on *average* wind patterns and emissions. The tilde emphasizes that these analogous quantities are long-term averages.

$$\widetilde{\Omega}_{od} \;=\; \tilde{\theta}_{od}\widetilde{E_o} \tag{12}$$

where

$$\tilde{\theta}_{od} = \frac{E[wind_{od}]}{distance_{od}} \tag{13}$$

The expected value of $wind$ in the numerator in equation 13 captures prevailing wind patterns at each origin; I construct these using 10-year annual average wind patterns by using the average number of fires each day as weights to account for local seasonality in fire activity. This method gives zero weight to days on which there are zero fires in a source location. The quantity $\tilde{\theta}_{od}$ captures exogenous physical determinants of source-receptor smoke exposure and together determine how exposed district d is to emissions in origin o.

5 Identification and Estimation of Model Parameters

Table 4 shows the model parameters that are estimated in this paper. Apart from the productivity elasticity of pollution, and the agglomeration and congestion elasticities, I estimate all the other parameters of the model. This section will present the research design and discuss results for each of these parameters. Summary statistics for the data used in the various parameter estimation exercises and for the pollution spillover elasticity of agricultural fires are provided in table 7.

5.1 Impact of Smoke from Crop Burning on PM2.5

The function $g(.)$ has been estimated using panel data on equation 3 in section 3.

5.2 Income and Pollution Elasticities of Migration (λ, η)

The equilibrium migration shares predicted by the quantitative model in equation 6 provide a means to separately identify η and λ - the income and pollution elasticities of migration - using data on migration shares across Indian districts.

In order to estimate this equation on migration shares data, we need to specify migration costs M_{od}. I assume that M_{od} take the form $M_{od} = exp(-m_{od})$, where m_{od} are parameterized such that migration costs are normalized and symmetric ($M_{oo} = 1$ and $M_{od} = M_{do}$).

$$m_{od} = \nu_1 ihs(dist_{od}) + \nu_2 \mathbb{1}(lang_{od}) + \nu_3 \mathbb{1}(state_{od})$$

Here $dist_{od}$ measures the physical distance between districts o and d, $\mathbb{1}(lang_{od})$ in an indicator for whether a different language is spoken in o and d and $\mathbb{1}(state_{od})$ in an indicator for whether district o and d belong to different states.

Taking the natural log of equation 6 gives us the stochastic version of the migration equation to take to the data

$$
\begin{aligned}
log(\pi_{od}) = {} & \eta\, log(w_d) && \text{[Income]} \\
& + \eta\lambda\, log(PM_d) && \text{[Pollution disamenity]} \\
& - \eta\nu_1 log(dist_{od}) - \eta\nu_2 \mathbb{1}(lang_{od}) - \eta\nu_3 \mathbb{1}(state_{od}) && \text{[Migration cost]} \\
& - V_o && \text{[Origin option value]} \\
& + \eta\, log(B_d) + \epsilon_{od} && \text{[Residual]}
\end{aligned}
$$

where $V_o = log(\sum_{k=1}^{N}[B_k M_{ok} PM_k^{\lambda} w_k]^{\eta}])$ is fixed within each origin, and the residual contains destination amenities and other idiosyncratic features that determine bilateral migration shares.

The identification challenges with η and λ are twofold: (1) there may be destination-specific amenities in the residual such as a coastal location that makes the location more desirable for high-wage individuals while also reducing PM2.5 levels due to the sea breeze, and (2) origin-destination specific omitted factors such as pre-existing migrant networks can affect current migration patterns, and those past networks may have been formed partly because the destination had higher past wages that also influence current wages.

The solution I adopt to these identification problems is to instrument for both *log(PM)* and *log(wage)*. I follow Tombe and Zhu (2019) in instrumenting for *log(wage)* with a bartik-style instrument that is constructed through a weighted average of national 5-digit industry code wages, with lagged local employment shares in 5-digit industries as the weights. I instrument for *log(PM)* with annual fire exposure from locations between 100-500 km away, following the recent literature (Khanna et al. 2023).[15]

I estimate equation 5.2 using the Poisson Pseudo-Maximum Likelihood (PPML) method

[15] I utilize the strength of each fire, measured using the Fire Radiative Power from the NASA FIRMS data base to maximize predictive power, given that a larger fire would emit more particulate matter.

of Silva and Tenreyro (2006), as detailed in equation 14. This has several advantages over OLS. First, unlike OLS, it handles zero values for migration count. Second, it respects the adding up constraint for migration count that such gravity models imply (Fally 2015). Third, because of Jensen's inequality, the least squares estimator of $log(L_{od})$ on the right hand side variables is generally an inconsistent estimator for the model elasticities, whereas PPML is consistent (Santos Silva and Tenreyro 2022).[16]

$$\begin{aligned}
L_{od} = exp(\ & \eta\, log(w_d) && \text{[Income]}\\
& + \eta\lambda\, log(PM_d) && \text{[Pollution disamenity]}\\
& + \eta\nu_1 ihs(distance_{od}) + \eta\nu_2\, \mathbb{1}(Lang_{od}) + \eta\nu_3\, \mathbb{1}(State_{od}) && \text{[Migration cost]}\\
& - \overline{V}_o && \text{[Origin option value]}\\
& + \epsilon_{od}) && \text{[Residual]}
\end{aligned} \tag{14}$$

Although the instruments noted above help solve the endogeneity problem, an estimation challenge arises for nonlinear panel models like PPML with IV as the incidental parameters problem makes estimation inconsistent. I solve that estimation challenge by following the method outline in Lin and Wooldridge (2019) who recommend adopting a control function approach that proceeds in three steps: (1) estimate the first stages using OLS and store the residuals from each of these first stages (2) include these residuals in the PPML estimation in a second stage, in addition to the original endogenous variables. The coefficients on the endogenous variables are now consistently identified, and the coefficients on the residuals provide a valid test for endogeneity of *log(PM)* and *log(wage)* (3) estimate standard errors using a panel bootstrap by repeating (1) and (2) on a randomly drawn sample.

[16] $log(L_{od})$ as the eexplanatory variable is equivalent to $log(\pi_{od})$ because $\overline{L}_o$ is absorbed by the origin fixed effect.

5.2.1 PPML Estimation Results

Table 3 presents the results from estimation of equation 14 using PPML. Column 1 presents results without correcting for the endogeneity of *log(wage)* and *log(PM)*. From a given origin district, a 1% higher PM2.5 level at a potential destination district is associated with 0.16% *higher* migration share to that district, whereas a 1% higher real wage at the destination district is associated with a 0.75% higher migration share to that district. However, the coefficient on *log(PM)* is not significantly different from zero. The positive coefficient on *log(PM)* is not to be interpreted as a causal estimate as it suffers from omitted variable bias: districts with high amenities (that are in the residual) may attract more workers, thus increases pollution from transport, a positive selection effect. The positive coefficient on *log(wage)* is positive as expected, but could also suffer from a similar endogeneity problem. There could be negative selection on wages: higher wage locations tend to also attract relatively more unskilled workers, and such high wage locations also usually have higher amenities that are in the residual.

Columns 2 and 3 report results from first stage regressions on the two endogenous variables. There are no available weak instrument tests for the case of two endogenous instruments in a nonlinear model, as is the case of the PPML estimator (D. J. Lewis and Mertens 2022; Andrews et al. 2019). Nevertheless, I report separate F-stats for the two instruments; in both cases these are above 10.[17] The control function approach involves including residuals from the two first stage regressions into the PPML model with endogenous regressors. Column 4 reports results from this process. The coefficients on the residuals show that both the *log(PM)* and *log(wage)* are indeed endogenous in column 1, with a positive and negative selection effect respectively.

The coefficient on *log(PM)* is -0.15: the causal effect of a 1% increase in relative PM2.5 levels between origin and destination is to reduce migration shares to the destination district by

[17] Weak instrument tests such as Cragg-Donald and Kleibergen-Paap are also not available for nonlinear panel models with instruments.

0.15%. Similarly, the causal effect of a 1% increase in relative wage levels between origin and destination is to increase migration shares to the destination district by 3.45%.

Table 3: Estimates for Income and Pollution-disamenity Elasticities of Migration

	Poisson	First Stage: PM	First Stage: Wage	Poisson w/ CF
	L_{od}	$log(pm)$	$log(wage)$	L_{od}
	(1)	(2)	(3)	(4)
log(pm) [$\eta\lambda$]	0.16			-0.15
	(0.16)			(0.16)
log(wage) [η]	0.75			3.45
	(0.17)			(0.77)
pm IV		0.21	0.07	
		(0.02)	(0.02)	
wage IV		-0.13	0.24	
		(0.03)	(0.04)	
Residual log(pm)				1.13
				(0.33)
Residual log(wage)				-2.07
				(0.72)
Estimation Method	PPML	OLS	OLS	PPML
Observations	360000	360000	360000	360000
First Stage F-stat		91.8	9.21	
Origin FE and migration costs	Y	Y	Y	Y

Notes: CF refers to control function. Sample consists of 600 districts. Clustered SEs in col 1; cluster bootstrapped SEs in cols 2-5.

6 Policy Counterfactuals

I now turn to the policy questions asked at the beginning of this paper. How do income gains from targeted pollution control depend on the productivity of cleaned-up places, and on the productivity gains from labor reallocation? The counterfactual policies hold all other factors such as trade costs or preferences unchanged. But in order to answer these questions through the quantitative model, I must take a stance on the the general equilibrium parameters that are not estimated in this paper. I source estimates from the literature and conduct robustness of the findings to different choices.

I calibrate a key parameter in the elasticity of labor productivity to PM2.5 levels (β) that governs aggregate productivity gains in partial equilibrium. This parameter has been estimated with US data on changes in the quantity of output produced by individual workers when they are exposed to exogenous variation in daily particulate matter levels. Chang et al. (2019) find a labor productivity elasticity of -0.09 to daily exogenous variation in PM2.5 levels for indoor pear-packers at a factory in the US while Graff Zivin and Neidell (2012) find an elasticity of -0.25 to daily Ozone (O_3) levels for outdoor fruit pickers at a farm in the US. These high-quality estimates are based on individual worker response to daily pollution exposure for indoor workers in manufacturing and outdoor workers in agriculture respectively. I set β to -0.17 as the median of these elasticities and show robustness to other choices (Neidell 2017). The main reason to take the median is so that the elasticity reflects differential impacts by the indoor/outdoor nature of work as well as the sector. Evidence on the nonlinearities at extreme levels of pollution seen in developing countries is lacking, although Fu et al. (2021) calculate a larger elasticity of -0.44 with nationally representative Chinese manufacturing data. I choose a more conservative estimate of -0.17 since evidence for India does not exist.

The agglomeration elasticity (ϕ) has been estimated by multiple studies before, with reviews in Rosenthal and Strange (2004) and Combes and Gobillon (2015). Estimates for the developed world seem to have converged on values between 0.01 and 0.02, but estimates of ϕ for developing countries are larger in magnitude and fewer in number. I benchmark ϕ to the value of 0.076 estimated by Chauvin et al. (2016) using wage data for Indian districts, relying on historical population density as the instrument for current density as is standard in this literature. I also conduct robustness around other choices. A higher value of ϕ would imply larger gains from reallocation toward denser cities.

The congestion elasticity (ψ) controls whether cities lose some of their amenity value when population rises. There are two principal sources of such congestion: a pure amenity value ψ_b that arises from competition for public goods such as parks, and an endogenous source arising from increases in housing rental rates ψ_r. These congestion components are on top of the amenity value arising from clean air that is estimated in this paper. There are comparatively few estimates for these elasticities in the literature. The pure amenity component ψ_b is 0 in the US data according to Albouy (2008) whereas Combes and Gobillon (2015) estimate a value of -0.04. But, as Imbert and Papp (2020) note, workers are willing to lose up to 35% of income by not migrating to cities due to urban disamenities that workers are unable to avoid; therefore the pure amenity component may be larger in India. As for the housing price elasticity, Bryan and Morten (2019) estimate a value of -0.08 for Indonesia. Given the prominence of informal housing in the developing world, estimates from Indonesia are a better fit for the Indian context. I set the congestion elasticity to -0.2 to account for the potentially larger pure amenity congestion disamenity in India, and conduct robustness to other choices. A larger magnitude of the congestion elasticity would reduce the incentive of workers to migrate to cities, reducing productivity gains from abatement.

6.1 Solving the Model

I implement the exact hat algebra method of Dekle et al. (2007) to solve for counterfactual *changes*. Solving for counterfactual changes eases calibration by eliminating many fixed components of the model such as productivities $\overline{A}$ and amenities $\overline{B}$. The second advantage of this method is that it only requires changes in migration costs and is therefore robust to any bias in the measurement of migration frictions that remains constant in the counterfactual. I only need to specify parameters of the model ($g(.), \eta, \lambda, \beta, \phi, \psi$) and initial values ($\pi_{od}, \overline{L}_o$) Table 4 summarizes model parameters and initial values.

Table 4: Model parameters and initial values

Parameter	Description	Value
$g(.)$	Impact of smoke exposure on PM2.5	Cubic fit
λ	Pollution-disamenity elasticity of migration	0
η	Income elasticity of migration	3.45
β^n	Productivity elasticity of Pollution	-0.17
ϕ	Agglomeration elasticity	0.076
ψ	Congestion elasticity	-0.2

Notes: Please see text for detail on estimation or calibration ↩

6.2 Simulations Hold Fixed Health Benefits from Policies

Before delving into the results, let us remind ourselves of the two policies under consideration. The crop burning policy reduces crop burning by 10% in Punjab and Haryana. The urban emissions policy reduces pollution by a uniform percentage amount in the largest cities such that the total population x change in pollution is equal for both these policies. As per standard regulatory guidelines from the US EPA and European Environmental Agency, these two policies would be rated similar (or exactly the same with linear dose-response functions). The crop burning policy targets emissions in rural areas and, due to avoided long-distance dispersion effects, also reduces pollution in downwind cities. On the other hand, the urban emissions policy reduces pollution exclusively in the 10 largest cities due to the nature of sources it targets (vehicle and cookstove emissions decay rapidly, and do not affect areas more than a few kilometers away).

I normalize the total population-exposure reduction to be the same in both the policies. As discussed in section 3.2, this normalization leads to similar health benefits from the two policies. A linear dose-response function would lead to identical health benefits, whereas a concave dose-response function for some health outcomes would produce slightly larger health benefits from the crop burning policy. The latter is the case because rural pollution levels are lower than urban levels, and a concave damage function implies higher damages (and hence benefits from control) at lower pollution levels.

The normalization itself is done by estimating the population x change in pollution for the crop burning policy, while holding the spatial allocation of labor fixed. I then calculate the percentage change amount in pollution that when applied equally to all 10 cities would produce the same population x change in pollution, keeping the population in those cities fixed. A uniform 7% reduction in PM2.5 levels in the 10 largest cities produces a similar health benefit to a 10% reduction in burning emissions. For every crop burning counterfactual I conduct, I re-estimate the uniform percentage reduction in PM2.5 for the 10 largest cities that would produce an equivalent population-exposure reduction. Figure 9 shows the change in PM2.5 levels across districts due to either policy.

6.3 Gains from Pollution Control due to Place-specific Productivity

Let us now analyze how income gains from these two health-equivalent policies depend on the productivity of places that they clean up. These results hold the spatial allocation of labor fixed in the policy counterfactuals. Table 5 displays these results. The first row reports gains in national income due to the crop burning policy while the second row reports the same for the urban emissions policy. Gains from the urban policy are 3 times the crop burning policy when accounting only for the pre-existing differences in productivity of places where pollution was reduced as a result of the two policies.

Table 5: Role of place-specific productivity differences

Policy	GDP gain
CRB control in northwestern India	0.32
Localized emissions control in 10 largest cities	0.91

Notes: CRB refers to crop residue burning. The numbers in this table are a percentage of initial GDP. These counterfactuals hold labor allocation fixed across space, as observed in the initial data.

6.4 Gains from Pollution Control due to Labor Reallocation

Next, I analyze how income gains from these two health-equivalent policies depend on the spatial reallocation of labor that they induce. This reallocation occurs because changes in expected pollution levels as a result of the control policies change the relative productivity and wages across locations, causing some marginal workers to receive higher utility from moving to a cleaned-up location.[18] The strnegth of the labor reallocation mechanism is governed by the two migration elasticites that were estimated earlier.

Table 6 displays income gains accounting for spatial reallocation of labor. Column 2 in the first (second) row reports *total* gains in national income, including both the place-based productivity and labor reallocation mechanisms, due to the crop burning (urban emissions) policy. Gains from the urban policy are ~6 times the crop burning policy when also accounting for the reallocation of labor induced by the pollution policies. The third column shows income gains exclusively from the labor reallocation mechanism. Almost none

[18] If the disamenity value of pollution were also included, some marginal workers would move as a result of direct utility effects of improved air quality, not just because of utility increases from higher wages. I explore this possibility in robustness tests.

of the total gains from the crop burning policy are due to labor reallocation, as opposed to more than half of the total gains from the urban emissions policy.

What explains these starkly different results? Figure **??** (**??**) maps which locations lose or gains workers as a result of the crop burning (urban emissions) policy. Both policies induce reallocation. However, the key difference is the places into which labor reallocation occurs. The crop burning policy induces reallocation into less productive rural areas that are disproportionately cleaned up due to the policy. On the other hand, the urban emissions policy reallocates workers into the most productive cities of India, and amplifying agglomeration economies as a result.

Table 6: Income gains from labor productivity differences and labor reallocation

Policy	Total GDP gain	GDP gain from reallocation
CRB control in northwestern India	0.34	0.02
Localized emissions control in largest cities	1.88	0.97

Notes: CRB refers to crop residue burning. The numbers in this table are a percentage of initial GDP. These counterfactuals allow spatial labor allocation to adjust after a change in pollution across space.

7 Conclusion

This paper studies the mechanisms by which targeted pollution control policies can produce income gains. Two features of pollution sources determine the importance of these mechanisms: the location of the source, and its long-distance pollution effect. I conduct policy simulations based on recent government programs that either target sources such as crop residue burning in rural areas of northwestern that disperse smoke over long distances, or localized emissions from vehicles and cookstoves that affect only local air quality in the 10 largest cities. These policy simulations hold fixed the total population exposure reduction from these two policies by normalizing pollution reduction from the urban emissions policy to estimated reductions in pollution over space. I develop a smoke dispersion model and estimate a pollution-smoke exposure relationship in order to quantify the pollution reduction from crop residue burning. Even though the two policies will be rated similar on health impacts since standard regulatory guidance use dose-response functions for mortality effects of pollution that are mostly linear, the two policies reduce pollution in very different places: rural areas for burning and urban areas for localized emissions.

I then show that increases in district pollution reduce worker in-migration in India, using exogenous variation in pollution driven by shifts in upwind burning activity. This spatial labor reallocation may be caused by lower expected wages due to pollution or the disamenity value of pollution. In general equilibrium, the distribution of pollution and workers is determined jointly through sorting across districts. To account for the movement of people and pollution across space, I develop a spatial equilibrium model of location choice that also incorporates a pollution dispersion model. I take the labor supply equation across districts predicted by the model to data on pairwise migration across Indian districts to estimate the income and pollution-disamenity elasticities. Utilizing instrumental variables to correct for endogeneity, I find an income elasticity of 3.45 and an amenity elasticity of -0.15, although the latter is not statistically different from zero.

I then simulate the two policies of interest. Income gains from the place-specific productivity mechanism for the urban emissions policy are almost 3 times larger than the crop burning policy, because health improvement for workers in cities generate larger economic value. The labor reallocation mechanism reinforces this effect: total income gains when also accounting for labor reallocaitona re almost 6 times larger for urban emissions policy. Reallocation accounts for <1% of the total income gains for crop burning since the reallocation induced by that policy is toward less productive rural areas. On the other hand, the urban emissions policy induces reallocation to the largest cities and amplifies existing agglomeration economies, and reallocation accounts for more than half of the total gains from urban emissions control.

Despite limited gains from reallocation for the crop burning policy that reduces emissions by 10% in northwestern India, I calculate a benefit-cost ratio of 96 using estimates of the marginal abatement cost per acre not burnt from Jack et al. (2022), and own estimates of how much crop area needs to be left unburnt to achieve 10% lower emissions. This suggests the failure of a Coasian bargaining process wherein other states, particularly in North India, could compensate farmers in Punjab and Haryana for a costly reduction in fires. This failure may be down to lack of regulation of the pollution externality at the appropriate level (Banzhaf and Chupp 2012; Lipscomb and Mobarak 2017; Kahn et al. 2015), or to low levels of economic development where credit constraints and weak regulatory capacity are common (Jayachandran 2022; Besley and Persson 2009; Jack et al. 2022).

Finally, this paper underlines the importance of accounting for how economic mechanisms interact with the physical features of pollution sources to determine income gains. This has implications for targeting pollution control in developing countries that may be fiscally constrained enough not to control pollution everywhere, and at the same time searching for policies that can cause income growth.

8 Bibliography

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9 Appendix

9.1 Appendix Tables

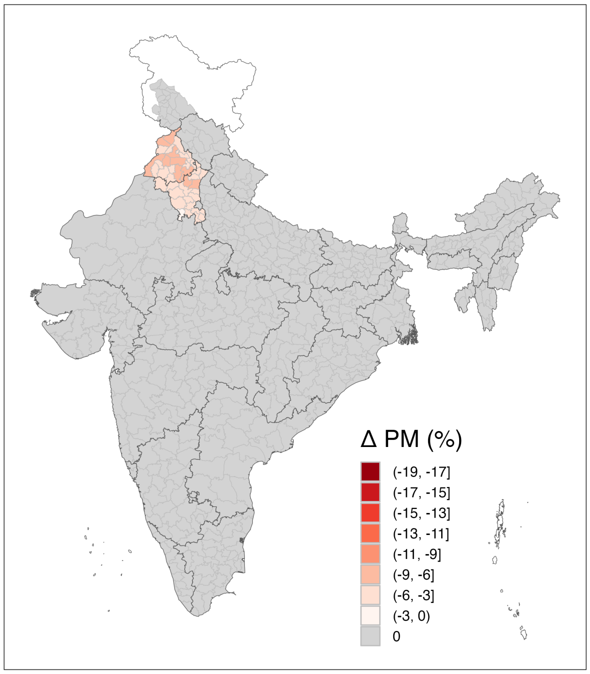
Table 7: Summary Statistics

Variable	N	Mean	SD	Min	Max
Panel A: District data for estimation of burning intensity δ, 2011)					
Worker count (million)	601	0.4	0.37	0.0006	3.1
Fire Emissions (Watts)	601	1275	3225	0	32845
Panel B: Pixel data for estimation of dispersal paraemter τ (2002-2016)					
PM2.5 (microgram/m3)	9255	56.3	27.1	10.4	148
Fire Exposure (Watts)	9255	554.2	311.1	90.6	2605
Panel C: District data for estimation of migration elasticies η and λ (2010)					
Migration count	360000	3289.1	87690	0	10144530
Wage (Rs)	360000	254	170	77	2757
PM2.5 (microgram/m3)	360000	55.6	25.5	12.1	123
Distance (km)	360000	1032.1	572	0	3005
Language indicator	360000	0.735	0.441	0	1
PM IV (Count)	360000	21850	42525	44.3	123696
Wage IV (Rs)	360000	239.789	105.071	102.577	991

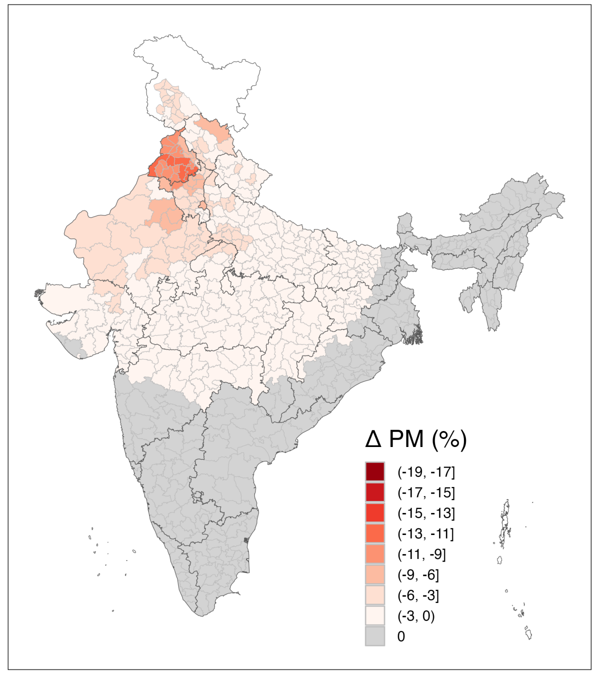
Notes: Summarizes the data used to estimate the main parameters of the quantitative model. Panel A presents district level data on worker count and fire activity for 601 districts. Panel B describes pixel level fire counts, fire exposures and particulate matter data at district level. Panel C describes pair-wise migration shares data across 600 districts from

9.2 Appendix Figures

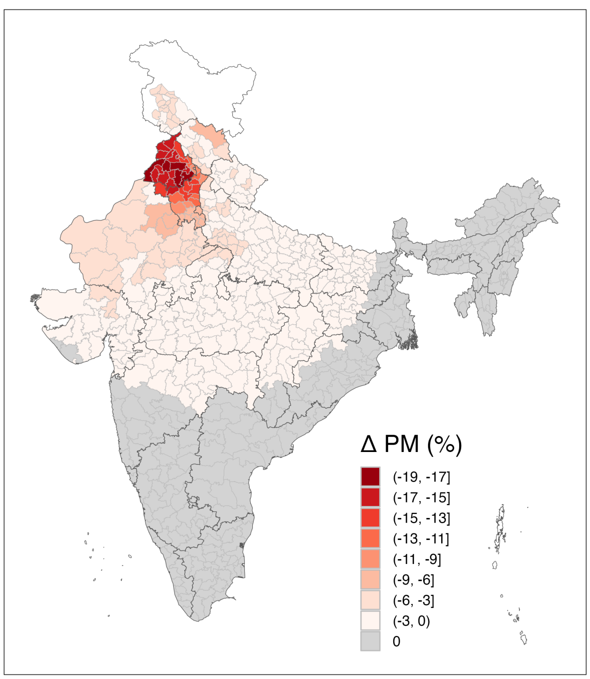
(a) Change in local pollution



(b) Change in spillover pollution



(c) Change in total pollution



(d) Change in labor

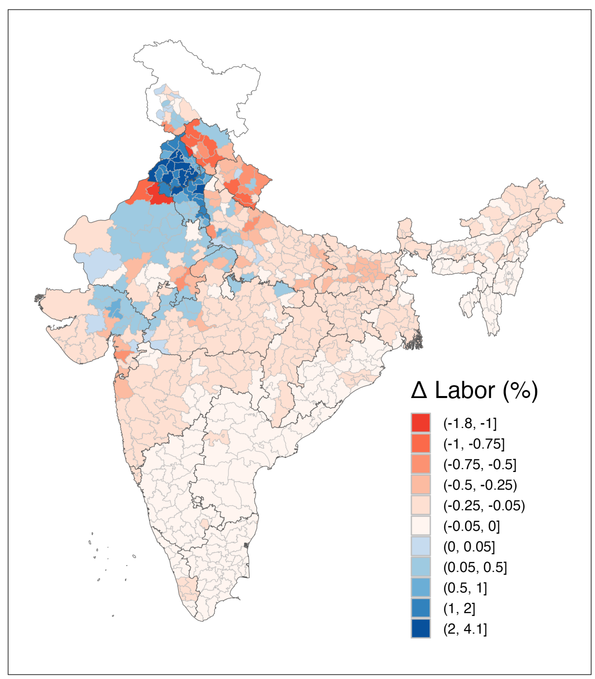
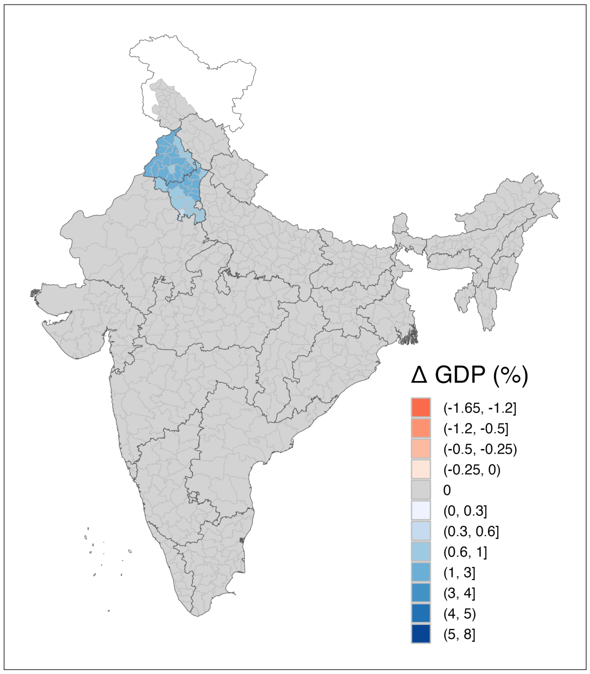
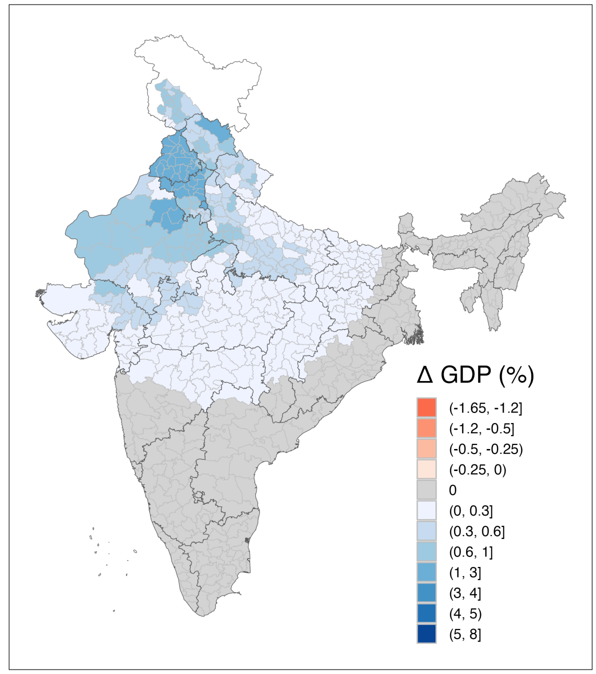


Figure 7: Counterfactual pollution and labor after Abatement Policy ↩

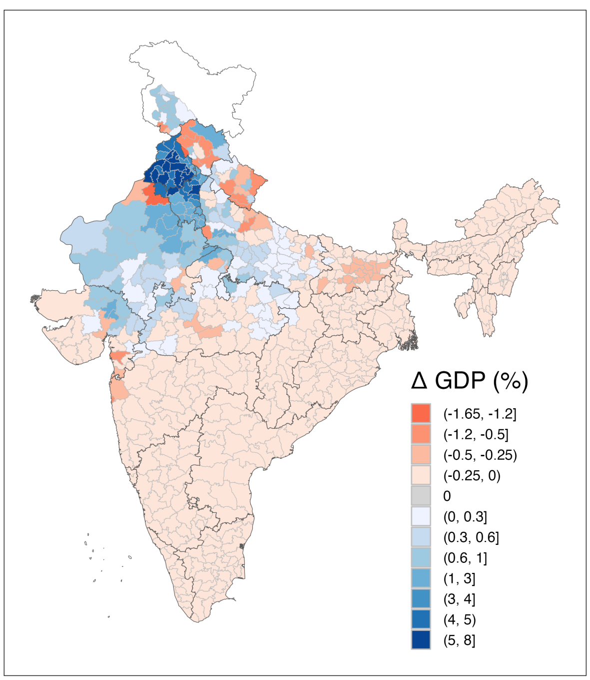
(a) PE Change in GDP from ↓ local pollution



(b) PE Change in GDP from ↓ spillover pollution



(c) GE change in total GDP



(d) GE Change in GDP per capita

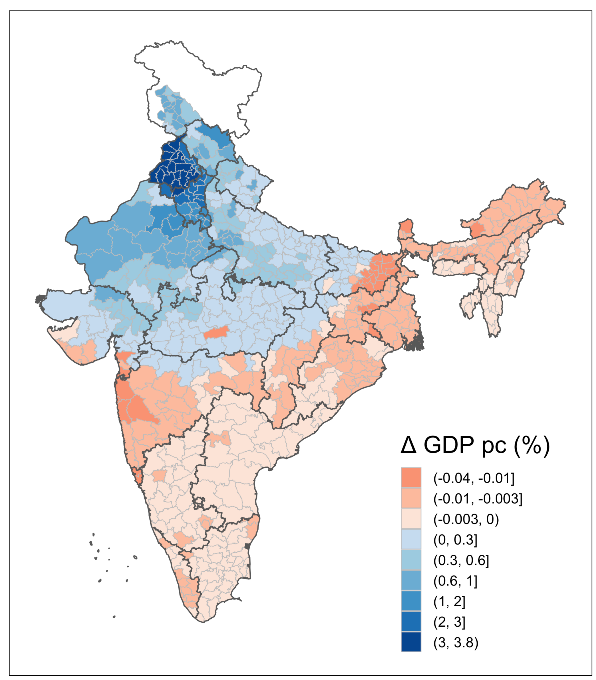


Figure 8: Counterfactual GDP and GDP per capita after Abatement Policy ↩

9.3 Other Functional Forms for Impact of Smoke Exposure on PM2.5

Table A.1 shows the results of a cubic fit for the impact of smoke exposure on PM2.5.

Table A.1: Effect of District Smoke Exposure on PM2.5

Dep var:	PM2.5
Smoke Exposure	0.86
	(0.46)
Smoke Exposure-squared	-0.04
	(0.02)
Smoke Exposure-cubed	0.0006
	(0.0002)
Observations	9,255

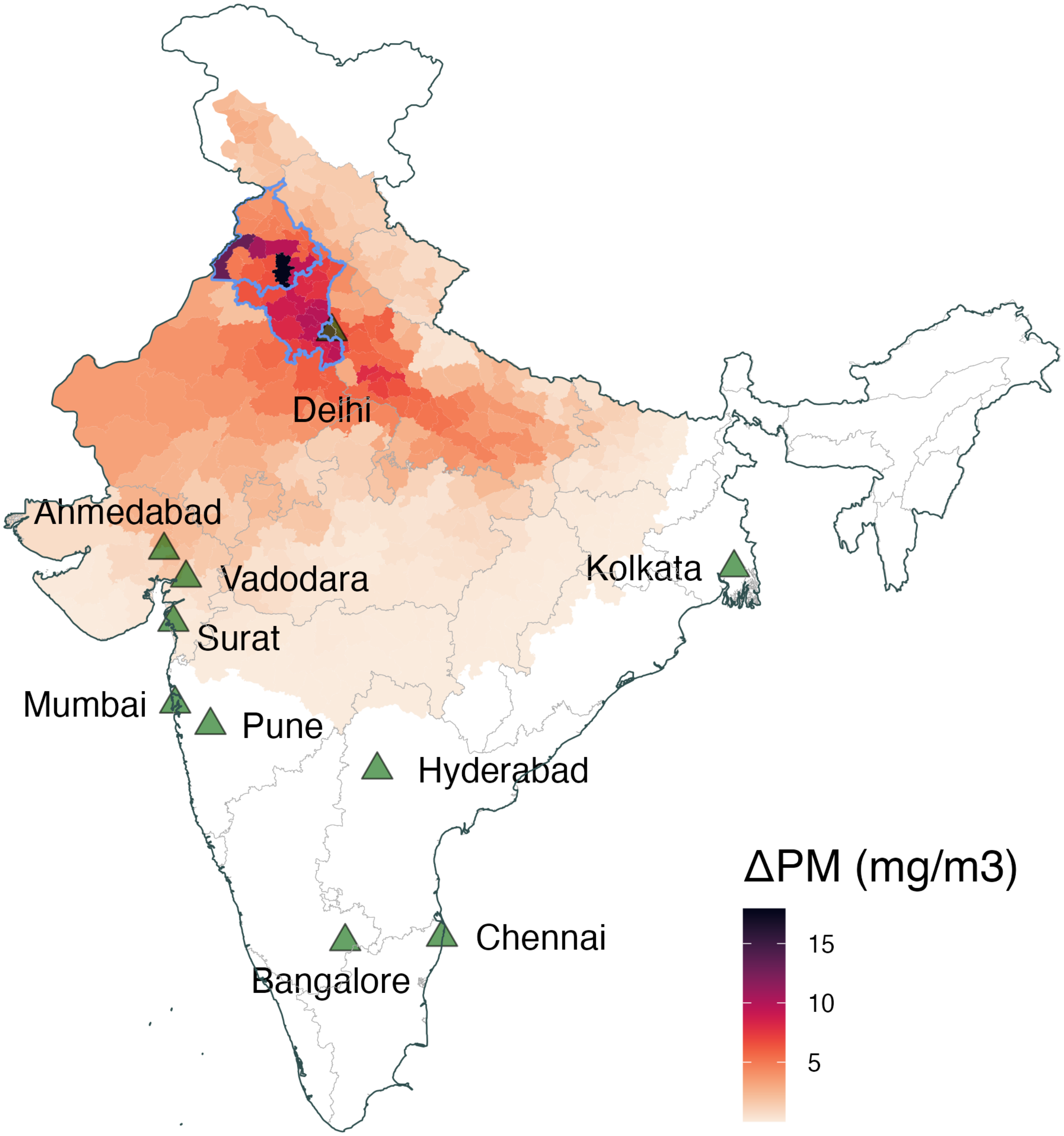
Notes: Years 2002-2016. SEs clustered at district X year.

Estimated functional forms other than a third order polynomial include linear and quadratic, logarithmic, inverse hyporbolic sine fits, and a log-log elasticity.

9.4 Causes of Crop Burning

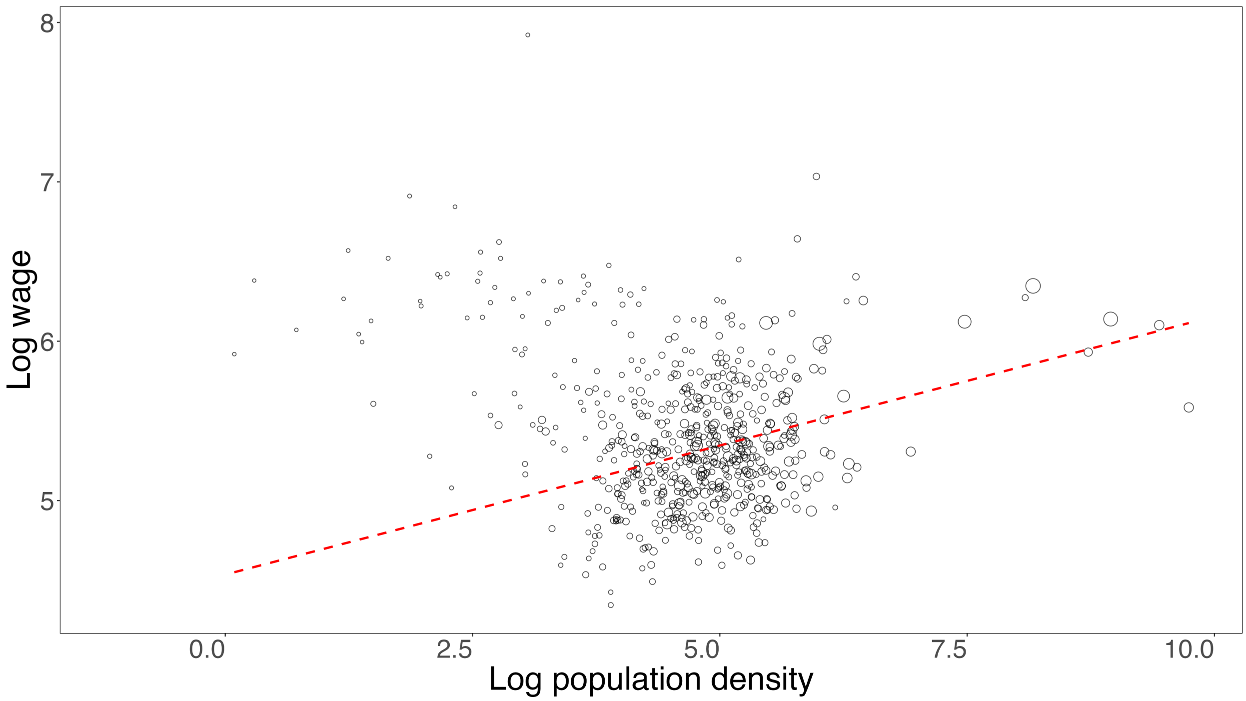
These two states of Punjab and Haryana are characterized by a rice-wheat cultivation system. In these rice-wheat systems, rice is cultivated during the monsoon or "Kharif" season (June-November) while the wheat crop is cultivated in the winter or "Rabi" season (December-April). The rice crop harvesting process leaves a residue in the field that must

(a) Change in PM from crop burning policy



(b) Change in PM from urban emissions policy

Figure A.1: Productivity Increases with Density



be removed before planting of wheat in early Rabi season. Wheat must also be planted in the first weeks of winter in order to get optimal yields. Fires are a cheap technology that can be used to remove this residue. The short duration between the rice harvest in late October and the optimal wheat planting window in early November further incentivizes farmers to burn the residue.

The rice-wheat system has its roots in the Green Revolution of the 1960s. Until then, North-Western India was a primarily wheat-growing region with little rice consumption or production locally. The advent of the Green Revolution brought with it many institutional innovations from the Indian State that increased agricultural productivity substantially across India. In the states of Punjab and Haryana, this took the form of massive subsidies for tubewells which could be used to access shallow groundwater to irrigate fields that did not have access to the pre-existing large canals systems built by the colonial British empire. This newfound access to groundwater allowed farmers to diversify their crop portfolio during the monsoon months by allowing the cultivation of water-intensive rice crop. The state of Punjab contributed less than 1% of India's rice in 1961; by the late 1990s this figure was up to 10%, even as total rice output across India also increased substantially. The use of fires to clear rice residue started in the 1990s. The earliest observations of fires from the NASA FIRMS database starting in 2002 clearly demonstrate that North-western India already had a disproportionate share of fires in Indian agriculture.

9.5 Burning Emissions are Linear in Crop Area

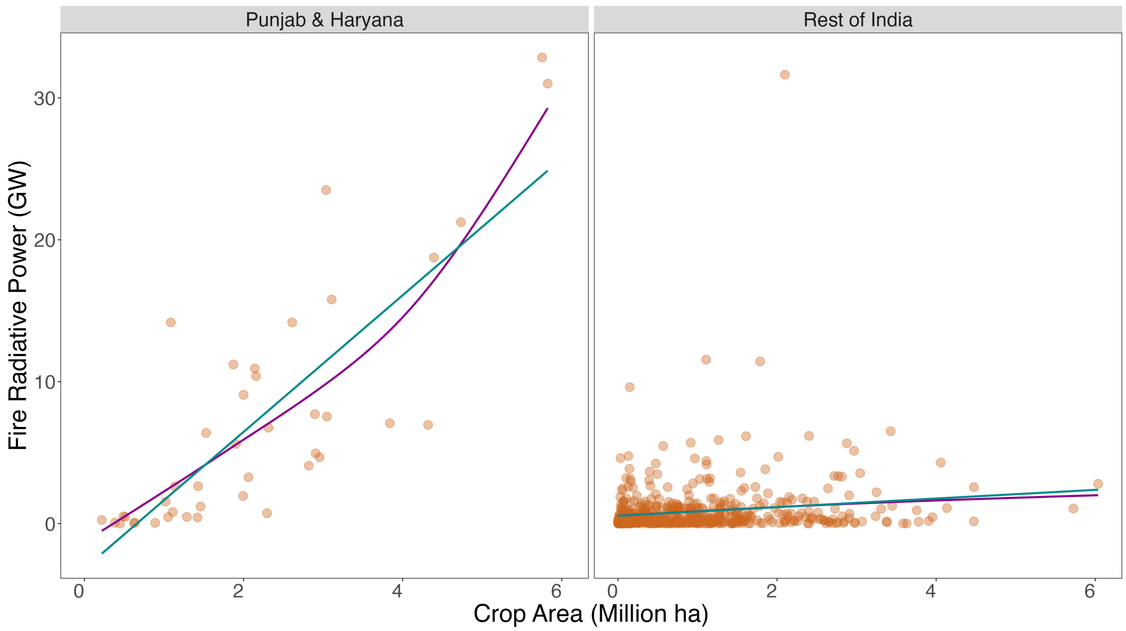
As discussed in 3, the main determinant of the extent of crop burning in each district is the quantity of rice and wheat produced, mediated by institutional features of that particular state. In order to calculate back-of-the-envelope abatement costs for the crop burning policy, we need to convert the 10% emissions reduction into an estimate of the crop area that is not burnt. Once we have that, we can use per-acre marginal abatement costs of $54 from Jack et al. (2022) to calculate total abatement costs.

In order to do this, I mode agricultural emissions $\widetilde{E}_d$ as a function of area under rice cultivation, where f_d^E captures both the rice residue that is produced and burnt in a given district. I distinguish between districts in Punjab and Haryana, and the rest of India since for the same amount of rice residue, there may be much less burning in the rest of India due to contextual and institutional differences, as described in 3.

$$E_d = f_d^E(RiceArea_d) \tag{15}$$

Figure A.2 demonstrates that institutional differences drive the increased prevalence of agricultural fires in Punjab and Haryana rice-wheat system. It also shows that the functional form of $f_d^E(.)$ is likely linear. Equation 16, shows the estimating equation. The dummy variable D_d turns on for districts in Punjab and Haryana only. E_d represents an-

Figure A.2: Burning Intensity Differs for Punjab and Haryana ↩



nual fire radiative power and $RiceArea_d$ is the total area under rice cultivation in district d. The state fixed effects capture any level differences in technology across states that may also drive the rate of burning. The objects of interest are δ^p and δ^{np}: the (linear) burning intensities of rice crop in Punjab and Haryana, and the rest of India.

$$\begin{aligned} E_d = \delta^p \ D_d * RiceArea_d \\ + \delta^{np} \ (1 - D_d) * RiceArea_d \\ + \bar{E}_{s(d)} + \epsilon_d \end{aligned} \tag{16}$$

Table ?? confirms the result shown in the figure A.2. The coefficient for districts in Punjab and Haryana is much larger than for the rest of the country, reflecting the higher prevalence of residue burning activity.

	Fire Radiative Power	
	Linear	Quadratic
Area x $\mathbb{1}$(Punjab/Haryana)	3.7	1.04
	(0.8)	(1.7)
Area^2 x $\mathbb{1}$(Punjab/Haryana)		0.7
		(0.33)
Area x $\mathbb{1}$(Rest of India)	0.4	0.47
	(0.16)	(0.42)
Area^2 x $\mathbb{1}$(Rest of India)		-0.05
		(0.09)
Observations	612	612
State FE	Y	Y

Power in gigawatts. Crop area in million ha. SEs clustered at state level

9.6 Cost-benefit Calculation for Crop Burning Policy

I calculate a back-of-the-envelope benefit-cost ratio for the crop burning policy, assuming that it can be achieved through a Payment for Ecosystem Services policy that would directly pay farmers not to burn. Jack et al. (2022) conduct an RCT where they show that such a policy can indeed lead to substantial reduction in burning activity. In particular, the treatment arm where they provide a portion of money upfront to alleviate credit constraints reduces burning by 10%. They also provide an abatement cost estimate of \$50 per acre of rice planted. The crop burning policy imposes a reduction in emissions of about 10% in Punjab and Haryana. Using the linear relationship between crop area and burning emissions in the previous section, this policy would require payment for about 10% of the total rice acreage of 11.12 million acres. Thus, I calculate a total abatement cost of (0.1*11.12*50)/1000 = $0.06 billion per year. Total GDP benefit for all of India is (0.34*1700)/100 = $5.78 billion per year, given a GDP of $1.7 trillion in 2011. This provides a benefit-cost ratio of 96. Some important caveats with this calculation are that the abatement costs might be nonlinear in rice acreage or differ for other districts of Punjab and Haryana that were not in the sample for Jack et al. (2022).