Agricultural Labor Exits Increase Crop Fires

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Abstract

Even as policy makers seek to encourage economic development by addressing misallocation due to frictions in labor markets, the associated production externalities – such as air pollution – remain entirely unexplored. Using a regression discontinuity design we show access to rural roads doubles the count of agricultural fires and causes a 1.25% increase in local PM2.5. Rural roads cause movement of workers out of agriculture, and induce farmers to use fire – a labor-saving but polluting technology – to clear agricultural residue or to make harvesting less labor-intensive.

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1 Introduction

The persistence of the agricultural productivity gap – a stylized fact that marginal product of labor is substantially lower in agriculture than in other sectors, especially in low- and middle-income countries – suggests that labor is greatly misallocated across sectors (Gollin, Lagakos and Waugh, 2014; Kuznets, 1955; Lewis, 1954). Understanding the causes of this labor misallocation, and identifying policies that enable structural transformation away from low productivity agriculture has been a central focus of development economics (Banerjee and Newman, 1998; Bryan, Chowdhury and Mobarak, 2014; Restuccia and Rogerson, 2017). However, these policies largely ignore production externalities associated with labor reallocation across sectors; by focusing exclusively on private productivity, these policies may over- or under-correct the extent of labor misallocation. In this paper we examine whether policies designed to reallocate labor across sectors generate environmental externalities.

The substitution between environmental quality – a form of capital that is 'depreciated' by the addition of pollutants – and factor inputs like labor has long been part of the concept of sustainability in environmental economics (Arrow et al., 1995; Solow, 1993). If sector-specific emission intensities are a function of labor inputs, then reallocation of labor across sectors can have important implications for local and aggregate emissions (Barrett, Ortiz-Bobea and Pham, 2020), for example, through the adoption of labor-saving technologies (Acemoglu, 2010; Allen, 2009; Davis, 2017; Habakkuk, 1962). By ignoring the effects of structural change to labor allocation on the environment, economists miss central relationships that are increasingly relevant to contemporary policy in environmentally vulnerable lower-income countries. We address this gap by providing evidence that movement of workers out of agriculture compels farmers to use a labor-saving but polluting technology – fire – resulting in increased particulate matter.

We exploit a natural experiment in rural road construction in India that singularly increased labor exits from agriculture while leaving most other economic outcomes unaffected (Asher and Novosad, 2020).[1] Using a regression discontinuity design that leverages

[1]Asher and Novosad (2020) find rural roads constructed under the Pradhan Mantri Gram Sadak Yojana (PMGSY) increased the availability of transportation services and led to a substantial reallocation of workers out of agriculture. They find no evidence for

a sharp increase in the likelihood of road construction at population thresholds, we show rural roads increase agricultural fires and particulate emissions. A new road results in a 70% increase in the number of fires (or 2.6 additional fires) within 10 km of the village and a 1.25% (0.5 μg/m^3) increase in PM2.5 levels in the village. The effect of rural roads on particulate pollution is driven almost entirely by increase in emissions from biomass burning, and concentrated in the winter harvest and post-harvest months. This is consistent with the explanation that agricultural fires (as opposed to, for example, vehicular emissions) are the primary mechanism linking rural roads to increased local PM2.5 levels.

Sub-sample analyses further bolster our primary result that agricultural labor exits increase crop fires. First, rural roads facilitate movement of workers out of agriculture, and increase agricultural fires and particulate emissions in districts where relative agricultural wage is lower (below median) at baseline, but not in districts where relative agricultural wage is higher (above median). Second, the effect of rural roads on agricultural fires and particulate emissions is concentrated in districts with a higher (above median) production of crops that benefit from use of fires in the face of agricultural labor exits at baseline, either to clear harvest residue off fields within a narrow time window before planting in the next season (rice) or to make harvest less labor-intensive (sugarcane). Together, precisely as one might expect, we find the increase in agricultural fires and particulate emissions is concentrated in districts with a higher production of rice or sugarcane *and* where relative agricultural wage is lower at baseline, with comparatively modest effects in other districts.

Our work provides the first evidence on the effects of labor reallocation from farm to non-farm sectors on environmental quality. Environmental economists have a keen interest in studying the implications of environmental policies for sectoral labor reallocation (Hafstead, Williams III and Chen, 2018; Walker, 2013). However, even as policy makers seek to encourage economic development by addressing misallocation due to frictions in labor markets, the environmental effects remain entirely unexplored. The issue is particularly salient in many low- and middle-income countries that are undergoing rapid

increases in assets or income. Farmers do not own more agricultural equipment, move out of subsistence crops, or increase agricultural production. We replicate their results in our sample.

structural transformation while simultaneously experiencing dangerously high levels of air pollution (Greenstone and Jack, 2015).

Our results also contribute to a broad literature examining trade-offs and synergies between economic development and environmental quality (Andreoni and Levinson, 2001; Arrow et al., 1995; Dasgupta et al., 2002; David I, Michael and Edward, 1996; Den Butter and Verbruggen, 1994; Grossman and Krueger, 1995; Stern, 2004). Within this literature, we join a small set of papers that examine the effects of anti-poverty programs on environmental quality (Alix-Garcia et al., 2013; Asher, Garg and Novosad, 2020; Behrer, 2020; Ferraro and Simorangkir, 2020; Gertler, Martinez and Rubio-Codina, 2012).[2,3]

The rest of the paper is organized as follows. Section 2 provides a brief background on agricultural fires in India and discusses how rural roads may affect agricultural fires. Section 3 describes the empirical analysis. Section 4 concludes.

2 Background

Air pollution remains one of the leading causes of mortality, accounting for 9 million premature deaths annually or roughly 16% of all deaths worldwide and a staggering 268 million disability-adjusted-life-years (Landrigan et al., 2018). Nowhere is the problem more pronounced than in India, which is home to 14 of 20 most polluted cities in the world. In fact, if the city of New Delhi, the capital of India, were to meet World Health Organization air quality standards, average life expectancy would increase by 10 years (Greenstone and Fan, 2019), roughly equivalent to the gains in life expectancy made by the country on average in the 21st century (Max Roser and Ritchie, 2013). Of course, a number of factors – both moderate but perpetual and seasonal but acute – contribute to the poor air quality in India. In this section we discuss use of agricultural fires in India that contribute to

[2]Previous work examining the relationship between rural road construction and environmental quality has focused on the effects on deforestation through increased demand for commercial timber (Asher, Garg and Novosad, 2020). They find rural roads do not affect local deforestation, but national highways cause substantial forest loss. In contrast, we provide evidence that even smaller-scale transportation infrastructure (rural roads) – by facilitating the movement of labor out of agriculture – increase agricultural fires and worsen local environmental quality.

[3]Our findings complement Behrer (2020) in particular; the author uses a differences-in-differences design to show India's Mahatma Gandhi National Rural Employment Guarantee Act (NREGA), which increased wages, induced farmers to invest in labor-saving technologies like combine harvesters, which leave more crop residue, increasing use of agricultural fires. We find evidence for a more direct channel: rural roads induce movement of workers out of agriculture, inducing farmers to use fire – a labor-saving technology – to clear agricultural residue.

as much as half of the particulate pollution in many parts of the country during winter months (Bikkina et al., 2019; Cusworth et al., 2018; Shyamsundar et al., 2019), and how rural roads may affect agricultural fires.

2.1 Agricultural Fires in India

Why do farmers use fire? Agricultural fires serve many purposes including (i) clearing harvest residue off fields in preparation for planting in the next season, (ii) making sugarcane harvesting less labor-intensive, and (iii) clearing undergrowth on fields left fallow between cropping seasons. Figure 1 shows wide spatial distribution of agricultural fires across districts in India.[4] We use satellite-based measures of agricultural fires based on detections of infrared radiation typical of biomass fires. Figure A.1 shows the increasing trend in the number of fires annually between 2003 and 2013, the period of study. In 2003, there were roughly 55,000 fires whereas in 2012 there were over 90,000 fires.

The use of fire is particularly prevalent in a coupled rice-wheat cropping arrangement – a system of agriculture widespread across India (Jain, Bhatia and Pathak, 2014; Prasad, Gangaiah and Aipe, 1999). In this system farmers grow rice during the monsoon season (*kharif*) from June to November, and wheat immediately following rice harvest during the winter season (*rabi*) from January to May. A narrow window of time between the harvest of rice (in October-November) and the planting of wheat (in December-January) requires large-scale and quick removal of crop residue and setting fire to crop residue is particularly helpful in this process.[5]

Fire also plays a role in the production process for sugarcane - an important crop across the country (Fair Labor Association, 2012). Farmers light sugarcane fields to remove the outer leaves around the cane stalk before harvesting the cane to make the process easier and require less manual labor (Jain, Bhatia and Pathak, 2014).

Finally, the use of fire is widespread alongside forest lands in central and north-east

[4] In Figure A.2 we report state-wise annual average number of fires between 2003 and 2013.

[5] Farmers have an average of only 13 days between the harvesting of rice and the sowing of wheat. On the other hand, in the case of the wheat harvest, farmers report a window of 46-48 days between wheat harvest and planting of rice. Consistent with time availability being a significant factor, nearly 90% of the farmers report that they engage in burning after the rice harvest. In contrast, with a longer interval available after the wheat harvest, only around 11% of the farmers use burning to clear residue after the wheat harvest (Kumar, Kumar and Joshi, 2015).

India that follow shifting cultivation, where fields are left fallow for more than a year, and farmers switch between alternate plots of land (Ramakrishnan, 1992; Venkataraman et al., 2006). Fallow fields are often overtaken by undergrowth, which need to be cleared before subsequent season's planting.

The Private Costs of Agricultural Fires: Although, fires offer an easy and inexpensive means of clearing agricultural residue, they also impose private costs on agricultural households. First, burning crop residue carries civil and criminal penalties under Section 188 of the Indian Penal Code and the Air and Pollution Control Act of 1981. While enforcement is not perfect, it is far from absent. For example, in 2016 alone, the Government of Punjab handed out a total of roughly USD 100,000 in fines.[6]

Second, crop residue burning decreases the productivity of agricultural land by destroying micro-nutrients in the soil, removing valuable fertilizer including nitrogen and phosphorus, and killing soil-borne deleterious pests and pathogens (Prasad, Gangaiah and Aipe, 1999; Smil, 1999; Stan, Fîntîneru and Mihalache, 2014; Swayer, 2019). Prior work has demonstrated that burning of rice and wheat residue can result in the loss of about 80% of nitrogen, 25% of phosphorus, 21% of potassium and 4 to 60% of sulphur from the soil (Mandal et al., 2004).

Third, source-apportionment studies suggest pollution from agricultural fires can raise local concentrations of PM2.5 to more than 1,000% above the WHO 24-hour guideline of $25ug/m^3$ (Balakrishnan et al., 2019; Bikkina et al., 2019; Liu et al., 2018).[7] Exposure to pollution from crop fires decreases birth weight, gestational length, and in utero survival (Rangel and Vogl, 2019), increases infant mortality (Pullabhotla, 2019), decreases child height for age and weight for age scores (Singh et al., 2019), decreases cognitive performance (Graff Zivin et al., 2020) and increases risk of acute respiratory infections (Chakrabarti et al., 2019).[8] Unsurprisingly, local households incur significant expenses to

[6]See e.g., https://www.downtoearth.org.in/blog/agriculture/stubble-burning-a-problem-for-the-environment-agriculture-and-humans-64912

[7]Local PM2.5 concentrations in almost all Indian villages are above the WHO 24-hour guideline of 25 ug/m^3 (Figure A.3).

[8]More broadly, air pollution has been shown to increase infant mortality (Arceo, Hanna and Oliva, 2016; Barrows, Garg and Jha, 2019; Heft-Neal et al., 2018; Jayachandran, 2009), reduce cognitive function (Ebenstein, Lavy and Roth, 2016), increase dementia (Bishop, Ketcham and Kuminoff, 2018), reduce labor productivity (Graff Zivin and Neidell, 2012) and labor supply (Hanna and Oliva, 2015), and increase elderly mortality (Deryugina et al., 2019). See Schraufnagel et al. (2019), for an exhaustive medical review.

mitigate the consequences of burning-induced air pollution: for example, people in rural Punjab spend roughly USD 1 million every year on treatment for ailments caused by stubble burning (Kumar, Kumar and Joshi, 2015).

Fourth, residue collected from the fields is of substantial economic value (Berazneva et al., 2018). Crop residue generated from the coupled rice-wheat cropping system can be used as livestock feed, which is in short supply across India, by roughly 40% (Kumar, Kumar and Joshi, 2015). Moreover, soil treated with crop residues can hold 5 to 10 times more aerobic bacteria and 1.5 to 11 times more fungi than soil from which residues were burnt, providing higher yields (Beri et al., 1992; Sidhu, Beri and Gosal, 1995).

2.2 Agricultural Fires and Rural Roads

Pradhan Mantri Gram Sadak Yojana (PMGSY) In 2000, an estimated 330,000 of India's 825,000 rural villages lacked any all-weather road access. The Pradhan Mantri Gram Sadak Yojana (PMGSY) – the Prime Minister's Village Road Program – was launched in 2000 with the goal of providing all-weather road access to unconnected villages across India. Importantly, the national program guidelines prioritized larger villages according to arbitrary thresholds based on the 2001 Population Census (Asher and Novosad, 2020). The guidelines aimed to connect all villages with populations greater than 1,000 by 2003, all villages with population greater than 500 by 2007, and villages with population over 250 after that.[9] These rules were to be applied on a state-by-state basis, meaning that states that had connected all larger villages could proceed to smaller localities; for instance, states with few unconnected villages with over 1,000 people used the 500-person threshold immediately.[10] Rural road construction under PMGSY began in 2000 and continued steadily through the end of the sample period in 2013 (Figure A.4).

[9]The unit of targeting in the PMGSY is the habitation, defined as a cluster of population whose location does not change over time. Revenue villages, which are used by the Economic and Population Censuses, are comprised of one or more habitations (National Rural Roads Development Agency, 2005). In this paper, we aggregate all data to the level of the revenue village.

[10]Some states did not comply with the threshold guidelines. Some states included several other prioritization guidelines and it is possible that political patronage played a role. See Asher and Novosad (2020) for more details. In the empirical exercise that follows we limit our analysis to states that complied with these guidelines and where we can show that there was a clear discontinuity in the probability of receiving a rural road around the relevant population thresholds.

How do rural roads affect agriculture? Asher and Novosad (2020) leverage the discontinuous increase at the aforementioned population thresholds for complying states using a fuzzy regression discontinuity design to show rural roads – constructed under PMGSY – cause a substantial increase in the availability of transportation services, but do not increase assets or income. We replicate the results from Asher and Novosad (2020) in Appendix B.[11] Farmers do not own more agricultural equipment, move out of subsistence crops, or increase agricultural production. They do find that rural roads lead to a large reallocation of workers out of agriculture. These impacts are most pronounced among the groups likely to have the lowest costs and highest potential gains from participation in labor markets: households with small landholdings and working age men. They find suggestive evidence that the growth in non-agricultural workers is due to greater access to jobs outside the village. Finally, they decisively rule out small changes in permanent migration, implying that their results are not the product of compositional changes to the village population. Overall, the main effect of rural roads is to facilitate the movement of workers out of agriculture with no major changes in agricultural outcomes, income or assets.[12]

How could rural roads affect agricultural fires? Labor exits from agriculture following rural road construction may decrease availability of farm labor or increase local costs of hiring labor. Decreased availability of farm labor or increased labor costs could lead farmers to use fires as a labor saving technology to clear rice harvest residue off fields in preparation for the subsequent season's wheat planting or to make sugarcane harvesting less labor-intensive. Indeed, the Government of India has long speculated that decreased availability of labor is one important reason for increase in agricultural fires over the last two decades (Department of Agriculture & Cooperation, 2014). This explanation is also

[11]Our sample is slightly smaller than the analysis sample in Asher and Novosad (2020) since we were unable to identify geographic coordinates – required to generate satellite-based measures of fire activity at the village level – for about 280 (2%) villages.

[12]In contrast, other studies that estimate the impacts of PMGSY use difference-in-differences design, finding rural roads improve agricultural outcomes: Shamdasani (2016) finds PMGSY increases use of expensive, productivity-enhancing inputs, such as fertilizer, hybrid seeds, manure, and hired labor. Similarly, Aggarwal (2018) finds districts with greater road construction under PMGSY observe an increase in use of fertilizer and hybrid seeds. However, consistent with Asher and Novosad (2020), these studies find no evidence that improvements in rural road infrastructure increases purchase of mechanized farm equipment (tractors/harvesters/threshers); Shamdasani (2016) also finds improvements in road connectivity induce movement of workers out of agriculture. We inform our discussion on how rural roads may affect agricultural fires based on findings from Asher and Novosad (2020) since other studies are limited in their ability to address the endogeneity of road placement.

consistent with results from a survey conducted with 150 agricultural households in rural Punjab that asked rice farmers why they burn crop residue (Kumar, Kumar and Joshi, 2015). Roughly 49% farmers indicated that burning was more economical; approximately 8% farmers were more specific and opined they were burning crop residue because they were unable to hire labor for manual removal of residue.

Other possibilities that would link road construction to fire use are changes in planting dates and adoption of technologies such as combine harvesters. While these are plausible pathways, we find no evidence to support these mechanisms.

First, rural roads may decrease the already short turn-around time between rice harvest and wheat planting even further. One, rural-road-induced labor exits may delay rice harvest, leaving little time to clear the residue before subsequent season's wheat planting. Two, road drainage and excavation may lower the water table in surrounding areas (Tsunokawa and Hoban, 1997). Therefore, rice planting might be delayed, and farmers may be rushed to harvest and clear the monsoon season's crop (rice) and plant winter season's crop (wheat) on time. In Appendix C, we examine the effect of rural roads on satellite-based measures of harvest (end-)date and planting date for the monsoon season crop (rice). We fail to find evidence that access to rural roads affect harvest or planting dates for rice.

Second, rural-road-induced labor reallocation out of agriculture may also affect number of agricultural fires by increasing adoption of technologies like combine harvesters. Behrer (2020) uses a difference-in-differences design to show India's Mahatma Gandhi National Rural Employment Guarantee Act (NREGA), which guaranteed rural employment, increased the incidence of agricultural fires. The author's results suggest wage growth associated with NREGA induced farmers to invest in labor-saving technologies like combine harvesters, which leave more crop residue, increasing use of agricultural fires. Given aforementioned evidence that rural roads do not increase ownership of mechanized farm equipment, such an indirect mechanism is unlikely to be operational in our study. Nevertheless, farmers often do not own their own combines but rather rent a combine (Shyamsundar et al., 2019). Therefore, we use the 1999 and 2006 Rural Economic and Demographic Survey to examine the effect of rural roads on village-level stock of agricultural machinery (Appendix D). We find no evidence to suggest that rural roads increase local stock of combines. We also fail to find evidence that rural roads increase household use of hired mechanized agricultural equipment (tractors, combine harvesters, threshers etc.).

Overall, this discussion suggests the primary mechanism through which rural roads may increase agricultural fires is reallocation of workers out of agriculture: burning crop residue and lighting sugarcane fields on fire becomes relatively economical compared to manual removal of crop residue and outer leaves around cane stalk.

3 Effect of Rural Roads on Agricultural Fires

3.1 Data Sources

Our primary analysis combines information on village-level rural road construction under PMGSY with satellite-based measures of agricultural fires and PM2.5 collapsed at the village level.

Rural Roads: We use the Socioeconomic High-resolution Rural-Urban Geographic Dataset (SHRUG) for information on village-level rural road construction dates under PMGSY (Asher et al., 2019). We merge data on roads with village-level shapefiles (Meiyappan et al., 2018, 2017). We follow Asher and Novosad (2020), who worked closely with the National Rural Roads Development Agency to identify the state-specific thresholds that were followed, to define our sample: our sample is comprised of villages from the following states, with the population thresholds used in parentheses: Chhattisgarh (500, 1,000), Gujarat (500), Madhya Pradesh (500, 1,000), Maharashtra (500), Orissa (500), and Rajasthan (500). We restrict our analysis to these states since these were the states that reasonably adhered to the population priority criterion set forth by the national government.

Agricultural Fires: We merge data on roads with satellite-detected fire activity data from NASA's Earth Observing System Data and Information System (EOSDIS) to capture annual agricultural fires within 10 kilometers of each village. The fire activity data are based on detections of infrared radiation that are a signature of biomass fires (Giglio, Csiszar and Justice, 2006). The underlying MODIS algorithm identifies a pixel (approximately one square kilometer area) with fire activity if at least one thermal anomaly is detected within that pixel. These data on thermal anomalies have been used extensively by atmospheric scientists to study the effects of agricultural fires on pollution in India and elsewhere (Liu et al., 2018). The MODIS data provides us with a daily, geocoded record of fire pixels from 2003 - 2013. We estimate annual counts of fires at the 10-kilometer radial buffer around the centroid of each village polygon.

Air Pollution: To generate pollution indicators at the village level, we rely on modeled PM2.5 pollution estimates from Van Donkelaar et al. (2016). These gridded data are derived from satellite measures of aerosol density, combined with chemical transport models and calibrated to global ground-based observations of PM2.5. The Van Donkelaar et al. (2016) data provide annual average PM2.5 values at $0.01^\circ \times 0.01^\circ$ resolution for 1998-2015. Furthermore, to examine seasonal impacts on air pollution, we complement these annual PM2.5 data with monthly data on black carbon and organic carbon emissions (precursors to particulate pollution) from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) (Gelaro et al., 2017). The MERRA-2 model apportions these emissions into those arising from biomass burning alone (which are driven by agricultural fires) and all other anthropogenic sources such as transportation, industrial emissions, or other combustion sources. This allows us to separately examine the impact of roads on total emissions and those arising from agricultural fires alone. The MERRA-2 data are gridded ($0.50^\circ \times 0.625^\circ$ resolution) estimates of emissions based on satellite and climate reanalysis measurements. We interpolate both biomass emissions and total emissions gridded values to each village's geolocation in our sample.

3.2 Empirical Strategy

To estimate the effect of rural roads on agricultural fires and PM2.5, we employ a fuzzy regression discontinuity design. Due to imperfect compliance of rural road construction with rules (population threshold) that determine award of rural roads under PMGSY, we use a two stage least squares specification with optimal bandwidth local linear regression (Gelman and Imbens, 2019; Imbens and Kalyanaraman, 2012):

$$\begin{aligned} Road_{vdst} &= \gamma_0 + \gamma_1 \mathbf{1}(pop_{vds} \geq T) + \gamma_2(pop_{vds} - T) + \\ &\quad + \gamma_3(pop_{vds} - T) * \mathbf{1}(pop_{vds} \geq T) + \boldsymbol{\theta}\mathbf{X_{vds}} + \mu_{d,h} + \rho_t + \nu_{vdst} \end{aligned} \tag{1}$$

$$\begin{aligned} Y_{vdst} &= \beta_0 + \beta_1 Road_{vdst} + \beta_2(pop_{vds} - T) + \\ &\quad + \beta_3(pop_{vds} - T) * \mathbf{1}(pop_{vds} \geq T) + \boldsymbol{\delta}\mathbf{X_{vds}} + \eta_{d,h} + \omega_t + \varepsilon_{vdst} \end{aligned} \tag{2}$$

$Road_{vdst}$ takes the value 1 if village v in district d in state s receives a PMGSY road by year t. Y_{vdst} is outcome of interest (number of agricultural fires, PM2.5) for village v in district d in state s in year t. The population of the village in 2001 is pop_{vds}, while T is the treatment threshold (either 500 or 1000, depending on the state). $\mu_{d,h}$ and $\eta_{d,h}$ are district-population threshold fixed effects - that is, an interaction of district dummies with an indicator variable that takes the value 1 if village is in a state where the treatment threshold is equal to $1,000$, and 0 otherwise. ρ_t and ω_t are year fixed effects. Thus, the RD estimates compare outcomes for villages within the same district but on opposite sides of the PMGSY population threshold in year t.

To ensure that our design follows closely with Asher and Novosad (2020), we include a vector of baseline (2001) village characteristics, $\mathbf{X_{vds}}$, as controls although excluding these controls does not alter our results appreciably. Specifically, we control for village amenities (primary school, medical center, electrification), agricultural characteristics including total agricultural land area, (log) share of irrigated agricultural land, and share of workers in agriculture, and village-level measures of socio-economic status and connectivity like literacy rate, share of inhabitants that belong to a scheduled caste, share of households owning agricultural land, share of households who are subsistence farmers, share of households earning over 250 INR cash per month (approximately 4 USD), and distance in km from the closest census town. We also control for count of fires or PM2.5 levels in 2001 when the outcome variable is count of fires or PM2.5 levels, respectively. We estimate equation (1) using an optimal bandwidth (84) with a triangular kernel that provides higher weights to observations close to the threshold (Calonico, Cattaneo and Titiunik, 2014). Standard errors are clustered at the village level.

In Appendix B, we present the mean values for various village baseline characteristics, including the set of controls that we use in all regressions; we find no significant differences when we use the RD specification to test for discontinuous changes at the threshold. We also show that the density of the village population distribution is also continuous across the treatment threshold; the McCrary test statistic is -0.010 (s.e. 0.048) (McCrary, 2008).

Figure A.5 shows the share of villages that received new roads between 2003 and 2013 at the treatment threshold. Roads built before 2008 were not prioritized according to the population threshold rule. However, there is a sharp discontinuous increase in the probability of treatment at the threshold from 2008. Crossing the treatment threshold raises the probability of treatment (rural road construction) by 10 percentage points in 2008; the probability of treatment at the threshold increases to 20 percentage points in 2013. Therefore, we will restrict our primary analysis to the period between 2008 and 2013.

3.3 Results

Figure 2 shows the graphical representation of the reduced form effect; i.e., the change in likelihood of rural road construction under PMGSY (Figure 2(a)) and count of agricultural fires at the (treatment) population threshold (Figure 2(b)). We observe a large and statistically significant increase in likelihood of rural road construction and number of fires for villages at the treatment threshold. Table 1 shows the corresponding point estimates. Column (1) presents the first stage result. Villages above the PMGSY population threshold observe a 23 percentage point increase in the likelihood of receiving a road. Column (2) shows the instrumental variable (IV) or local average treatment effects (LATE); we instrument access to rural roads with the PMGSY population threshold. Villages with rural road access observe a 70% increase (2.6 additional fires) in the annual number of fires, compared to villages that do not have access to a rural road.

We corroborate our results by examining the consequent effect of rural roads on local air quality. Our outcome is a satellite-based estimate of the annual average ambient PM2.5 concentrations for each village (Van Donkelaar et al., 2016). Figure 2(c) shows the graphical representation of the reduced form effect of rural roads on PM2.5. We observe a statistically significant increase in PM2.5 for villages at the population threshold that determines rural road construction under PMGSY. Table 1 Column (3) shows the IV or LATE point estimates where we instrument access to rural roads with PMGSY population threshold; villages with rural road access observe a (0.5 μg/m^3) 1.3% increase in annual average PM2.5, compared to villages that do not have access to a rural road.[13]

How large are these effects? The effects of rural roads on fires are economically meaningful. A global study finds that an increase of 10 μg/m^3 in the two-day moving average of PM2.5 concentrations is associated with increases of 0.68% in daily all-cause mortality (Liu et al., 2019). Extrapolated to our paper, the estimated increase of 0.5 μg/m^3 in local PM2.5 concentrations increases daily all-cause mortality by 0.03%.

Are increased local PM2.5 levels driven by vehicular emissions? Given that rural roads increased the availability of transportation services such as government buses (Appendix B), it is plausible that vehicular traffic and not agricultural fires relate rural roads to local particulate emissions. We directly test for this possibility by comparing the effects of rural roads on fires and particulate pollution in the winter harvest and post-harvest months – months in which access to rural roads increases agricultural fires (October through March) – with the effects of rural roads on particulate pollution during the rest of the year (April through September).[14] If agricultural fires and not vehicular emissions are the primary mechanism linking rural roads to increased local PM2.5 levels, one would expect to see the effects of rural roads on particulate pollution concentrated from October

[13]These results are robust to excluding baseline controls (Figure A.6; Table A.1).

[14]Decreased availability of farm labor or increased labor costs – following rural road construction – could lead farmers to use fires as a labor saving technology to clear rice harvest residue off fields in preparation for the subsequent season's wheat planting or to make sugarcane harvesting less labor-intensive. Crop fires associated with burning of rice residue occur between October and December (Jain, Bhatia and Pathak, 2014; Kumar, Kumar and Joshi, 2015; Prasad, Gangaiah and Aipe, 1999). Crop burning associated with the sugarcane harvest takes place between December and March (Directorate of Economics & Statistics, 2019). Therefore, we examine the effects of rural roads on agricultural fires and particulate pollution between October and March and compare it to the effects of rural roads on agricultural fires and particulate pollution in the rest of the year.

through March, with comparatively modest effects in the rest of the year. Indeed, we find rural roads increase both agricultural fires and particulate pollution from all sources in the winter harvest and post-harvest months of October to March, with comparatively modest to zero effects in the rest of the year (Figure A.7; Table 2).[15]

If however, use of transportation services is concentrated in the harvest months, the above test would not rule out vehicular emissions as a cause for increased local PM2.5 level. Therefore, we further show the impact on particulate pollution is driven almost entirely by the increase in emissions from biomass burning (Figure A.8; Table 2, Columns 4-5) with no effect on emissions from other (non-biomass burning) anthropogenic sources (Figure A.9; Table 2, Columns 6-7). These results suggest that agricultural fires as opposed to, for example, vehicular emissions are the primary mechanism linking rural roads to increased local PM2.5 levels.

Do agricultural labor exits increase crop fires? We support our primary result – agricultural labor exits from road construction lead to increases in crop fires – with heterogeneity analyses.

First, rural roads facilitate movement of workers out of agriculture and increase agricultural fires in districts where relative agricultural wage is lower (below median) at baseline, but not in districts where relative agricultural wage is higher (above median) at baseline.[16] The effects of rural roads on labor exits from agriculture and the increase in non-agricultural manual labor share is driven by districts with lower relative agricultural wage rates at baseline (Figure E.1; Table E.1). Correspondingly, the increase in agricultural fires (Figure E.2; Table E.2) and particulate emissions (Figure E.2; Table E.2) is concentrated in districts with lower relative agricultural wage rates at baseline, with comparatively modest effects in districts with higher relative agricultural wage rates at baseline.

[15] The PM2.5 data is available only at the annual level. Therefore, to examine seasonal effects, we use monthly emissions data from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) (Gelaro et al., 2017). We focus on black carbon and organic carbon, the two major pollutants commonly associated with biomass burning, and which form precursor elements that lead to PM2.5 particles' formation in the atmosphere (Cusworth et al., 2018).

[16] The employment and unemployment surveys conducted by the National Sample Survey Organization (NSSO) of India collect data on the daily activities for the past seven days for all household members above four years of age. We use the 55^{th} round of the NSSO (1999 - 2000) and compute the average earnings per day worked in casual labor for individuals aged 18-60 residing in rural areas by dividing the weekly earnings by the number of days worked. We then calculate the district-level relative agricultural labor wage rate as the sample-weighted average of the ratio of the daily wage rate for casual labor in the agricultural sector to the non-agricultural sector. For districts in our sample, this ratio ranges from 0.1 to 1.3, with a median of 0.46. We split the sample into higher and lower relative agricultural wage rate districts based on the sample median.

Second, the effect of rural roads on agricultural fires is concentrated in districts with a higher (above median) baseline production of crops that benefit from use of fires in the face of agricultural labor exits, either to clear harvest residue off fields within a narrow time window before planting in the next season (rice) or to make harvesting less labor-intensive (sugarcane).[17] Figure F.1 presents the spatial distribution of average annual fire activity and of the share of rice and sugarcane grown across districts in our analysis sample. A simple eyeball test suggests fire counts are higher in districts where the share of rice or sugarcane area are above the median at baseline compared to districts where the share of rice or sugarcane area are below the median. More formally, indeed, the effects of rural roads on agricultural fires (Figure F.2; Table F.1) and particulate emissions (Figure F.2; Table F.1) is driven by districts with higher share of rice or sugarcane acreage at baseline, with comparatively modest effects in districts with lower share of rice and sugarcane acreage at baseline.

Together, precisely as one might expect, we find the increase in agricultural fires (Figure G.1; Table 3) and particulate emissions (Figure G.1; Table 3) is concentrated in districts that observe a higher production of rice or sugarcane *and* where relative agricultural wage is lower at baseline, with comparatively modest effects in other districts. Agricultural labor exists are higher in districts where relative agricultural wage rate is lower; therefore, presumably, farmers in these districts face higher labor costs due to rural road construction. Consequently, farmers in districts within this sub-sample where rice or sugarcane production is higher will drive the of adoption fire as a labor saving technology to clear rice residue – within a short time window – before planting next season's crop or to make sugarcane harvesting less labor-intensive.[18]

[17] We match districts in the analysis sample to agricultural data obtained from the ICRISAT District Level Database. The ICRISAT District Level Data are available online from the following website: http://data.icrisat.org/dld/src/crops.html. We use data for the year 2001 to classified higher/lower rice or sugarcane districts based on the sample median of acreage share for the respective crops.

[18] One concern we haven't addressed thus far is whether rural-road-induced movement of labor out of agriculture and associated impacts on agricultural fires are driven by farm labor pulled into rural road construction in the short-run. As evidence against such an explanation, in Appendix H we show the effects of rural roads on crop fires are undiminished in the longer-run, observed in time periods following completion of rural roads.

4 Conclusion

In this paper, we leverage a natural experiment in rural road construction to show that resulting labor exits lead to an increase in agricultural fires and particulate matter in barely treated relative to barely untreated villages. In effect, labor exits motivate the adoption of fire as a labor-saving but polluting technology to clear agricultural residue or to make harvesting less labor-intensive.

The persistence of the agricultural productivity gap has generated considerable interest amongst governments and international agencies to devise policies that reduce frictions in labor reallocation across sectors. Our research does not imply such efforts are misguided or should be discouraged. Instead, our results underscore the need to complement these policies with strategies to mitigate their potential negative environmental externalities. In our context, future research could investigate the design and implementation of monetary and non-monetary incentives to alter farmers' decisions to engage in using fire in agriculture in the face of soaring labor costs (Jack and Jayachandran, 2019; Jack, Kousky and Sims, 2008; Jayachandran et al., 2017).

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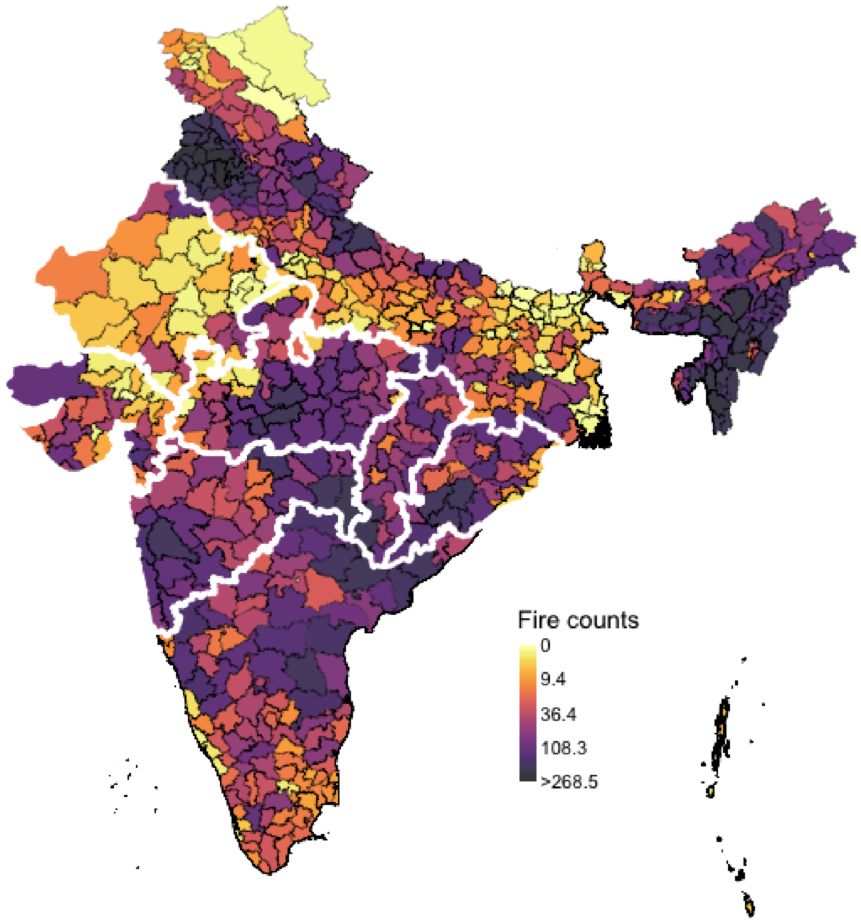
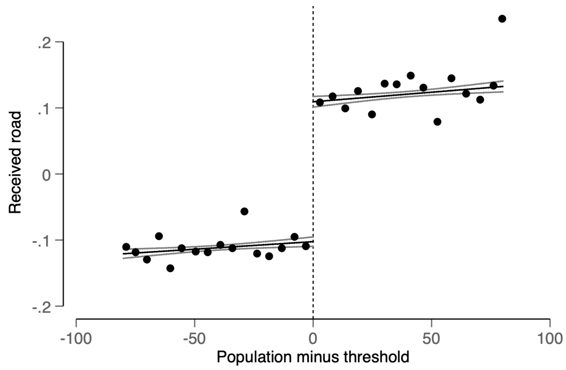
Figures and Tables

Figure 1: Spatial distribution of fire activity across districts

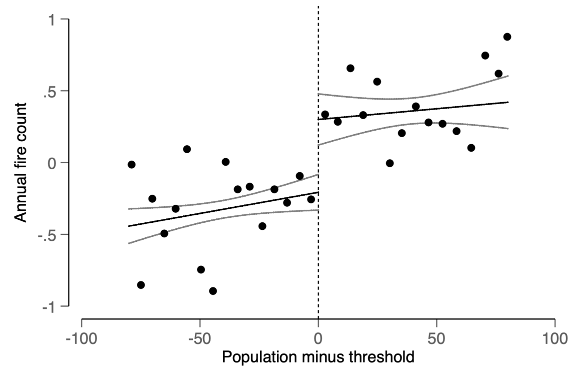


Notes: Figure shows the mean annual number of fire pixels detected in each district over India from MODIS satellite data for the period 2003 to 2013. States in our analysis sample are highlighted via white borders. The mean fire counts range from a minimum of 0 to a maximum of 1968, with mean of 108.6. The legend shows the values at the 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the average annual fire counts.

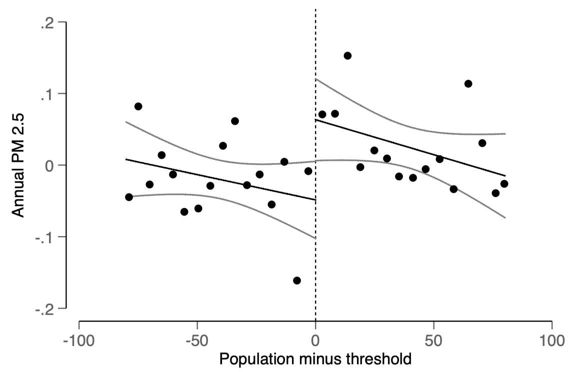
Figure 2: Impact of roads on fire activity and emissions: regression discontinuity plots



(a) Rural Roads



(b) Annual Fires



(c) Annual PM2.5

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of the outcomes (after controlling for all variables in the main specification other than population) as a function of the normalized 2001 village population relative to the threshold. Figure (a) shows the probability of a village receiving a new road between 2008 to 2013. Each point represents the mean of all villages in a given population bin. Figure (b) plots the residualized annual number of fires between 2008 - 2013. Figure (c) plots the residualized average annual PM2.5 from 2008-2013. Estimates in all figures control for district-threshold fixed effects, year fixed effects, and baseline village characteristics in 2001. Figures (b) and (c) also include baseline 2001 fire counts and baseline PM2.5 respectively as controls. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000 depending on the state.

Table 1: Regression discontinuity results: 1^{st} stage and IV estimates for impact of rural road construction on agricultural fires and pollution

	New road	Annual fire activity	Annual average PM2.5
	(1)	(2)	(3)
	First stage	IV	IV
Above threshold pop.	0.230***		
	(0.017)		
Road built		2.587***	0.468**
		(0.988)	(0.214)
N	66,894	66,894	66,894
Control group mean	0.19	3.86	44.85

Notes: Table shows regression discontinuity treatment estimates of the the first stage (probability of receiving a new road) and theeffect of new village roads on agricultural fire activity and PM 2.5. The sample consists of the panel of villages for the 5 year period from 2008 - 2013 "Above threshold pop." is an indicator for a village population being above the treatment threshold. Column (1) shows the first stage, with the dependent variable taking the value one if the village received a new road during 2008-2013. Columns (2) and (3) present the IV estimates of the treatment effects of new roads on annual fire counts around each village measured within a 10 km radius and annual average PM 2.5 ($\mu g/m^3$), respectively. Regressions include district-threshold fixed effects, year fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table 2: Regression discontinuity results: impact of rural road construction on fire activity and emissions - winter harvest and post-harvest months vs. rest of the year

Panel A: Winter harvest and post-harvest months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fires	All sources		Biomass burning		Other sources	
		Black carbon	Organic carbon	Black carbon	Organic carbon	Black carbon	Organic carbon
Road built	1.826***	0.223*	2.863*	0.221**	2.869**	-0.0001	-0.0007
	(0.583)	(0.115)	(1.509)	(0.112)	(1.450)	(0.0002)	(0.0008)
N	66,894	66,894	66,894	66,894	66,894	66,894	66,894
Control group mean	1.96	30.69	123.41	1.29	15.61	29.400	107.802
Panel B: Rest of the year							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fires	All sources		Biomass burning		Other sources	
		Black carbon	Organic carbon	Black carbon	Organic carbon	Black carbon	Organic carbon
Road built	0.424	0.112	-0.371	-0.013	-1.932	-0.0002	-0.0008
	(0.665)	(0.297)	(3.393)	(0.282)	(3.178)	(0.0002)	(0.0008)
N	66,894	66,894	66,894	66,894	66,894	66,894	66,894
Control group mean	1.83	31.28	129.72	1.88	21.92	29.399	107.796

Notes: Table shows regression discontinuity IV treatment estimates of the effect of new village roads on levels of agricultural fire activity, black carbon and organic carbon emissions in the winter harvest and post-harvest months (Panel A) and the rest of the year (Panel B). Winter harvest and post-harvest period comprises the months from October - March. Fire activity is measured in counts and emissions measured are in nano-gram per square meter per second ($ng/m^2/s$). Columns (2) and (3) show impact on emissions from all sources, columns (4) and (5) are emissions from biomass burning only, and columns (6) and (7) are emissions from other (non-biomass burning) sources. All regressions control for district-threshold FE, year FE and baseline controls. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table 3: Regression discontinuity results: impact of rural road construction on annual agricultural fire activity and pollution across high versus low relative agricultural wage rate districts and rice/sugar cropped areas

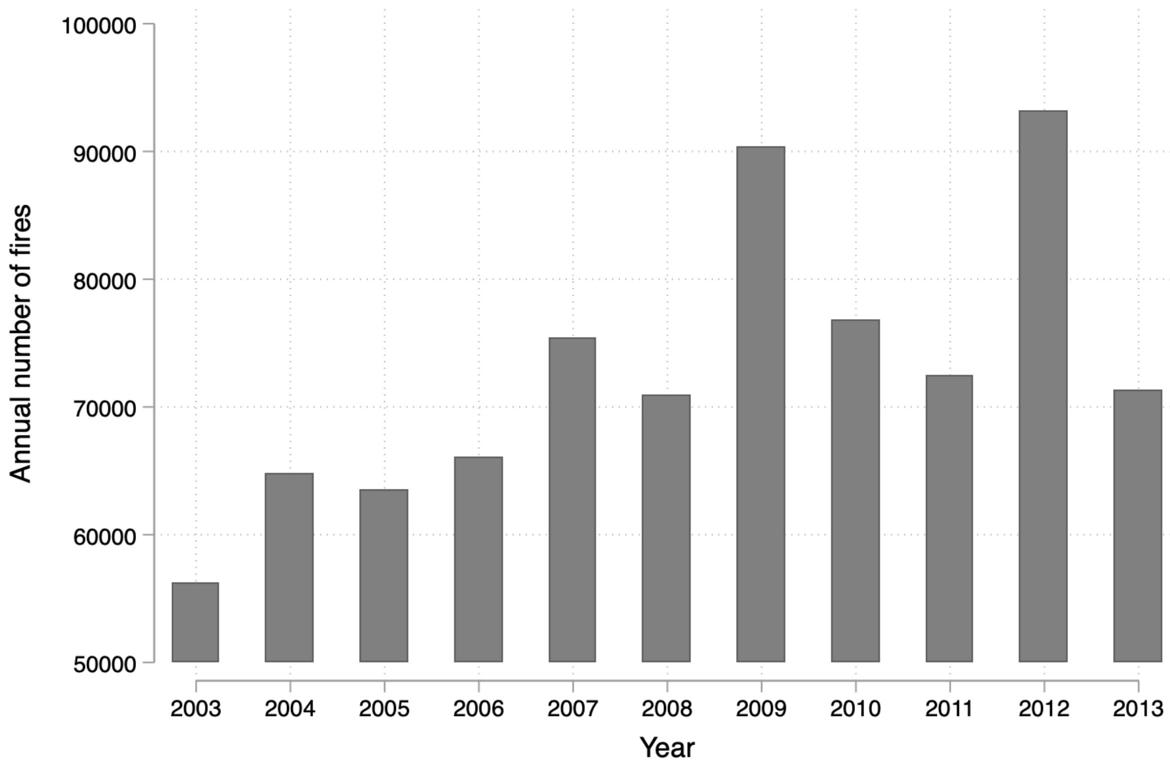
	Low rel. ag. wage with high rice or high sugar		High rel ag. wage or low rel. ag wage with low rice & low sugar	
	(1)	(2)	(3)	(4)
	Fires	PM 2.5	Fires	PM 2.5
Road built	6.828**	1.382***	1.185	0.320
	(3.083)	(0.507)	(0.882)	(0.236)
N	26,538	26,538	37,290	37,290
Control group mean	4.57	40.80	3.39	47.86

Notes: Table shows regression discontinuity IV estimates of receiving a new road on village-level annual fire activity and village-level annual average PM 2.5 ($\mu g/m^3$). The sample consists of the panel of villages for the 5 year period from 2008 - 2013. "Low rel. ag. labor wage with high rice or high sugar" sample consists of districts which had low (below sample median) agricultural labor wages relative to non-agricultural labor wage rates in rural areas *and* had high (above sample median) share of cropped area under rice or sugarcane at baseline (2001). "High rel ag. wage or low rel. ag wage with low rice & low sugar" consists of villages within districts which had either (i) high (above median) relative agricultural wage rates or (ii) low relative agricultural wage rates with low rice and sugar cropped areas. Rural agricultural and non-agricultural daily labor wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Rice and sugar cropped areas are based on ICRISAT district level data for 2001. Regressions include district-threshold fixed effects, year fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Supplementary Appendices

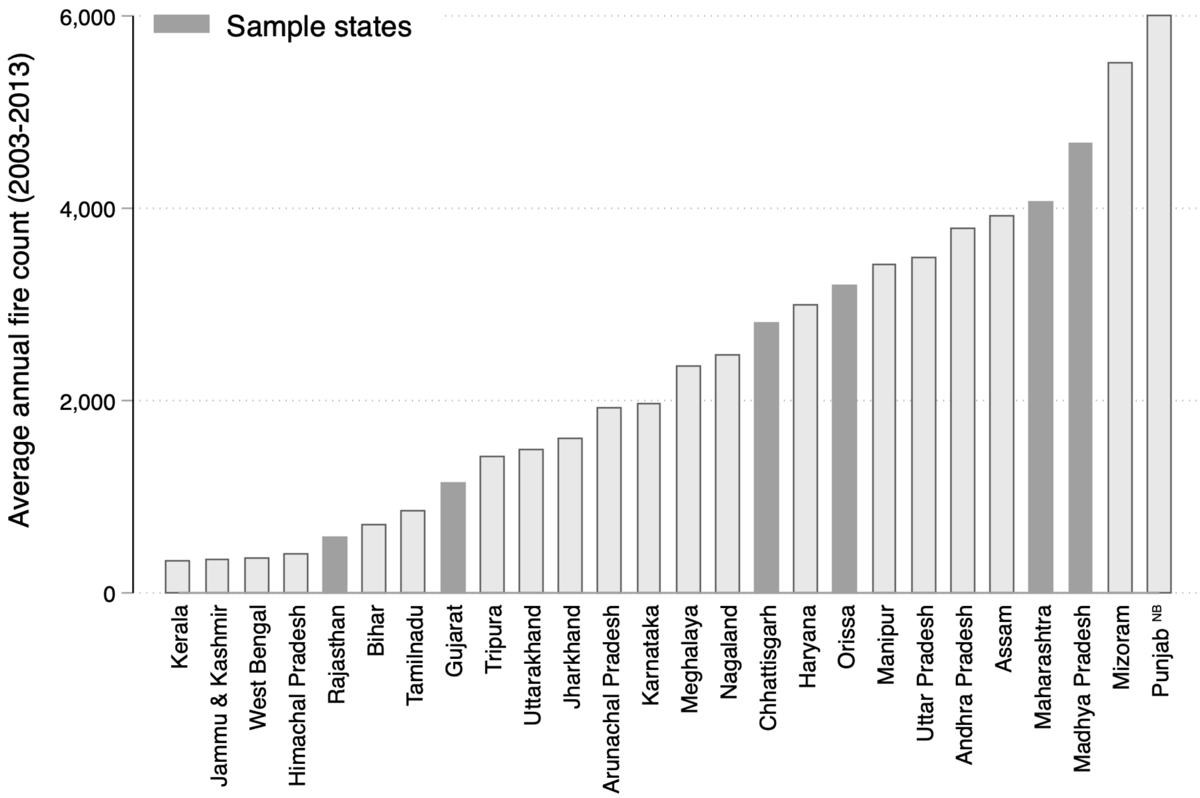
A Appendix: Figures and Tables

Figure A.1: Annual number of fires detected over India



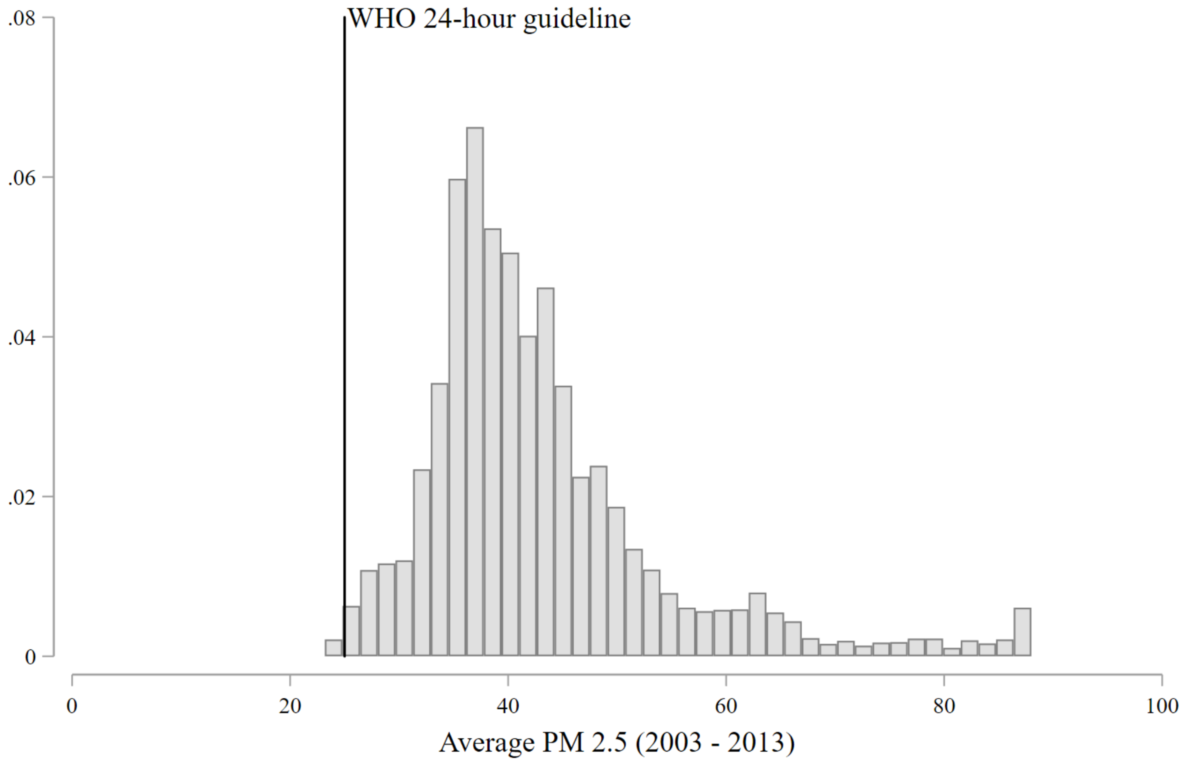
Notes: Figure shows the number of fire pixels detected each year over India from MODIS satellite data.

Figure A.2: Annual average fire counts per state



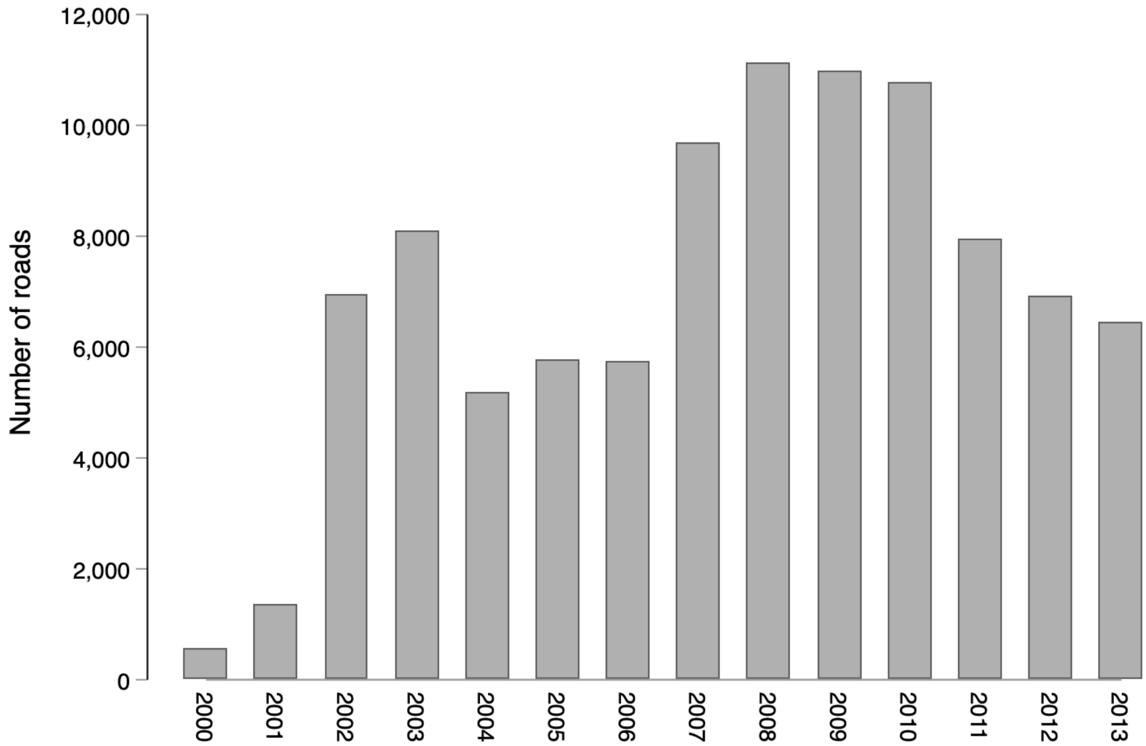
Notes: Figure shows the annual average fire counts for 2003 - 2013 for each state. States in the analysis sample are highlighted in darker shaded bars. Note that the value for Punjab is truncated at 6000 for ease of visual representation. The average fire counts per year for Punjab is ≈ 16,000 fires.

Figure A.3: Distribution of annual average PM2.5 at the village level



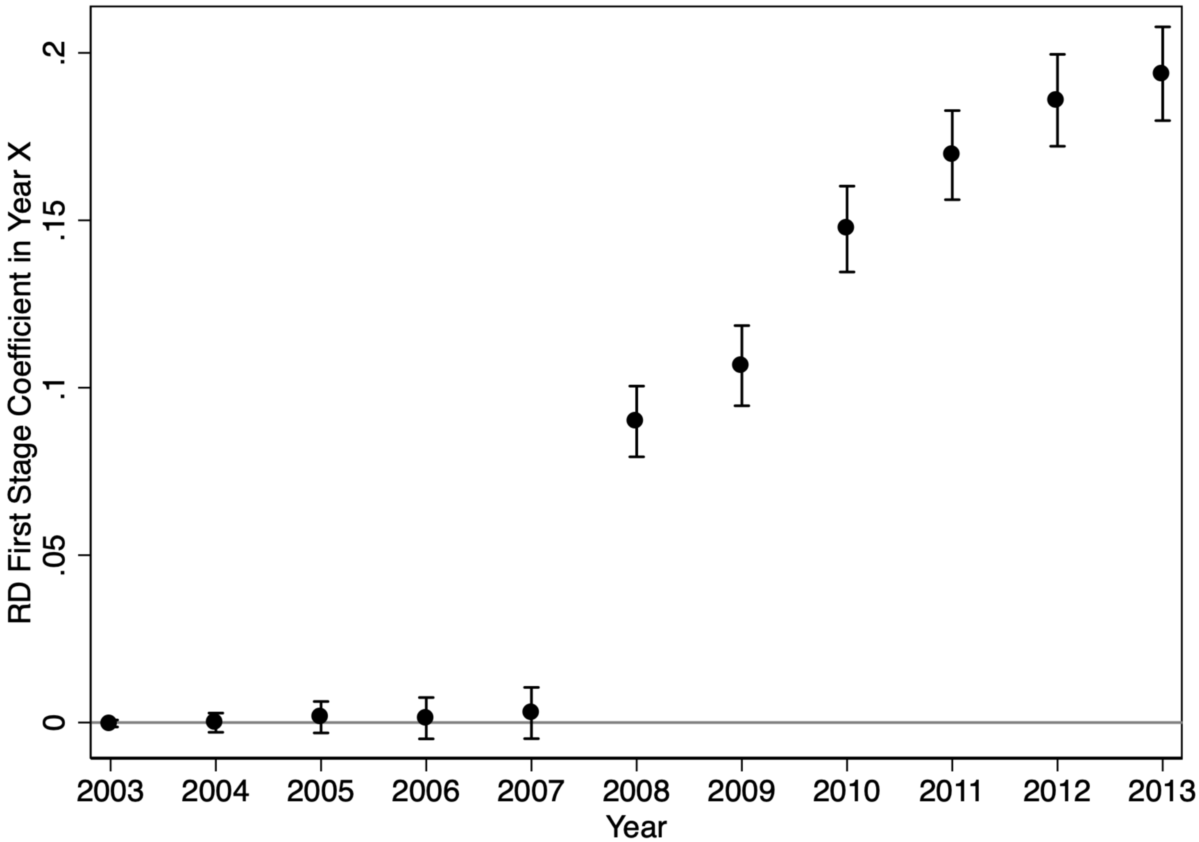
Notes: Figure plots the distribution of average PM 2.5 ($\mu g/m^3$) between 2003 and 2013 at the village level. The vertical line indicates the WHO 24-hour guideline of 25 $\mu g/m^3$.

Figure A.4: Roads constructed per year under the PMGSY



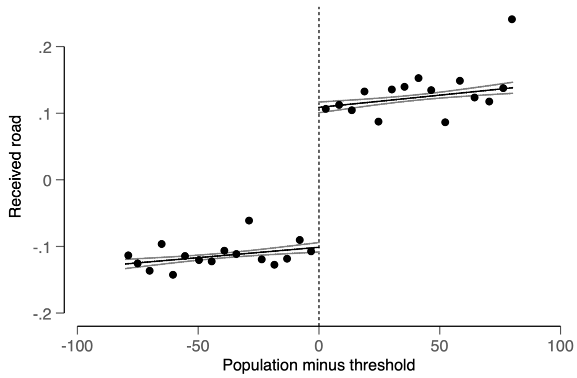
Notes: Figure shows the total number of roads constructed per year under the PMGSY for all of India. The road construction data is drawn from Asher and Asher and Novosad (2020) and Asher et al., (2019).

Figure A.5: Regression discontinuity first stage: likelihood of road construction at population threshold

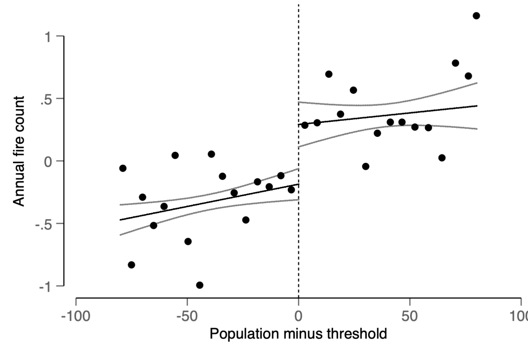


Notes: Figure shows the first stage effect of being above the population threshold on the likelihood of receiving a new road. It shows regression discontinuity estimates from a separate regression run for each year in the sample. Estimates control for district-threshold fixed effects and baseline village characteristics in 2001. Standard errors are clustered at village level.

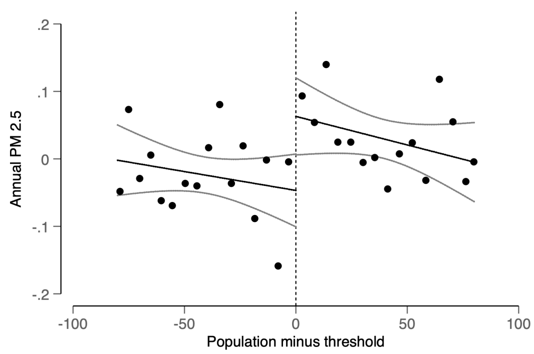
Figure A.6: Impact of roads on fire activity and emissions: regression discontinuity plots (without baseline controls)



(a) Rural Roads



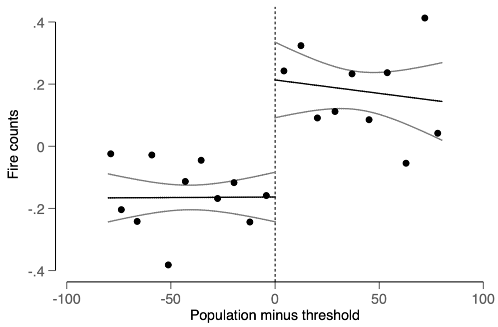
(b) Annual Fires



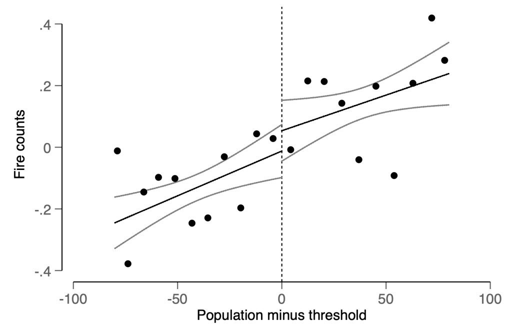
(c) Annual PM2.5

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of the outcomes as a function of the normalized 2001 village population relative to the threshold. Figure (a) shows the probability of a village receiving a new road between 2008 to 2013. Each point represents the mean of all villages in a given population bin. Figure (b) plots the residualized annual number of fires between 2008 - 2013. Figure (c) plots the residualized average annual PM2.5 from 2008-2013. Estimates in all figures control for district-threshold fixed effects and year fixed effects. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000 depending on the state.

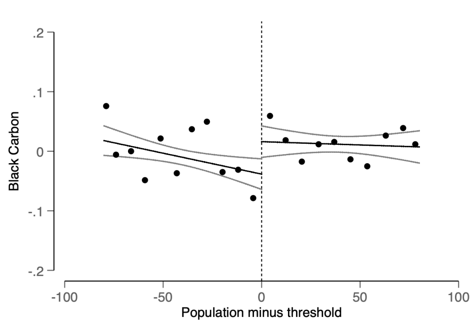
Figure A.7: Impact of roads on fire activity and emissions - winter harvest and post-harvest months vs. rest of the year (2008 - 2013): regression discontinuity graphs



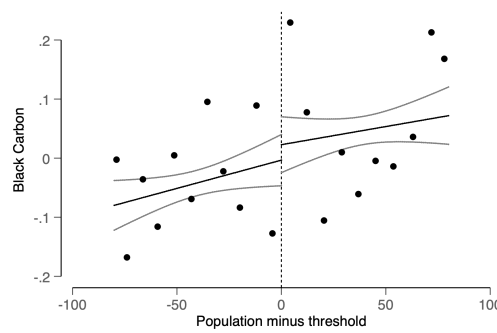
(a) Agricultural fires: Oct - Mar



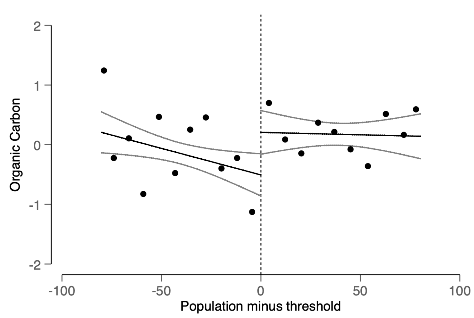
(b) Agricultural fires: Apr - Sep



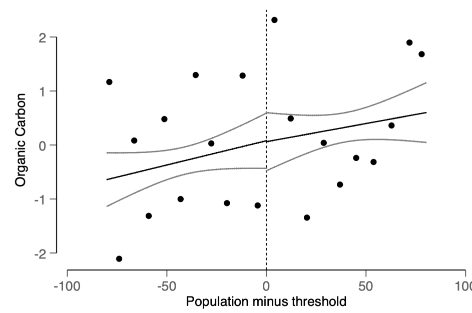
(c) Black carbon: Oct - Mar



(d) Black carbon: Apr - Sep



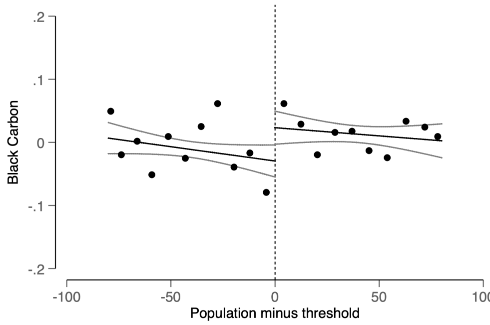
(e) Organic carbon: Oct - Mar



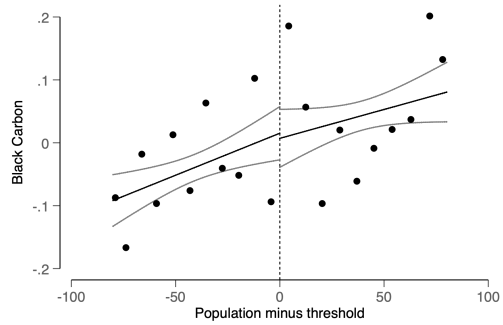
(f) Organic carbon: Apr - Sep

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of the outcomes as a function of the normalized 2001 village population relative to the threshold. Panels (a) and (b) show the reduced form RD plot for agricultural fires across during the winter harvest and post-harvest months vs. the rest of the year, respectively. Panels (c) and (d), similarly, show the reduced form effect on total black carbon emission rates (biomass burning and other anthropogenic sources) (in $ng/m^2/s$) . Panels (e) and (f) portray the same for total organic carbon emissions from all sources (Figure A.8 shows corresponding plots for emissions from biomass burning alone). Winter harvest and post-harvest period comprises the months from October - March. Each point represents the mean of all villages in a given population bin. All estimates control for district-threshold fixed effects, year fixed effects, and baseline characteristics. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

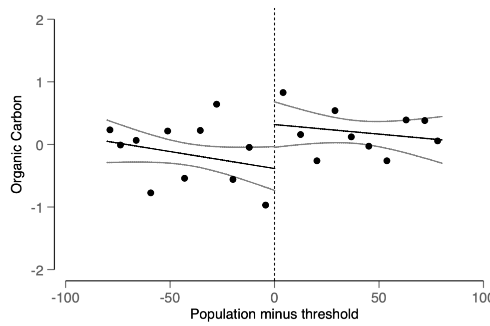
Figure A.8: Impact of roads on emissions from biomass burning - winter harvest and post-harvest months vs. rest of the year (2008 - 2013): regression discontinuity graphs



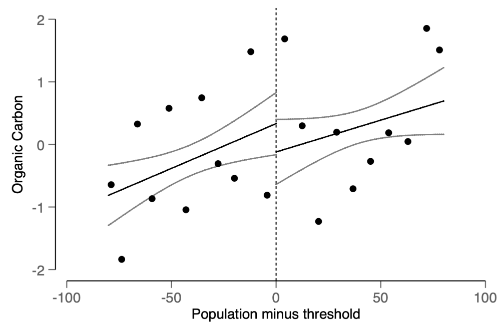
(a) Black carbon: Oct - Mar



(b) Black carbon: Apr - Sep



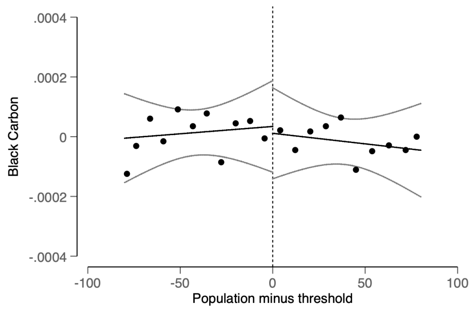
(c) Organic carbon: Oct - Mar



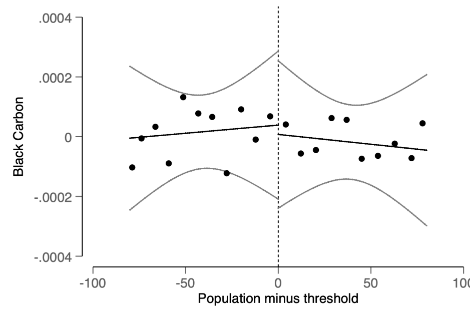
(d) Organic carbon: Apr - Sep

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of the outcomes as a function of the normalized 2001 village population relative to the threshold. Panels (a) and (b) show the reduced form RD plot for black carbon emissions from biomass burning (in $ng/m^2/s$) across during the winter harvest and post-harvest months vs. the rest of the year, respectively. Panels (c) and (d), similarly, show the reduced form effect on organic carbon emissions from biomass burning. Winter harvest and post-harvest period comprises the months from October - March. Each point represents the mean of all villages in a given population bin. All estimates control for district-threshold fixed effects, year fixed effects, and baseline characteristics. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

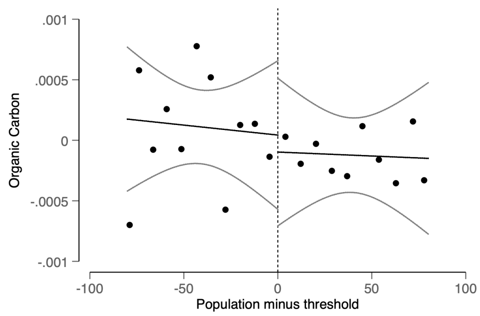
Figure A.9: Impact of roads on emissions from non-biomass burning sources - winter harvest and post-harvest months vs. rest of the year (2008 - 2013): regression discontinuity graphs



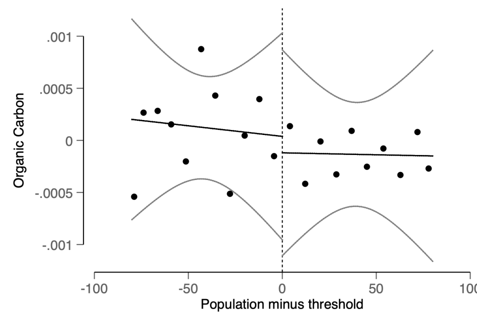
(a) Black carbon: Oct - Mar



(b) Black carbon: Apr - Sep



(c) Organic carbon: Oct - Mar



(d) Organic carbon: Apr - Sep

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of the outcomes as a function of the normalized 2001 village population relative to the threshold. Panels (a) and (b) show the reduced form RD plot for black carbon emissions from sources other than biomass burning (in $ng/m^2/s$) across during the winter harvest and post-harvest months vs. the rest of the year, respectively. Panels (c) and (d), similarly, show the reduced form effect on organic carbon emissions from non-biomass sources. Winter harvest and post-harvest period comprises the months from October - March. Each point represents the mean of all villages in a given population bin. All estimates control for district-threshold fixed effects, year fixed effects, and baseline characteristics. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

Table A.1: Regression discontinuity results without baseline controls: 1^{st} stage and IV estimates for impact of rural road construction on agricultural fires and pollution

	New road	Annual fire activity	Annual average PM2.5
	(1)	(2)	(3)
	First stage	IV	IV
Above threshold pop.	0.229***		
	(0.017)		
Road built		2.503**	0.457**
		(0.998)	(0.217)
N	66,894	66,894	66,894
Control group mean	0.19	3.86	44.85

Notes: Table shows regression discontinuity treatment estimates of the effect of new village roads on agricultural fire activity and PM 2.5. The sample consists of the panel of villages for the 5 year period from 2008 - 2013 "Above threshold pop." is an indicator for a village population being above the treatment threshold. Column (1) shows the first stage, with the dependent variable taking the value one if the village received a new road during 2008-2013. Columns (2) and (3) present the IV estimates of the treatment effects of new roads on annual fire counts around each village measured within a 10 km radius and annual average PM 2.5 ($\mu g/m^3$), respectively. Regressions include district-threshold fixed effects and year fixed effects. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

B Appendix: Replication of Asher and Novosad (2020)

Table B.1: Regression discontinuity sample: summary statistics and balance

Variable	Full sample	Below threshold	Over threshold	Difference of means	p-value on difference	RD estimate	p-value on RD estimate
Primary school	0.959	0.955	0.964	0.01	0.02	-0.018	0.59
Medical center	0.166	0.155	0.177	0.02	0.00	-0.098	0.13
Electrified	0.430	0.414	0.447	0.03	0.00	-0.015	0.86
Distance from nearest town (km)	26.490	26.378	26.613	0.24	0.58	-3.445	0.34
Land irrigated (share)	0.281	0.276	0.287	0.01	0.05	-0.025	0.59
Ln land area	5.152	5.094	5.215	0.12	0.00	-0.110	0.30
Literate (share)	0.457	0.454	0.461	0.01	0.01	-0.012	0.61
Scheduled caste (share)	0.143	0.141	0.145	0.00	0.24	-0.020	0.51
Land ownership (share)	0.733	0.733	0.732	-0.00	0.75	0.013	0.71
Subsistence ag (share)	0.435	0.438	0.432	-0.01	0.26	0.024	0.57
HH income > INR 250 (share)	0.754	0.752	0.757	0.00	0.37	-0.022	0.65
N	11149	5857	5292				

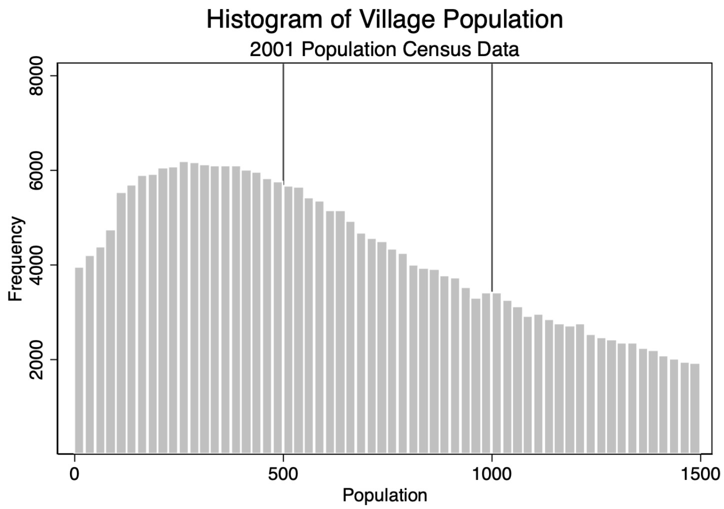
Notes: This table replicates results from Asher and Novosad (2020) showing the mean values for village characteristics, measured in the baseline period. The first eight variables come from the 2001 Population Census, while the final three (below the line) come from the 2002 BPL Census. Columns 1-3 show the unconditional means for all villages, villages below the treatment threshold, and villages above the treatment threshold, respectively. Column 4 shows the difference of means across Columns 2 and 3, and Column 5 shows the p-value for the difference of means. Column 6 shows the regression discontinuity estimate, following the main estimating equation, of the effect of being above the treatment threshold on the baseline variable (with the outcome variable omitted from the set of controls), and Column 7 is the p-value for this estimate, using heteroskedasticity robust standard errors.

Table B.2: Regression discontinuity results: impact on indices of major outcomes

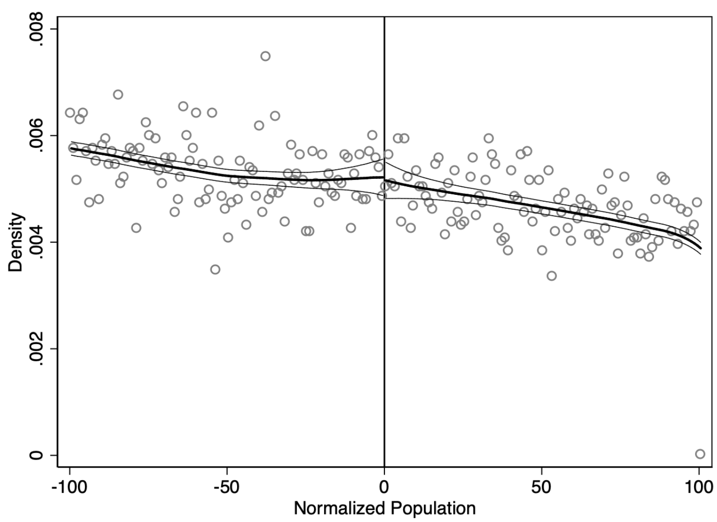
	(1) Transportation	(2) Ag. occupation index	(3) Firms	(4) Agriculture	(5) Consumption
Road built	0.432**	-0.376**	0.239	0.041	0.016
	(0.190)	(0.162)	(0.160)	(0.127)	(0.138)
N	11,149	11,149	10,403	11,149	11,149
Control group mean	-0.02	-0.00	0.01	0.00	-0.00
R^2	0.17	0.28	0.30	0.54	0.50

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on effect of a new road on indices of the major outcomes in each of the five families of outcomes: transportation, occupation, firms, agriculture, and welfare. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Figure B.1: Distribution of running variable



(a) Histograph of Village Population



(b) McCary Test

Notes: The graph replicates results from Asher and Novosad (2020) showing the distribution of village population around the population thresholds. The top panel is a histogram of village population as recorded in the 2001 Population Census. The vertical lines show the program eligibility thresholds at 500 and 1,000. The bottom panel uses the normalized village population (reported population minus the threshold, either 500 or 1,000). It plots a non-parametric regression to each half of the distribution following McCrary (2008), testing for a discontinuity at zero. The point estimate for the discontinuity is -0.010, with a standard error of 0.048.

Table B.3: Regression discontinuity results: impact of rural road construction on transportation

	(1) Govt. bus	(2) Pvt. bus	(3) Taxi	(4) Van	(5) Autorickshaw
Road built	0.131**	0.131*	0.012	-0.015	0.068
	(0.056)	(0.076)	(0.049)	(0.055)	(0.044)
N	11,149	11,149	11,149	11,149	11,149
Control group mean					
R^2	0.30	0.09	0.09	0.43	0.26

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on availability of transportation services at the village level. Columns (1) - (5) estimate the impact of new roads on five categories of transport services available at the village level. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table B.4: Regression discontinuity results: impact of rural road construction on occupation and income source

	Occupation		Income source	
	(1) Agriculture	(2) Manual labor	(3) Agriculture	(4) Manual labor
Road built	-0.101**	0.087**	-0.046	0.002
	(0.044)	(0.044)	(0.045)	(0.044)
N	11,149	11,149	11,149	11,149
Control group mean				
R^2	0.28	0.26	0.31	0.28

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on occupational choice and income source. Column (1) shows the effect on share of workers in agriculture. Column (2) shows the effect on share of workers in non-agriculture manual labor. Columns(3) and (4) show the impact on share of households in the village that report their main income source as agriculture and manual labor, respectively. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table B.5: Regression discontinuity results: impact of rural road construction on employment in village non-farm firms

Panel A: Log employment growth

	Total	Livestock	Manufacturing	Education	Retail	Forestry
Road built	0.242	0.228	0.246	0.124	0.320**	-0.108
	(0.162)	(0.190)	(0.197)	(0.145)	(0.157)	(0.111)
N	10,403	10,403	10,403	10,403	10,403	10,403
Control group mean	2.95	0.69	0.91	1.50	1.23	0.17
R^2	0.30	0.42	0.24	0.18	0.23	0.35

Panel B: Level employment growth

	Total	Livestock	Manufacturing	Education	Retail	Forestry
Road built	2.789	-1.940	2.441	0.258	1.812	2.475
	(7.780)	(3.402)	(3.914)	(0.994)	(1.583)	(4.148)
N	10,403	10,403	10,403	10,403	10,403	10,403
Control group mean	32.31	6.86	5.88	5.12	4.55	2.88
R^2	0.30	0.46	0.18	0.13	0.16	0.36

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on employment in village level non-farm firms. Panel A shows the impact on log employment in all non-farm firms and Panel B present same estimates using levels. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table B.6: Regression discontinuity results: impact of rural road construction on agricultural yields

	NDVI			EVI		
	(1)	(2)	(3)	(4)	(5)	(6)
	Max - June	Cumulative	Max	Max - June	Cumulative	Max
Road built	0.025	0.001	0.014	0.040	-0.001	0.023
	(0.027)	(0.013)	(0.014)	(0.034)	(0.016)	(0.019)
N	11,052	11,051	11,052	11,052	11,051	11,052
Control group mean	8.24	10.52	8.81	7.96	10.17	8.48
R^2	0.70	0.88	0.80	0.71	0.85	0.69

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on village-level measures of agricultural activity using three different NDVI-based proxies for agricultural yields. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table B.7: Regression discontinuity results: impact of rural road construction on agricultural inputs

	(1) Mech.	(2) Irri.	(3) Own ag. land	(4) Non-cereal/pulse	(5) Cult. land (log)
Road built	-0.008	-0.009	0.004	0.001	-0.063
	(0.013)	(0.029)	(0.040)	(0.076)	(0.117)
N	11,148	11,149	11,149	8,000	10,884
Control group mean	0.04	0.14	0.57	0.40	5.04
R^2	0.24	0.40	0.29	0.45	0.46

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on the impact of roads on agricultural inputs. Column 1 estimates the impact on the share of households owning mechanized farm equipment, Column 2 the share of households owning irrigation equipment, Column 3 the share of households owning agricultural land, Column 4 an indicator for whether a village lists a non-cereal and non-pulse crop as one of its three major crops, and Column 5 the log total cultivated land (sample restricted to villages reporting non-zero values). Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table B.8: Regression discontinuity results: impact of rural road construction on consumption and asset ownership

Panel A: Consumption indicators and asset index

	Consumption per capita (log)	Night lights (log)	Share of HH earning $\geq 5k$	Asset index
Road built	0.013	0.036	-0.008	0.122
	(0.040)	(0.169)	(0.032)	(0.135)
N	11,149	10,826	11,149	11,149
Control group mean	9.56	1.58	0.15	-0.01
R^2	0.42	0.66	0.25	0.52

Panel B: Individual asset ownership

	Solid house	Refrigrator	Any vehicle	Phone
Road built	0.038	0.005	-0.007	0.020
	(0.030)	(0.013)	(0.024)	(0.041)
N	11,149	11,149	11,149	11,149
Control group mean	0.22	0.04	0.14	0.44
R^2	0.66	0.26	0.38	0.48

Notes: This table replicates results from Asher and Novosad (2020) showing regression discontinuity treatment estimates of the effect of new village roads on indicators of consumption and asset ownership. Panel A, Column (1) shows the impact on imputed log consumption per capita (see Asher and Novosad (2020), Data Appendix for details). Column (2) estimates the effect on log of mean total night light luminosity in 2011-13. Column (3) is the share of households whose highest earning member earns more than INR 5000 per month. Column (4) is village-level average of the primary component of indicator variables for all household assets. Panel B shows the impact on the share of households owning major assets. Regressions include district-threshold fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

C Appendix: Harvest and Planting Dates

In this section, we evaluate the effect of rural roads on harvest and planting dates. We procure satellite-based measures of harvest (end-)dates and planting dates for the kharif season, aggregated up to the village level from 250 m pixel data. The planting and harvest dates are estimated using Enhanced Vegetation Index (EVI) data from MODIS and were validated using ground data [19]. Harvest (planting) date is measured as the median pixel value of the harvest (planting) dates within a 10 km buffer around the village. Unfortunately, these data are not available for states that followed population thresholds to determine rural road construction under PMGSY. Therefore, we are not able to use a regression discontinuity design. Instead, we estimate the following event study specification:

$$\Delta Date_{v,d,y} = \sum_{\tau,\tau\neq-1} \delta_\tau D_{t^0+\tau} + \lambda_v + \mu_{d,y} + \alpha_y X_v + \varepsilon_{v,d,y} \tag{3}$$

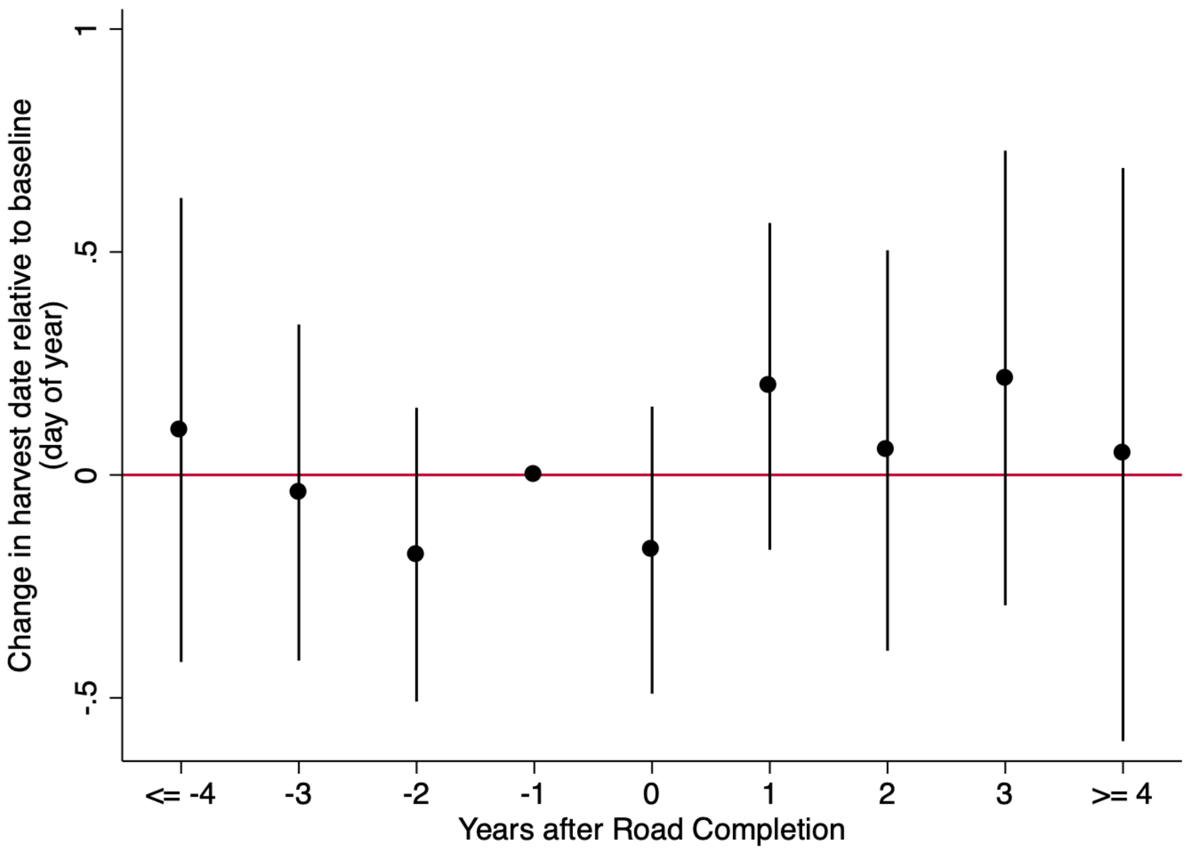
where $\Delta Date_{v,d,y}$ is the change in harvest or sowing date for village v, located in district d in year y from the baseline (2002). $D_{t^0+\tau}$ are event time indicator variables that capture the average treatment effect, where τ indicates the year relative to when a village receives access to a rural road, with the year prior to treatment being the excluded category. λ_v are village fixed effects and $\mu_{d,y}$ are district-by-year fixed effects. Village fixed effects control for time-invariant unobservables at the village level (e.g., soil type). District-by-year fixed effects control for time-varying district-specific confounders. For instance, the National Rural Employment Guarantee Scheme was rolled-out in a staggered manner across India between 2006 and 2008. Lastly, we include an interaction of baseline village characteristics X_v with year fixed effects α_y. Standard errors are clustered at the village level.

The identifying assumption here is that there exist no village-specific time-varying confounders that are correlated with both access to rural roads as well as local agriculture. E.g., if rural roads are placed in villages where agricultural activities are changing, our estimates would be biased. While lack of pre-trends would bolster our confidence in said assumption, if change in local agriculture and rural road construction were to occur simultaneously, our estimates will still be biased.

Figures C.2 and C.1 present our results. First, we don't find evidence for any pre-trends. Second, and more importantly, we fail to find evidence that access to rural roads affects either harvest or planting dates. The point estimates are small and statistically insignificant.

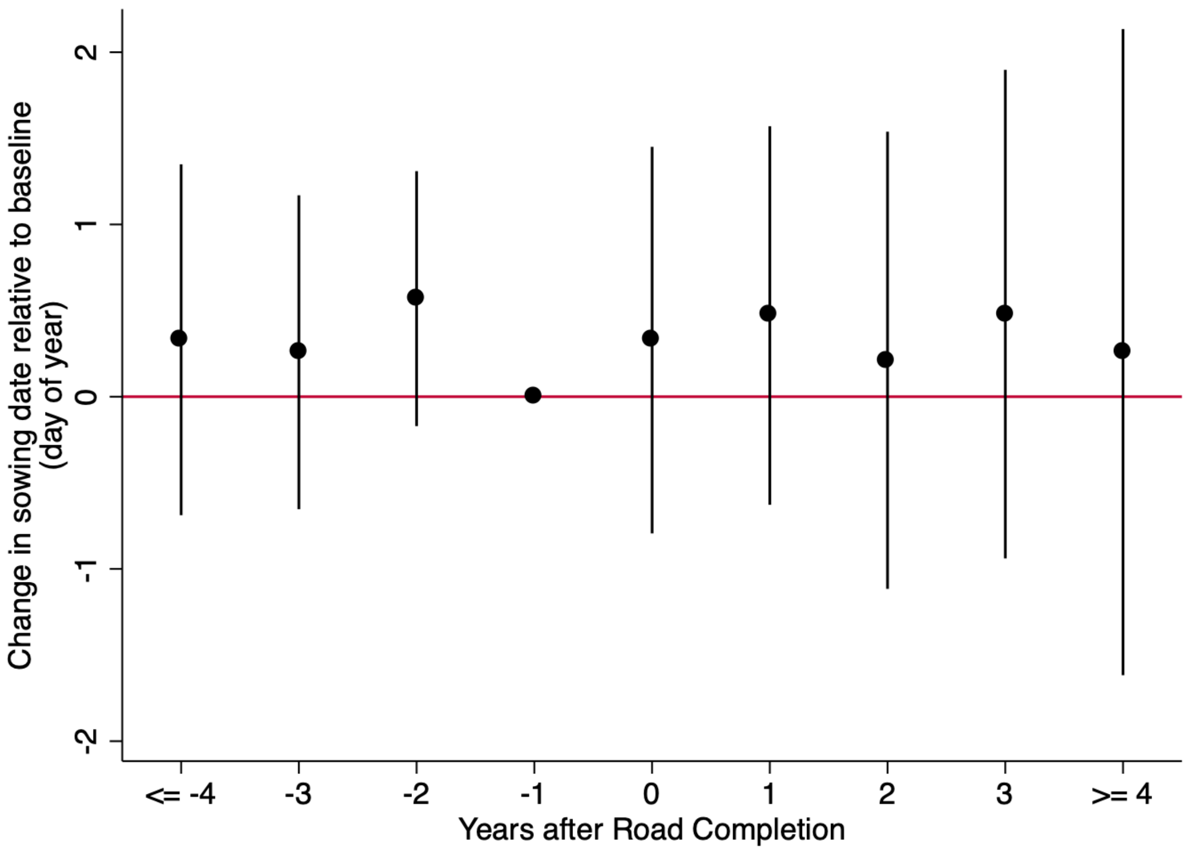
[19]We are grateful to Meha Jain, School for Environment and Sustainability, University of Michigan, for sharing these data.

Figure C.1: Event study estimates: Effect of access to rural roads on monsoon (kharif) harvest date



Notes: The graph shows event study estimates for the effect of new roads on monsoon harvest dates. Sample is limited to the states of Punjab, Haryana, Uttar Pradesh, and Bihar for which satellite-based sowing date measures are available. The sample period is 2003-2013. The dependent variable is the change in harvest completion day from the baseline (2002). The horizontal axis shows the event year relative to the year of road completion. Each point shows the coefficient and confidence interval on each event-time fixed effect relative to the omitted category which is the year before road completion ($t = -1$). All regressions include village FE, district $\times$ year fixed effects and the interactions of year fixed effects with baseline village characteristics and harvesting date/week in 2002. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Figure C.2: Event study estimates: Effect of access to rural roads on monsoon (kharif) sowing date



Notes: The graph shows event study estimates for the effect of new roads on monsoon sowing dates. Sample is limited to the states of Punjab, Haryana, Uttar Pradesh, and Bihar for which satellite-based sowing date measures are available. The sample period is 2003-2013. The dependent variable is the change in day of sowing from the baseline (2002). The horizontal axis shows the event year relative to the year of road completion. Each point shows the coefficient and confidence interval on each event-time fixed effect relative to the omitted category which is the year before road completion ($t = -1$). All regressions include village FE, district $\times$ year fixed effects and the interactions of year fixed effects with baseline village characteristics and sowing date/week in 2002. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

D Appendix: Rural Economic and Demographic Survey (REDS)

We use village- and household-level surveys from the 1999 and 2006 rounds of the Rural Economic and Demographic Survey (REDS), administered by the National Council of Applied Economic Research (NCAER), to estimate the effect of rural roads on the local stock of combine harvesters and use of hired mechanized agricultural equipment. REDS is a nationally representative survey of rural households in India spanning 221 villages across 100 districts in 17 major states. It includes a village survey that collects information on the village-level stock of agricultural machinery. The household questionnaire provides detailed information on the use of agricultural inputs, including the use and cost of hired mechanized equipment.

Since rural roads constructed under PMGSY were not determined by population threshold before 2008, we cannot use a regression discontinuity design. Instead, we estimate simple difference-in-difference specifications. 'Treat' is an indicator variable that takes the value 1 if a village receives a rural road between 1999 and 2006, 0 otherwise. 'Post' is an indicator variable that takes the value 1 if the year is 2006, 0 otherwise. 'TreatXPost' captures the effect of the construction of a rural road between 1999 and 2006.

Table D.1 estimates the effect of rural roads on the village-level stock of combine harvesters. Using a village-panel regression with village and year fixed effects, we fail to find an economically or statistically significant impact on the village-level stock agricultural machinery across a variety of agricultural implements either on the extensive (Panel A) or the intensive margin (Panel B). In particular, we see no effect on the presence or number of combine harvesters. Next, using a household-panel regression with household and year fixed effects, we fail to detect an impact on the use of hired mechanized agricultural equipment at the household level (Table D.2).

Table D.1: Impact of roads on village-level stock of agricultural machinery - REDS village panel

Panel A: Present (Yes = 1)

	Combines	Threshers	Tractors	Power tillers
Treat X Post	0.001	0.005	0.016*	0.021
	(0.009)	(0.015)	(0.010)	(0.014)
Sample mean	0.08	0.61	0.88	0.24
N	442	442	442	442
R^2	0.58	0.77	0.80	0.59

Panel B: Log count

	Combines	Threshers	Tractors	Power tillers
Treat X Post	0.007	0.017	0.033	0.029
	(0.023)	(0.045)	(0.026)	(0.030)
Sample mean	0.10	1.40	2.48	0.42
N	442	442	442	442
R^2	0.54	0.76	0.90	0.54

Notes: Table reports regression estimates showing the impact of receiving a PMGSY road in agricultural machinery stock at the village level. Sample used is village level panel from REDS 1999 - 2006. The coefficient "Treat X Post" takes the value 1 in the post (2006) year for villages that receive a road by 2006. Regressions include village and year fixed effects. Standard errors in parentheses clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

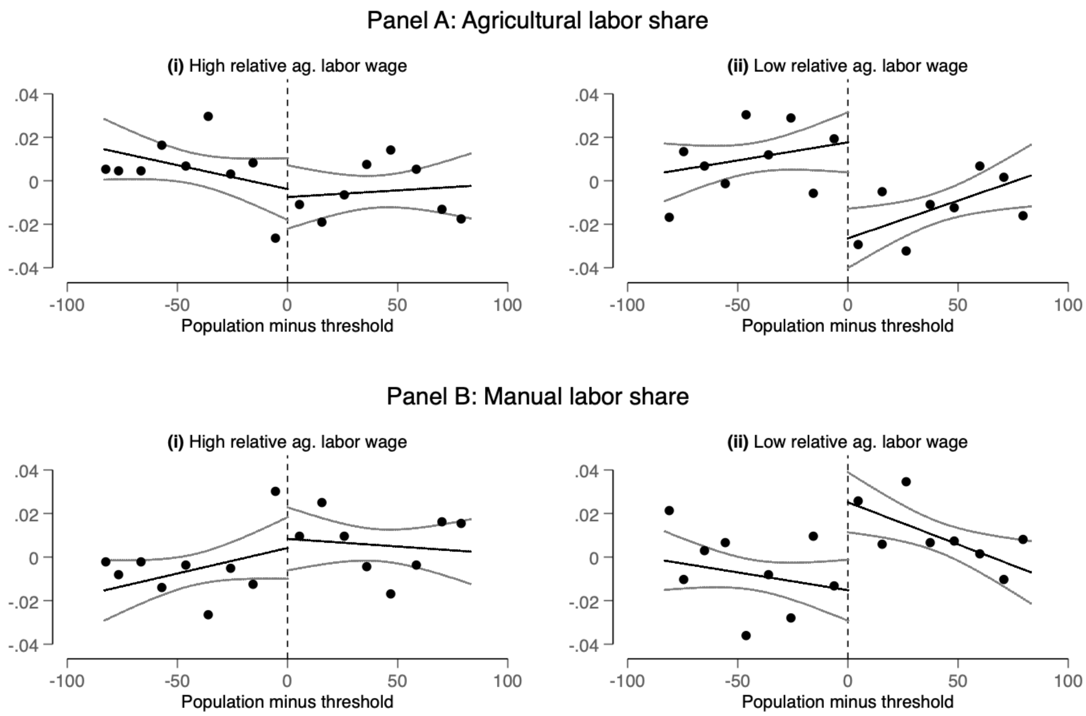
Table D.2: Impact of roads on household use of mechanized agricultural equipment - REDS household panel

	(1)	(2)	(3)	(4)
	Used? (Yes=1)	Log cost	Log cost per acre	Share of total cost
Treat X Post	0.002	-0.048	-0.046	-0.004
	(0.010)	(0.081)	(0.070)	(0.004)
Sample mean	0.67	4.77	3.91	0.15
N	6090	5548	5548	5474
R^2	0.57	0.60	0.62	0.69

Notes: Table reports regression estimates showing the impact of receiving a PMGSY road on household use of tractors, harvester, threshers or other mechanized equipment. Sample used is household panel from REDS 1999 and 2006. The coefficient "Treat X Post" takes the value 1 in the post (2006) year for households in villages that receive a road by 2006. Regressions include household and year fixed effects. Columns (1), (2) and (4) also control for cropped area. Standard errors in parentheses clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

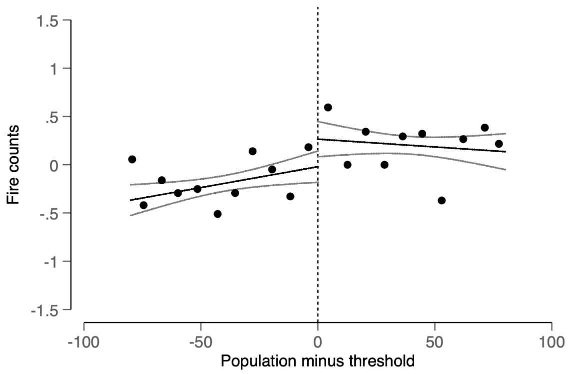
E Appendix: Heterogeneity by relative agricultural labor wage at baseline

Figure E.1: Heterogeneity by relative agricultural labor wages at baseline: Impact on share of village labor in agriculture and non-agricultural sectors across – regression discontinuity graphs

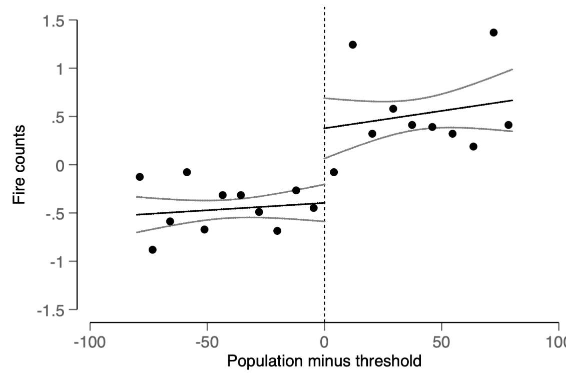


Notes: Graphs show regression discontinuity estimates by plotting the residualized values of village-level share of manual labor in agriculture (Panel A) and non-agricultural sectors (Panel B), after controlling for all variables in the main specification other than population, as a function of the normalized 2001 village population relative to the threshold. Figure (i) of each panel plots the RD relationship for the sample consisting of districts which had high (above sample median) agricultural labor wages relative to non-agricultural labor wage rates in rural areas at baseline. Figure (ii) of each panel shows the same for villages within districts with below median relative agricultural wage rates. The outcome variables are based on the Socioeconomic and Caste Census 2011-2012 (see (Asher and Novosad, 2020) for details). Baseline rural agricultural and non-agricultural daily labor wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Each point represents the mean of all villages in a given population bin. Estimates in both panels control for district-threshold fixed effects, year fixed effects, and baseline village characteristics in 2001. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

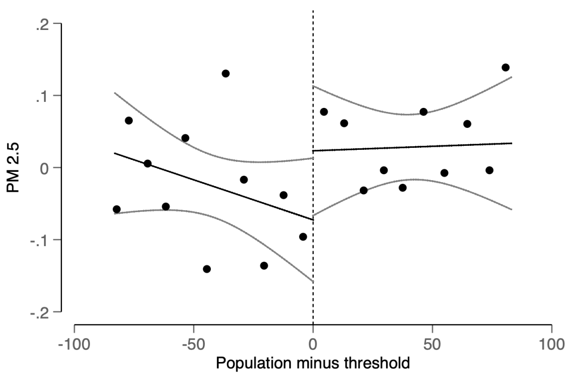
Figure E.2: Heterogeneity in impact on annual agricultural fire activity across high versus low relative agricultural wage rates at baseline: regression discontinuity graphs



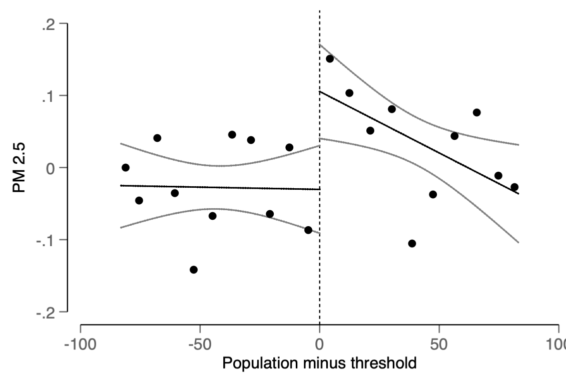
(a) Fires: High relative ag. labor wage



(b) Fires: Low relative ag. labor wage



(c) PM: High relative ag. labor wage



(d) PM: Low relative ag. labor wage

Notes: Graphs show regression discontinuity estimates by plotting the residualized values of outcomes (after controlling for all variables in the main specification other than population) as a function of the normalized 2001 village population relative to the threshold. Panels (a) and (b) show results for the annual number of fires between 2008 - 2013 , while (c) and (d) show the same annual average PM 2.5 ($\mu g/m^3$). Panels (a) and (c) plots the RD relationship for the sample consisting of districts which had high (above sample median) agricultural labor wages relative to non-agricultural labor wage rates in rural areas at baseline. Panels (b) and (d) show the same for villages within districts with below median relative agricultural wage rates. Rural agricultural and non-agricultural daily labor wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Each point represents the mean of all villages in a given population bin. Estimates in both panels control for district-threshold fixed effects, year fixed effects, and baseline village characteristics in 2001. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

Table E.1: Regression discontinuity results: impact of rural road construction on share of village labor in agriculture and non-agricultural sectors across relative agricultural labor wage rates

	Share of labor in agriculture		Share of non-agricultural manual labor	
	(1) High rel. ag. wage	(2) Low rel. ag. wage	(3) High rel. ag. wage	(4) Low rel. ag. wage
Road built	-0.029	-0.241***	0.030	0.205**
	(0.046)	(0.093)	(0.046)	(0.092)
N	5,403	5,484	5,403	5,484
Control group mean	0.49	0.46	0.45	0.46

Notes: Table shows regression discontinuity IV estimates of the impact of receiving a new road on share of manual labor at village-level in agriculture and non-agricultural sectors. The outcome variables are based on the Socioeconomic and Caste Census 2011-2012 (see (Asher and Novosad, 2020) for details). "High rel. ag labor wage" sample consists of districts which had high (above sample median) agricultural labor wages relative to non-agricultural labor wage rates, while "Low rel. ag labor wage" sample are districts with below median relative agricultural wage rates. Wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Regressions include district-threshold fixed effects, year and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

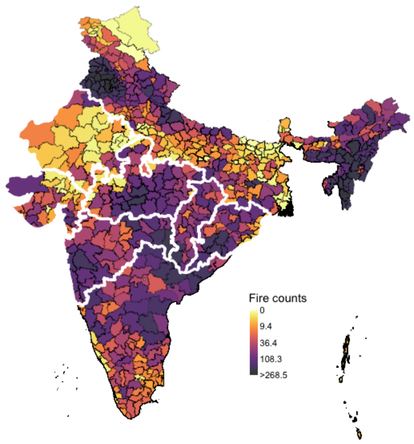
Table E.2: Regression discontinuity results: impact of rural road construction on annual agricultural fire activity and pollution across high versus low relative agricultural wage rates at baseline

	High rel. ag. wage		Low rel. ag. wage	
	(1) Fires	(2) PM 2.5	(3) Fires	(4) PM 2.5
Road built	1.428	0.372	4.765**	0.698*
	(0.983)	(0.240)	(2.156)	(0.388)
N	32,412	32,412	32,898	32,898
Control group mean	3.77	47.76	3.99	42.10

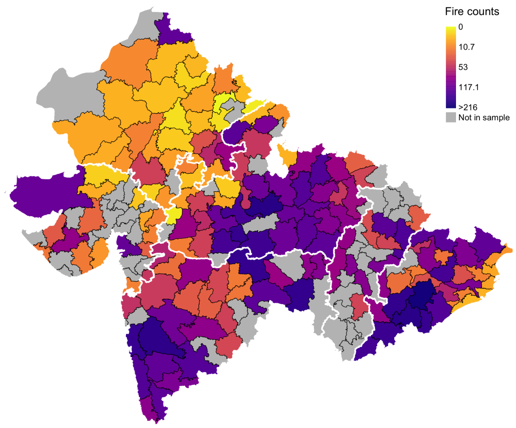
Notes: Table shows regression discontinuity IV estimates of receiving a new road on village-level annual fire activity and PM 2.5 ($\mu g/m^3$). The sample consists of the panel of villages for the 5 year period from 2008 - 2013. "High rel. ag labor wage" sample consists of districts which had high (above sample median) agricultural labor wages relative to non-agricultural labor wage rates, while "Low rel. ag labor wage" sample are districts with below median relative agricultural wage rates. Wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Regressions include district-threshold fixed effects, year fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

F Appendix: Heterogeneity by crops grown

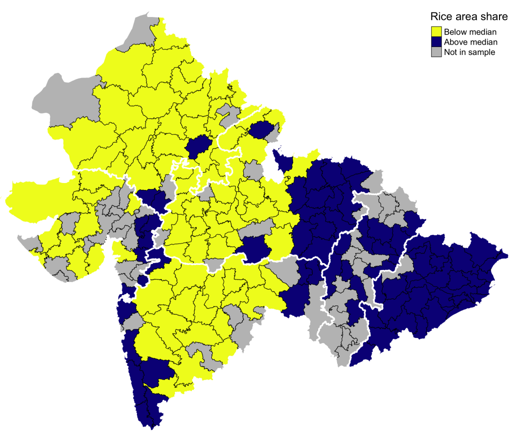
Figure F.1: Spatial distribution of average annual fire activity and baseline rice and sugarcane acreage shares



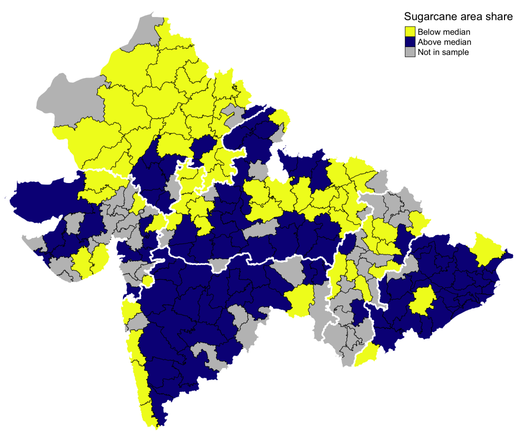
(a) Average annual fire counts across India



(b) Average annual fire counts



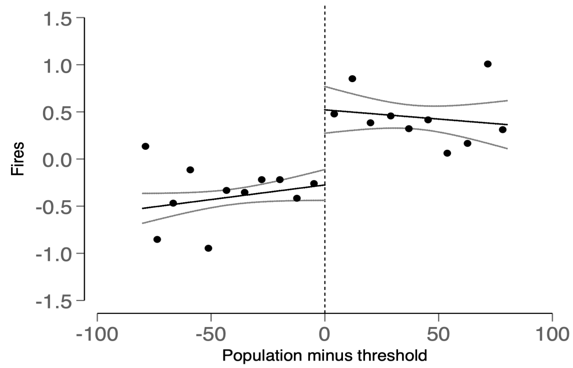
(c) Rice area share



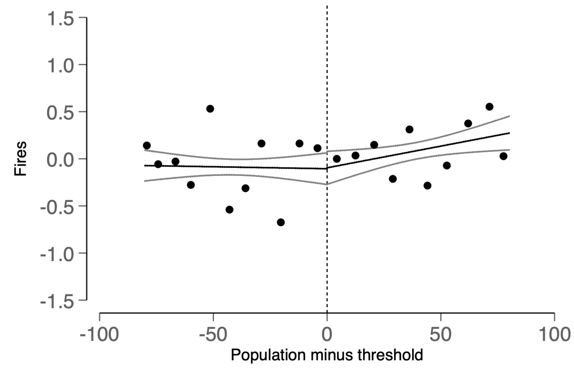
(d) Sugarcane area share

Notes: Panels (a) and (b) show the mean annual number of fire pixels detected in each district from MODIS satellite data for the period 2003 to 2013 for whole of India and within the sample districts, respectively. Panels (c) and (d) show districts with above/below sample median share of cropland under rice and sugarcane, respectively, at baseline (2001).

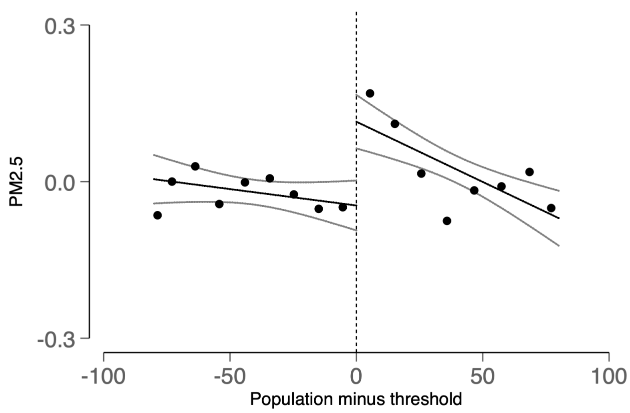
Figure F.2: Heterogeneity in impact on annual agricultural fire activity and pollution across high rice *or* high sugarcane districts versus low rice *and* low sugar districts: regression discontinuity plots



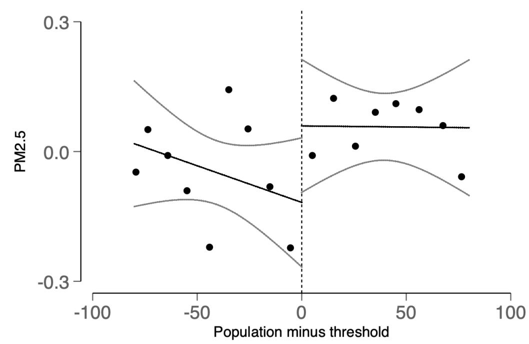
(a) Fires: High rice *or* high sugar



(b) Fires: Low rice *and* low sugar



(c) PM 2.5: High rice *or* high sugar



(d) PM 2.5: Low rice *and* low sugar

Notes: Graph shows regression discontinuity estimates by plotting the residualized values of outcomes as a function of the normalized 2001 village population relative to the threshold (after controlling for fixed effects and all baseline variables in the main specification other than population). Panels (a) and (b) plot the regression discontinuity relationship for annual fire counts, while panels (c) and (d) show the same for annual average PM 2.5 ($\mu g/m^3$). The sample used is the panel of villages for the 5 year period from 2008 - 2013. Panels (a) and (c) plot the RD relationship for the sample consisting of districts having high (above sample median) rice *or* sugarcane acreage share at baseline. Panels (b) and (d) shows the same for sample of villages within districts with low (below sample median) rice *and* sugarcane acreage share at baseline. Each point represents the mean of all villages in a given population bin. Estimates in all panels control for district-threshold fixed effects, year fixed effects, and baseline village characteristics in 2001. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

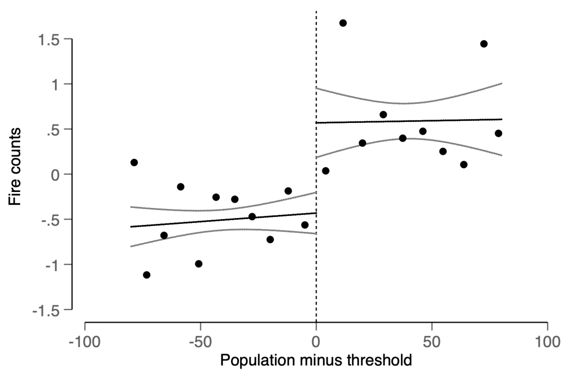
Table F.1: Regression discontinuity results: impact of rural road construction on annual agricultural fire activity and pollution across high rice *or* high sugarcane districts versus low rice *and* low sugar districts

	High rice or high sugar		Low rice and low sugar	
	(1)	(2)	(3)	(4)
	Fires	PM 2.5	Fires	PM 2.5
Road built	5.228***	1.074***	0.276	0.301
	(1.922)	(0.327)	(0.630)	(0.308)
N	46,386	46,386	15,960	15,960
Control group mean	4.53	41.45	2.21	54.31

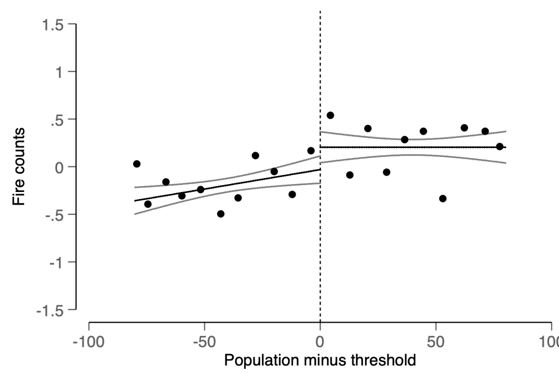
Notes: Table shows regression discontinuity IV estimates of receiving a new road on village-level annual fire activity and annual average PM 2.5 ($\mu g/m^3$). The sample consists of the panel of villages for the 5 year period from 2008 - 2013. "High rice or high sugar" sample consisting of districts having high (above sample median) rice *or* sugarcane acreage share at baseline (2001). "Low rice and low sugar" sample consists of districts with below median acreage share of rice and below median sugarcane acreage share at baseline. Regressions include district-threshold fixed effects, year fixed effects and baseline control variables. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

G Appendix: Heterogeneity by relative agricultural wage and crops grown

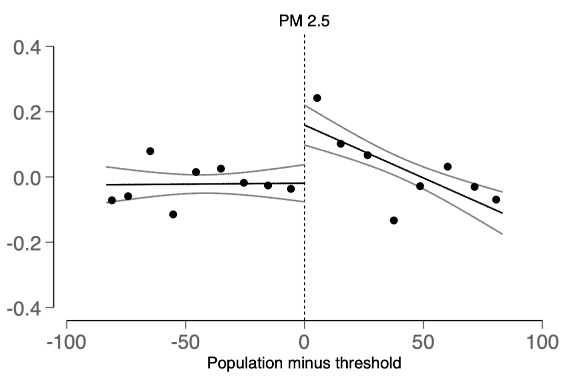
Figure G.1: Heterogeneity in impact on annual agricultural fire activity across high versus low relative agricultural wage rate districts and rice/sugar cropped areas: regression discontinuity graphs



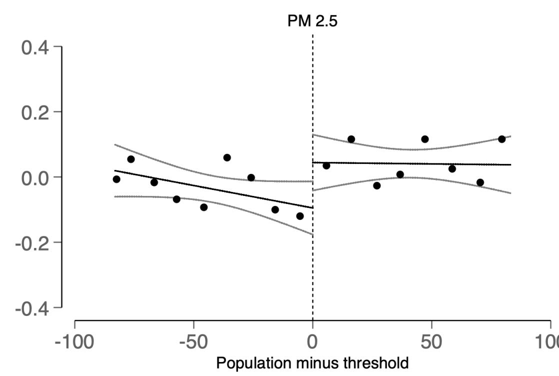
(a) Low ag. labor wage with high rice or sugar



(b) High ag. labor wage or low wage with low rice & low sugar



(c) Low ag. labor wage with high rice or sugar



(d) High ag. labor wage or low wage with low rice & low sugar

Notes: Graph shows regression discontinuity estimates by plotting the residualized values of outcomes as a function of the normalized 2001 village population relative to the threshold (after controlling for fixed effects and all baseline variables in the main specification other than population). Panels (a) and (b) plot the regression discontinuity relationship for annual fire counts, while panels (c) and (d) show the same for annual average PM 2.5 ($\mu g/m^3$).. Panels (a) and (c) plots the RD relationship for the sample consisting of districts which had low (below sample median) agricultural labor wages relative to non-agricultural labor wage rates in rural areas *and* had high (above sample median) share of cropped area under rice or sugar at baseline. Panels (b) and (d) shows the same for villages within districts which had either (i) high (above median) relative agricultural wage rates or (ii) low relative agricultural wage rates with low rice and sugar cropped areas. Rural agricultural and non-agricultural daily labor wage rates are based on the 1999 - 2000 NSSO survey data (Round 55). Rice and sugar cropped areas are based on ICRISAT district level data for 2001. Each point represents the mean of all villages in a given population bin. Estimates in both panels control for district-threshold fixed effects, year fixed effects, and baseline village characteristics in 2001. Population is centered around the state-specific threshold used for road eligibility - either 500 or 1000, depending on the state.

H Appendix: Longer-run effect of roads on fires and pollution

Table H.1: Regression discontinuity results: longer-run impacts of roads on fires and pollution

	Panel A: Impact on fires in year: (IV estimates)				
	(1) 2009	(2) 2010	(3) 2011	(4) 2012	(5) 2013
Road completed by 2008	3.228*	3.688*	6.723**	5.338**	5.173*
	(1.744)	(2.005)	(2.641)	(2.260)	(3.090)
Road completed by 2009		3.538*	6.450**	5.121**	4.963*
		(1.922)	(2.548)	(2.173)	(2.970)
Road completed by 2010			4.949***	3.929**	3.807*
			(1.919)	(1.642)	(2.262)
N	11,149	11,149	11,149	11,149	11,149
Control group mean	3.93	3.56	4.30	4.56	3.70
	Panel B: Impact on PM 2.5 in year: (IV estimates)				
	(1) 2009	(2) 2010	(3) 2011	(4) 2012	(5) 2013
Road completed by 2008	0.855*	0.846*	1.108**	0.627	1.196***
	(0.454)	(0.434)	(0.492)	(0.396)	(0.434)
Road completed by 2009		0.811*	1.063**	0.602	1.147***
		(0.416)	(0.475)	(0.381)	(0.420)
Road completed by 2010			0.815**	0.462	0.880***
			(0.360)	(0.291)	(0.316)
N	11,149	11,149	11,149	11,149	11,149
Control group mean	45.12	43.19	42.36	43.15	46.72

Notes: Each cell in table shows regression discontinuity IV treatment estimates from a separate regression. The first row in Panel A shows the effect of new village roads completed by 2008 on levels of agricultural fire activity in each subsequent year. Second and third rows of Panel A similarly show the effect of roads completed by 2009 and 2010 on fires in each subsequent year, respectively. Panel B similarly shows the impact of roads completed on pollution levels in each subsequent year. Road completion is instrumented using an indicator for baseline (2001 Census) village population above the program threshold. All regressions control for district-threshold FE, year FE and baseline controls. Standard errors in parentheses are clustered at village level. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.