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Shandal, Monica

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ESSAYS IN DEVELOPMENT AND ENVIRONMENTAL ECONOMICS

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DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Monica Shandal

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The Dissertation of Monica Shandal
is approved:

Professor Peter Christensen, Co-Chair

Professor Ariel Zucker, Co-Chair

Professor Justin Marion

Professor Asha Sundaram

Donald Smith
Interim Vice Provost and
Dean of Graduate Studies

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Abstract

Essays in Development and Environmental Economics

by

Monica Shandal

This dissertation examines how public policy and infrastructure shape environmental quality, local economic activity, governance, and health. Across three chapters, it combines spatial data, village-level survey evidence, and quasi-experimental research designs to study the effects of environmental and infrastructure policies in Indonesia and India.

The first chapter studies the environmental consequences of China's 2018 National Sword policy, which restricted waste imports and redirected large volumes of plastic waste toward Southeast Asia. Global plastic waste generation has increased significantly over the past two decades, while recycling rates have remained low, and high-income countries continue to export low-quality waste to countries with limited processing capacity. Using spatial and temporal variation in exposure to waste pollution, this chapter estimates the causal effect of increased plastic inflows on fine particulate matter ($PM_{2.5}$) across Indonesia. The analysis integrates satellite-derived pollution data, machine-learning-identified waste sites, wind direction, and international trade records. Difference-in-differences estimates for non-fire seasons show that post-policy $PM_{2.5}$ concentrations increased by approximately 5% to 10% within 3 km of waste sites, with effects diminishing rapidly over distance. Wind direction and proximity to waste-receiving ports further amplify these effects. The findings provide evidence of cross-border pollution leakage from international waste trade and highlight the need for coordinated global policy responses.

The second and third chapters, coauthored with Santosh Kumar Gautam and Ariel Zucker, study India's Pradhan Mantri Gram Sadak Yojana (PMGSY), the world's largest rural-road program. Both chapters use a novel village-level survey designed around the program's rollout and a new instrument for road connectivity: a village's population rank among other unconnected villages in its district.

The second chapter asks whether connecting rural villages to road networks pulls resources away from villages or strengthens local economies and governing institutions. Roads appear to support agricultural markets, raising staple-crop prices by 1.3 standard deviations and diversifying agricultural output. They also support non-agricultural markets, as casual labor gains primacy over agriculture. Yet increases in casual labor are concentrated within connected villages, while an index of migration falls by 0.8 standard deviations. Roads also strengthen local governance: an index of government visits rises by 1.1 standard deviations and political engagement increases by 0.9 standard deviations. Higher wages on government construction projects and lower prices at government ration shops are also consistent with reduced corruption. Rather than draining villages of workers, rural roads contribute to more vibrant local economies and stronger governing institutions.

The third chapter examines the effect of rural-road connectivity on child health and access to health services. Exploiting quasi-random variation in road placement, the analysis finds that motorable-road access reduces the child mortality index by 1.13 standard deviations and under-five mortality by 5.0 percentage points. Road connectivity also improves access to frontline health workers, increasing the health-worker access index by 0.50 standard deviations. There is limited evidence that these gains are driven by shorter travel times to health facilities or greater use of institutional delivery, suggesting instead that roads may improve child survival by helping health workers reach remote villages.

To my parents, Amita and Rajinder.

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Completing a PhD has given me the space to grow not only as a researcher, but also as an individual. It has allowed me to pursue questions that matter to me, explore new places and ideas, and work toward dreams that once felt very far away. I will always be grateful for this experience and for the many people who helped make it possible.

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Finally, I would like to thank my husband, Jonathon. Thank you for moving to America and joining me on this journey. Your support, patience, and perspective carried me through many of the hardest moments, while your ability to make me laugh kept the difficult ones from feeling quite so heavy. Exploring California with you has been a dream, and it's became a home because we built a life here together. Thank you

for believing in me, celebrating every success, and standing beside me through every setback. I cannot wait to see where our next adventure takes us.

To everyone who stood by me throughout this journey, thank you from the bottom of my heart.

Chapter 1

Beyond Borders: Impacts of the Plastic Waste Trade in Indonesia

§ 1.1 Introduction

Global plastic waste generation has increased rapidly over recent decades, more than doubling from 2000 to 2019 and reaching 353 million tonnes, while less than 9% is recycled (OECD, 2022). Majority of waste is generated in high-income countries and exported to lower- and middle-income countries in an effort to reduce their domestic waste burden (Hook et al., 2018). The overall welfare effects of this trade remain theoretically ambiguous. Imported waste may provide private benefits by supplying low-cost recyclable materials, supporting informal sorting networks, and creating income opportunities in recycling and waste-processing sectors (Medina, 2008). However, these benefits may be offset by environmental externalities if imported waste exceeds local processing capacity and is dumped, burned, or otherwise mismanaged.

This tradeoff is particularly significant in countries with limited waste-management infrastructure. Many waste-receiving countries have lower disposal costs, weaker environmental regulation, and limited enforcement capacity, creating conditions under which imported plastic waste may be handled unsafely (Atalar, 2024; Velis and Cook, 2021). In many low- and middle-income countries, plastic waste is incinerated, dumped in landfills, or burned in open pits. These practices emit harmful air pollutants, contribute to microplastic contamination in ecosystems and food chains, and disrupt livelihoods through the accumulation of waste (Pathak et al., 2023; Raes et al., 2021; Barends, 2020; Syverson, 2023). The resulting environmental and health risks disproportionately affect communities located near waste sites, where residents are exposed to mismanaged waste and often rely on informal occupations such as waste sorting and picking (Winters, 2023; Tontoton, 2022). Despite growing concern, quantitative evidence on the local air quality and subsequent health consequences of imported plastic waste in receiving countries remains limited.

This study examines these consequences by leveraging a significant, policy-induced shock to global plastic waste flows: China's 2018 National Sword policy. Prior to the policy, China was the world's largest importer of plastic waste and received more than half of globally traded recyclable plastic waste (Brooks et al., 2018; Atalar, 2024). The National Sword policy sharply restricted imports of plastic and other solid waste to reduce domestic waste accumulation and limit the inflow of contaminated materials (Brooks et al., 2018; Li and Mu, 2024). Following the implementation, China's imports of waste plastic and paper declined substantially, while the value of remaining imports increased, indicating a shift toward cleaner and higher-quality materials (Tran et al., 2021; Tian et al., 2021; Li and Mu, 2024).However, waste generation did not decline, rather waste flows were redirected toward other lower- and middle-income countries, particularly in Asia and the Pacific. Many of these countries reported imports of waste plastic and used paper doubled in the immediate period following the policy (Tran et al., 2021; Thakur, 2023).

This setting provides a useful empirical context for studying cross-border environmental leakage. The redirection of waste following the National Sword policy aligns with the pollution haven and waste haven hypotheses, which posit that stricter environmental standards in one jurisdiction can shift pollution-intensive activities or waste to locations with weaker regulation (Copeland and Taylor, 2003; Shapiro, 2016; Balkevicius et al., 2020). Previous research has documented forms of cross-border pollution displacement. Tanaka et al. (2022) and Litzow et al. (2023) demonstrate that tighter U.S. standards on lead air pollution reduced domestic airborne lead but increased used lead-acid battery exports to Mexico, worsening pollution and human-capital outcomes near recycling facilities. Bombardini and Li (2020) find that greater export-market access increased pollution and infant mortality in China. In the context of plastic waste, Atalar (2024) shows that the National Sword policy redirected European plastic waste from China to Turkey, contributing to open burning and dumping. However, evidence on the local air-quality effects from the redirected plastic waste in major receiving countries remains limited.

The net welfare implications of cross-border waste flows remain uncertain. Some studies emphasize that cross-border spillovers are not detrimental, as trade may generate efficiency gains or facilitate technology transfer (Levinson, 2010; World Bank, 2020). For instance, Davis and Kahn (2010) demonstrate that liberalization of used-vehicle trade under NAFTA increased the movement of used cars from the United States to Mexico but reduced average vehicle emissions per mile in both countries. Whether similar positive effects can occur in the plastic waste trade depends on whether imported waste is productively recycled or instead overwhelms local waste-management systems. A central empirical challenge is that researchers rarely observe what happens to imported waste after arrival: the proportions recycled, stored, dumped, or burned are difficult to measure directly.

This study focuses on one important downstream externality: local air pollution. The analysis examines whether the National Sword-induced redirection of plastic waste increased $PM_{2.5}$ exposure around waste sites in Indonesia, a major waste-receiving country with strained regulatory capacity and waste-management infrastructure (Bosquet, 2023). High-resolution data are assembled for 373 waste sites identified by Global Plastic Watch and combined with satellite-based $PM_{2.5}$ concentration measurements, trade data, port locations, and wind direction. Together these data provide a framework to observe and qualify the effects of place waste. Using a difference-in-differences design, the study compares changes in pollution near and farther from waste sites before and after the policy. The analysis also examines whether effects are larger near ports that received waste imports and in areas located downwind of waste sites. The results indicate that $PM_{2.5}$ pollution increased near waste sites after the policy, with effects concentrated near waste sites and larger near waste-receiving ports, consistent with localized pollution from waste accumulation, sorting, and burning.

This study makes three main contributions. First, it adds to the literature on cross-border leakage and the pollution haven and waste haven hypotheses by demonstrating how an environmental policy in China can shift pollution burdens to communities in a developing receiving country (Tanaka et al., 2022; Litzow et al., 2023; Bombardini and Li, 2020; Kellenberg, 2012). Second, it offers a new insights on the National Sword policy by examining local air pollution in a major receiving country , where existing literature has primarily focused on China, the United States, or aggregate trade flows(Vedantam et al., 2022; Li and Mu, 2024; Lin et al., 2023; Atalar, 2024). Third, it contributes to the broader literature on plastic waste, environmental quality, and health by providing causal evidence on how imported waste can affect local $PM_{2.5}$ exposure in a low- and middle-income setting (Velis and Cook, 2021; Barends, 2020). By linking waste-site locations to high-resolution pollution data, ports, and wind direction, this study moves beyond aggregate trade-flow evidence and examines the local exposure consequences faced by nearby communities.

The remainder of the paper is structured as follows. Section 2 describes the relevant background and policy context. Section 3 outlines the data. Section 4 presents the empirical strategy and discusses the identification assumptions. Section 5 presents the results. Section 6 concludes.

§ 1.2 Background

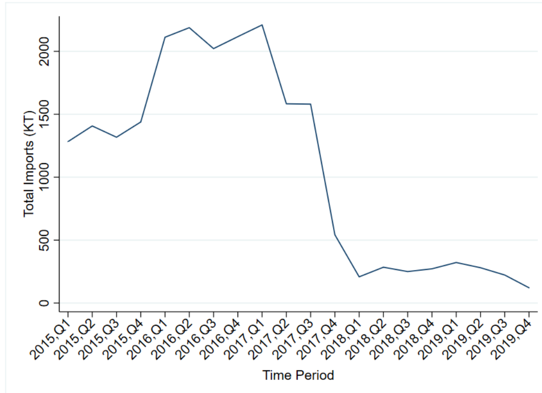
1.2.1 China and the National Sword policy

China's rise as a global hub for plastic waste began in the early 1990s, alongside rapid industrialization and the expansion of its manufacturing sector, which generated strong demand for inexpensive secondary materials (Atalar, 2024). This demand encouraged high-income countries, particularly in North America and Europe, to export large quantities of paper, plastics, and metals to China for recycling (Atalar, 2024). By 2017, the EU and the United States sent roughly 95% and 70% of their collected plastic waste destined for recycling to China, respectively (Katz, 2019). As a result, China received more than half of the world's recyclable plastic waste (Brooks et al., 2018) (Figure 1.1).

Several structural factors made China an attractive destination for imported waste. Strong demand from its manufacturing and plastics industries created a stable market for imported scrap (Atalar, 2024). Favorable shipping economics also lowered the cost of transporting waste to China, since containers carrying Chinese exports often returned relatively empty, reducing backhaul freight rates for waste plastics (Atalar, 2024). Low labor costs allowed firms to sort and process mixed or contaminated waste that high-income countries were unwilling to handle domestically. At the same time, weak environmental controls allowed dirty recycling, informal processing, and open burning to proliferate in certain regions (Katz, 2019; Brooks et al., 2018).

Over time, the environmental costs of this model became increasingly visible. Pollution from informal recycling and open burning contributed to elevated $PM_{2.5}$ levels, groundwater contamination, and hazardous working conditions, prompting public concern and a shift in China's environmental governance priorities (Katz, 2019). Regulatory changes began with Operation Green Fence, a 10-month campaign launched in 2013 that intensified inspections of imported scrap and tightened enforcement of contamination standards, resulting in more frequent rejection of substandard shipments (Zhang, 2015). Around the same time, China revised its Environmental Protection Law, with late-2015 amendments introducing higher fines, uncapped daily penalties for ongoing violations, and stronger liability for responsible officials (Zhang, 2015; Carra, 2015; CRW, 2014). These reforms were enforced through more frequent inspections, crackdowns on polluters, and stronger implementation of environmental targets, leading to increases in environmental penalty cases and total fines (Liu, 2015).

Figure 1.1: Waste Imports into China



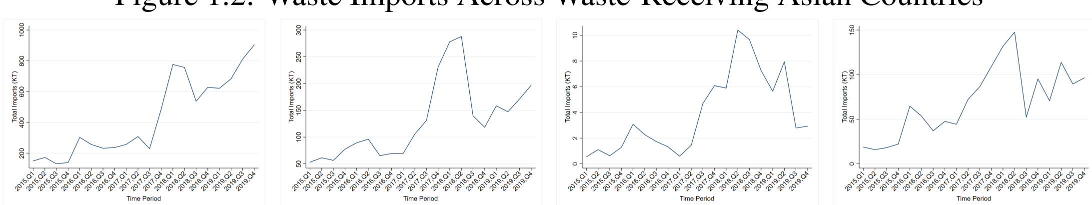
Note: The figure reports annual plastic and paper waste imports into China, calculated by summing quarterly exports from consumption centers in North America, Europe, and Oceania. Imports are expressed in kilotons. Data are from UN Comtrade records.

Against this backdrop, the Ministry of Environmental Protection announced the National Sword policy in 2017, with implementation beginning in early 2018 (World Trade Organization, 2017; Brooks et al., 2018). The policy restricted imports of 24 waste categories, including plastic waste, unsorted paper, waste textiles, and certain industrial residues (World Trade Organization, 2017). Its core objective was to reduce the inflow of contaminated and low-quality waste into China, forcing exporters either to improve the quality of exported material or to find alternative destinations. Following the National Sword policy, Chinese imports of waste plastic and paper fell roughly 80–90% for plastic and by more than 50% for paper, while the unit value of remaining imports increased, reflecting a shift toward cleaner material (Tran et al., 2021; Tian et al., 2021; Li and Mu, 2024). Figure 1.1 shows the sharp decline in waste imports to China after the implementation of the policy.

1.2.2 Waste Redirection

Although the National Sword policy reduced the inflow of low-quality waste to China, it also triggered a global reorganization of waste trade. Waste that had previously been shipped to China was diverted to other developing countries, particularly in Asia, where labor costs are low and environmental enforcement is weaker (Lee Ray et al., 2019; Atalar, 2024). Between 2016 and 2018, Southeast Asian countries experienced a 171% increase in plastic waste imports (Greenpeace, 2018) (Figure 1.2). This pattern is consistent with the waste haven mechanism described in the literature: stricter environmental regulation in one country can shift pollution-intensive activities and management burdens to countries with less stringent standards (Balkevicius et al., 2020; Atalar, 2024). Indonesia stands out as a key recipient of these redirected flows. In the wake of the National Sword policy, imports of plastic waste to Indonesia more than doubled, as shown in Figure 1.3. Reports have traced imported plastic to villages near industrial areas, landfills, recycling facilities, and open accumulations, where it is frequently mixed with domestic waste (gaia, 2019; Paddock, 2019; Brock et al., 2021). These inflows placed additional pressure on a waste-management system already facing rapid growth in domestic waste generation and limited disposal capacity.

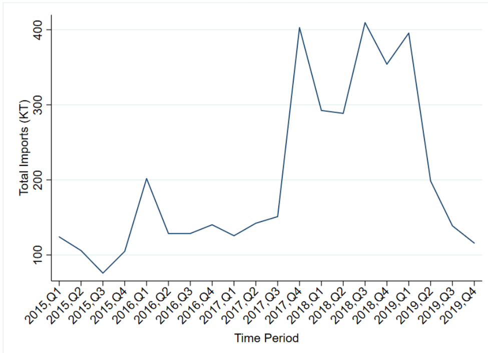
Figure 1.2: Waste Imports Across Waste-Receiving Asian Countries



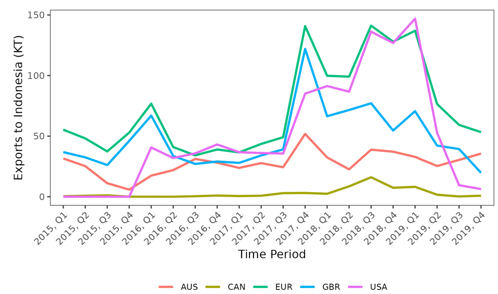
(a) India (b) Malaysia (c) Philippines (d) Thailand

Note: The figure reports annual plastic and paper waste imports into each destination country, calculated by summing quarterly exports from consumption centers in North America, Europe, and Oceania. Imports are expressed in kilotons.

Figure 1.3: Waste Imports in Indonesia: Total and Breakdown



(a) Waste Importation for Indonesia
Note: The figure shows total plastic and paper waste imports into Indonesia, measured in kilotons and calculated as the sum of quarterly exports from North America, Europe, and Oceania. Data are from UN Comtrade records.



(b) Waste Importation Breakdown
Note: The figure shows quarterly plastic and paper waste exports to Indonesia, in kilotons, from the United States, Canada, the United Kingdom, the European Union, and Australia. Data are from UN Comtrade records.

1.2.3 Imported waste to local pollution

The pathway from imported waste to local pollution in Indonesia is shaped by the country's recycling and informal sorting networks (Figure 1.4). Industrial demand, brokers, and recyclers drive the importation of waste. After the National Sword policy, some recycling and sorting activities shifted from China to other Asian destinations, including Indonesia (Neilson, 2025). Imported waste often arrives as mixed or contaminated material, including paper-waste bales containing dirty plastic residuals (Gardiner, 2023). These materials must be sorted before they can be used by paper mills, recyclers, or other industrial users.

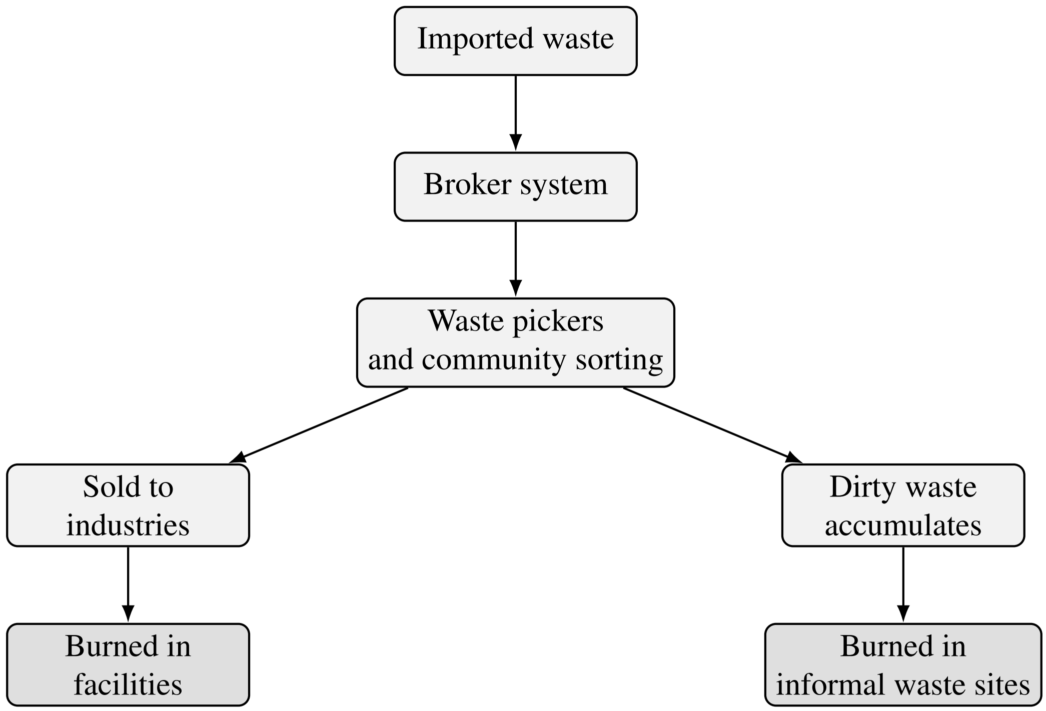
In practice, waste pickers, local workers, and households often participate in this sorting process. Reports describe villagers using streets, yards, and community spaces to separate paper, plastic, and other waste (World Economic Forum, 2019; IUCN NL, 2025). Recoverable materials are processed and sold onward to industries, while low-value residuals often accumulate in communities, enter open dumps, or are sold as inexpensive fuel for small industries such as tofu, chalk, or lime factories. These residuals may then be burned, creating a direct pathway from increased waste inflows to local air pollution (Petrlik et al., 2019; gaia, 2019).

Indonesia entered this period with an environmental legal framework that included the Environmental Protection and Management Law No. 32/2009 (of Indonesia, 2009). In practice, however, enforcement has not kept pace with rising waste generation and increasing imports. A significant share of solid waste is mismanaged, with open dumping and burning driven by limited collection services, restricted landfill capacity, and fragmented institutional responsibilities (Velis and Cook, 2021; Bosquet, 2023). Local agencies often lack the staff, resources, and political support needed to consistently enforce standards, while governance challenges weaken the deterrent effect of existing sanctions (Indriyati and Rosnawati, 2024).

Recent assessments suggest that about half of Indonesia's plastic waste is burned in open-air pits, while about one-fifth is dumped on land or leaks into waterways; the remainder is managed through a combination of formal and informal systems (Ritchie et al., 2023; Velis and Cook, 2021). These practices worsen air pollution, contribute to microplastic contamination, and disproportionately affect communities located near waste sites and industrial clusters (Bosquet, 2023; Syverson, 2023).

Collectively, these conditions establish a plausible mechanism linking the National Sword policy to localized air pollution in Indonesia. Imported waste does not need to be dumped directly at ports to generate environmental harm. Instead, it can move through brokers, recyclers, informal sorters, paper mills, and small industrial users before contaminated residuals are dumped or burned near communities. This study investigates whether the redirection of global waste flows following the National Sword policy resulted in measurable increases in local $PM_{2.5}$ exposure around waste sites and waste-receiving areas in Indonesia.

Figure 1.4: Imported Waste to Local Pollution Flowchart



§ 1.3 Data

The analysis combines satellite-derived environmental, administrative, and web-scraped data to quantify exposure to redirected plastic waste and its impact on air pollution in Indonesia. The following section describes the data sources utilized.

1.3.1 Waste Trade

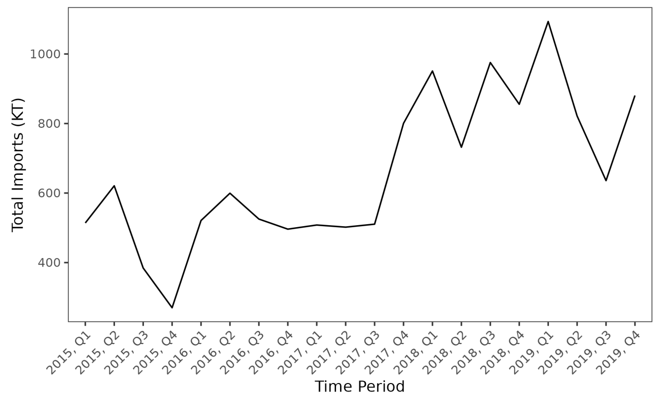
To capture changes in international waste flows, monthly import and export data for plastic and paper waste were obtained from the UN Comtrade database for China and

Indonesia. The analysis focuses on Harmonized System (HS) codes directly affected by the National Sword policy that include plastic waste: Plastic Waste (3915100000, 3915200000, 3915300000, 3915901000, 3915909000) and Unsorted Waste Paper (4707900090) (World Trade Organization, 2017).[1] Unsorted waste paper is included due to the fact that exported bales typically contain 5–30% plastic contamination, indicating that restrictions on paper waste also influence plastic waste flows (Karlsson et al., 2023). These data are used to construct quarterly series documenting changes in waste imports into China and Indonesia before and after the policy, as shown in Figures 1.1 and 1.3a.

Data from Indonesia's Central Bureau of Statistics (Badan Pusat Statistik, BPS) were also collected to validate overall waste imports and to disaggregate import patterns. These data, available at the 6-digit HS code level, reveal a pattern for total plastic waste imports similar to that observed in the UN Comtrade series, but with substantially larger volumes. This difference arises because the BPS figures represent all waste importation and are not limited to high-consumption centers. The increase in waste imports in 2018 exceeds 400 kilotons in the BPS data, compared with approximately 150 kilotons in the export-based Comtrade series (Figure 1.5). The BPS data further identify the destination provinces of imported plastic waste, indicating that the majority of imports are directed to the Capital Region of Jakarta, with additional inflows to East Java, Central Java, Riau Islands, and North Sumatra (Table 1.1).

[1] Data downloaded from UN Comtrade consist of export flows from high-consumption countries (North America, Europe, and Oceania) to China and Indonesia. Similar figures are found when looking at Indonesia's import data.

Figure 1.5: Government Recorded Plastic and Paper Waste Imports into Indonesia



Note: The figure reports annual plastic and paper waste imports into Indonesia, calculated by summing quarterly imports and expressed in kilotons. Data are from the Government of Indonesia Central Bureau of Statistics (BPS) import records.

Table 1.1: Annual Waste Imports (kT) by Province

	2015	2016	2017	2018	2019
Jakarta (Special Capital Region)	1252.64	1460.17	1676.72	2523.31	2245.22
Central Java	34.24	46.59	60.80	87.57	138.30
East Java	489.43	625.49	553.57	760.58	908.95
Riau Islands	6.51	5.66	16.27	127.92	131.97
North Sumatra	6.53	4.10	13.59	13.94	6.73

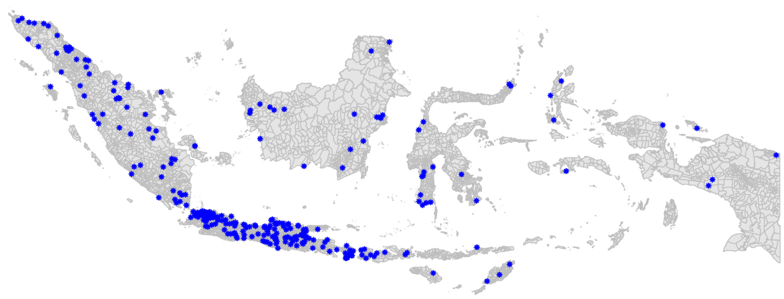
Note: Annual waste imports are measured in kilotons. Values are aggregated by destination province for 2015–2019 from the Government of Indonesia Central Bureau of Statistics Importation Records.

1.3.2 Waste sites

Waste site locations are obtained from the Minderoo Foundation's Global Plastic Watch (GPW) platform, which utilizes European Space Agency satellite imagery and a machine-learning algorithm to identify plastic waste accumulations globally (Foundation, 2022) (Figure 1.6). These data identify 373 waste accumulation sites within

Indonesia, including 253 pre-existing sites observed before January 2018 and 120 sites that first appeared after the National Sword policy. Details on site characteristics are provided in Table 1.2. Pre-existing waste sites are, on average, larger and located in rural areas, while new waste sites are primarily observed in more densely populated urban areas.

Figure 1.6: Waste-Site Locations in Indonesia



Note: The figure shows the locations of waste sites in Indonesia identified by Global Plastic Watch.

To enhance the reliability of the GPW classifications, identified sites are cross-checked against official and NGO lists of legal landfill and waste management facilities. Specifically, site locations are compared with entries in the national solid waste information system (SIPSN, 2023) and with facility lists compiled by local environmental NGOs, including Nexus3, Ecoton, and Waste4Change.[1]

Further analysis of waste site locations across countries and their temporal changes are provided in Appendix A.1.

[1] Verification draws on information obtained through meetings with Indonesian government agencies and NGOs.

Table 1.2: Summary Statistics for Waste Sites

Group	N	Variable	Mean	SD	Min	Max
		Site Area	7,737.30	22,718.14	22.00	279,459.00
All	373	Population Density	9,938.12	13,357.34	34.00	68,139.00
		Elevation	91.11	175.06	0.00	1,325.00
		Site Area	8,629.27	25,284.69	28.00	279,459.00
Pre-Existing	253	Population Density	8,777.75	10,347.40	34.00	48,095.00
		Elevation	99.77	191.25	0.00	1,325.00
		Site Area	5,908.77	16,179.75	22.00	116,770.00
New	120	Population Density	12,384.58	17,947.53	70.00	68,139.00
		Elevation	72.83	133.58	1.00	859.00

Note: Characteristics for waste sites in Indonesia. Data from Global Plastic Watch.

1.3.3 Air pollution

Air pollution is measured using monthly average $PM_{2.5}$ concentrations from the Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis. The ACAG data provides global $PM_{2.5}$ concentrations (μg/m^3) at a $0.01° \times 0.01°$ resolution (approximately 1 km $\times$ 1 km) by integrating satellite, simulation, and ground-based monitor sources (Van Donkelaar et al., 2021). Aerosol optical depth from multiple satellites (MODIS, VIIRS, MISR, SeaWiFS) and their respective retrievals (Dark Target, Deep Blue, MAIAC) are combined with GEOS-Chem simulations, weighted by their relative uncertainties as determined using ground-based sun photometer (AERONET) observations. This approach produces geophysical estimates that explain most of the variance in ground-based $PM_{2.5}$ measurements (Van Donkelaar et al., 2021). The fire season months of August through October are excluded from the analysis, as fires disproportionately affect cells distant from waste sites.[1]

Figure 1.7 show that $PM_{2.5}$ concentrations increased following the implementa-

[1] To address this, the satellite-based fire data will be incorporated in further iterations of this project (Copernicus Climate Change Service, 2019). Preliminary findings on the presence of fires near waste sites are reported in Appendix A.2.

tion of the policy. This finding is consistent with the hypothesis that the redirection of imported waste intensified open-air burning and other waste-processing activities, thereby increasing local air pollution.

Temporal changes in pollution by country are presented in Appendix A.3.

Figure 1.7: Average Monthly $PM_{2.5}$ Pollution by District

(a) Pre-policy (2015–2017)

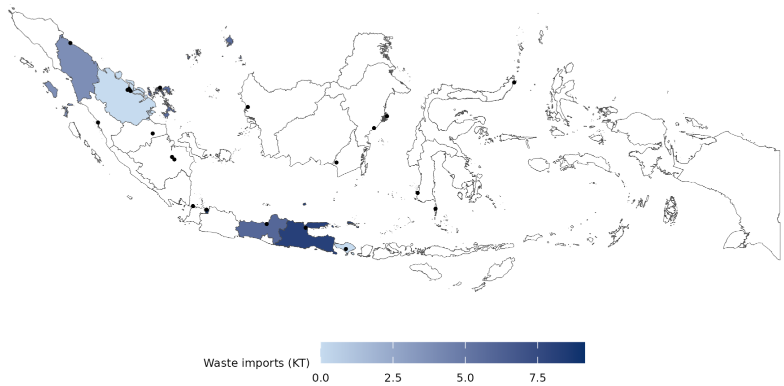
(b) Post-policy (2018–2019)

Note: Cell-level $PM_{2.5}$ concentrations ($\mu g/m^3$) from the ACAG data are averaged across cells within each district. Panel (a) reports averages from January 2015 to December 2017, and Panel (b) reports averages from January 2018 to December 2019. Fire-season months (August through October) are excluded from both averages.

1.3.4 Port Data

Information on Indonesian sea and container ports is scraped from Sea Rates, which provides geocoded locations and basic characteristics of shipping terminals (SeaRates, 2024). A total of 159 ports are identified, including 21 deep-sea container terminals capable of handling large international vessels. These deep-sea ports serve as primary entry points for imported waste. Province-level import data indicate that waste imports are concentrated in provinces hosting at least one deep-sea terminal (Figure 1.8).

Figure 1.8: Provincial Waste Importation and Deep Sea Shipping Ports



Note: Log import data from BPS Indonesia, with deep sea ports.

1.3.5 Wind

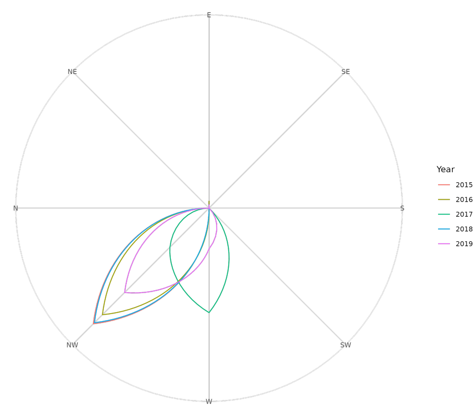
To refine exposure measures, the analysis incorporates dominant wind direction. Wind speed and direction data from the ERA5 reanalysis are used to construct downwind exposure measures, improving identification of communities more likely to receive emissions from waste-burning sites (Copernicus Climate Change Service, 2024).

To identify how $PM_{2.5}$ pollution disperses from waste sites, high-frequency atmospheric data from the ERA5 reanalysis are utilized. This dataset provides four daily measures of wind direction at a grid resolution of approximately 10 km by 10 km for a height of 10 m above the ground surface, compiled from January 1, 2015, to December 31, 2019. To align with the pollution analysis, the fire season (August to October) is excluded to prevent bias from unrelated rural $PM_{2.5}$ spikes.

Daily wind direction is calculated using the U and V vector components. For each cell, daily directions are binned into eight cardinal and ordinal groups: N, NE, E, SE, S, SW, W, and NW. The dominant wind direction for each cell-month is determined by identifying the direction group with the highest frequency of daily observations. Although monthly average degrees are also calculated, the dominant direction frequency is used to ensure the model accurately captures cells consistently situated downwind within the atmospheric plume of a waste site.

Wind patterns across the Indonesian archipelago exhibit high regional stability during the study period. As shown in Figure 1.9, the most prominent wind direction is North-West (NW), which remains the dominant vector from 2015 through 2019.

Figure 1.9: Dominant Downwind Direction by Year



Note: Dominant annual wind direction based on ERA5 wind data. Wind direction is calculated using the eastward and northward components of wind at 10 m.

§ 1.4 Empirical Strategy

The research design exploits the sharp timing of China's National Sword policy, which sharply reduced Chinese imports of plastic waste in early 2018 and redirected waste flows to receiving countries such as Indonesia. This strategy compares changes in

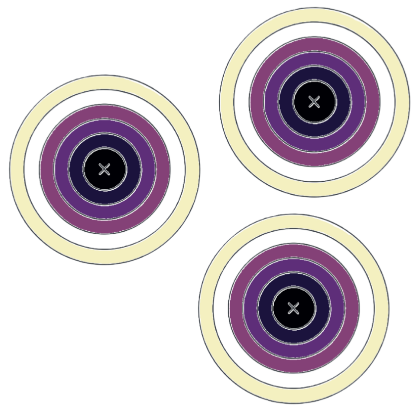
$PM_{2.5}$ concentrations before and after the policy across locations with varying exposure levels due to proximity to waste sites and ports.

A monthly panel dataset of $PM_{2.5}$ concentrations for every 1 km $\times$ 1 km grid cell in Indonesia from January 2015 to December 2019 is constructed using ACAG data. For each cell, the distance to the nearest waste site is calculated. Indonesia's annual fire season, from August through October, is excluded from the analysis due to the significant impact of fires on $PM_{2.5}$ pollution. The resulting sample consists of approximately 450,000 cells within 45 km of a waste site, observed nine times per year. The primary empirical specifications employ a difference-in-differences framework that utilizes both temporal variation (pre- versus post-policy) and spatial variation (proximity to waste sites).

1.4.1 Difference in Difference with Waste Sites

This specification compares $PM_{2.5}$ concentrations in grid cells near waste sites with those farther away, before and after the implementation of the National Sword in January 2018. Figure 1.10 illustrates the spatial comparison underlying the difference-in-differences design. For each waste site (marked by X), pollution is measured in concentric 3 km distance bins. The treatment group consists of cells located in bins closer to the waste site, while the control group consists of cells in the furthest distance band (42–45 km, shown in yellow). The empirical strategy outlined in equation (1.1) compares the change in pollution from the pre-policy to the post-policy period in nearer bins relative to the change observed in the furthest bin.

Figure 1.10: Near–Far Difference-in-Differences Design



Note: Waste sites are denoted by an "X." Nearby cells constitute the treatment group, while more distant cells constitute the comparison group.

Let c index grid cells, j index waste sites, and t index time periods. The primary outcome variable is the monthly $PM_{2.5}$ concentration, denoted $Pollution_{c,t}$.

$$Pollution_{c,t} = \sum_{d=1}^{14} \beta_d \left(Post_t \times \mathbb{1}\{Bin_c = d\}\right) + \gamma_c + \rho_t + \delta_{j,m} + \varepsilon_{c,t} \tag{1.1}$$

where $Post_t$ is an indicator equal to 1 for months after January 2018, γ_c are cell fixed effects, ρ_t are month-year fixed effects, and $\delta_{j,m}$ are nearest site-by-month-of-year fixed effects ($Site_j \times Month$) that flexibly control for site-specific seasonal patterns in pollution. To study how the effect attenuates with distance, cells are divided into distance bins around their nearest waste site. Let Bin_c^d denote an indicator for distance bin d, where $d \in [1, 15]$ corresponds to distance bands from 0–3 km up to 42–45 km. The furthest bin (42–45 km), $d = 15$, is omitted as the reference category. The coefficient β_d captures the post-policy change in $PM_{2.5}$ for cells in distance band d, relative to the post-policy change in the furthest (least exposed) distance band.

Equation (1.1) is estimated using the full sample of waste sites as the baseline specification. The model is then re-estimated on a restricted subsample that includes only waste sites located near ports (i.e., within 50 km of a deep-sea container terminal) in provinces that receive waste and those that do not. This restriction focuses the analysis on locations most plausibly affected by changes in imported plastic waste flows following the National Sword policy while holding the econometric specification constant.

1.4.2 Identifying Assumptions and Pre-trends

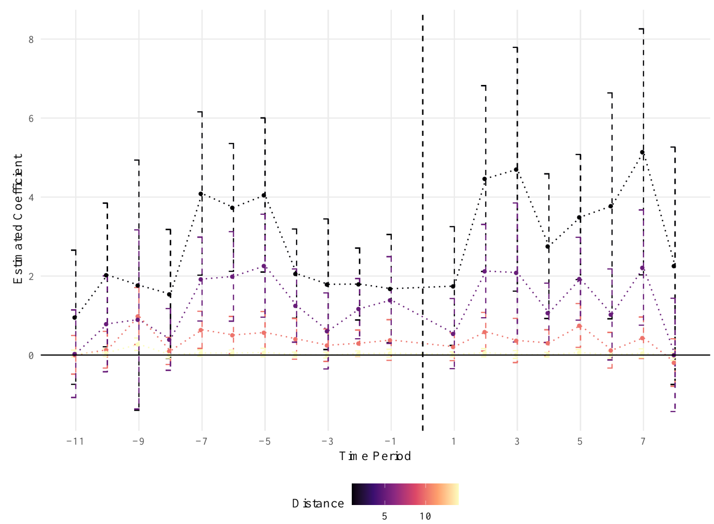
The identifying assumption is that, absent the 2018 policy change and conditional on the included fixed effects, cells near and far from their closest waste site would have followed parallel trends in monthly pollution. To assess the plausibility of this assumption, an event-study specification is estimated that interacts distance bins with a full set of quarter indicators relative to the policy:

$$PM_{2.5,c,q} = \alpha + \sum_{d} \sum_{q \neq q_0} \theta_{d,q}, \mathbf{1}Bin_c = d \times \mathbf{1}Quarter = q + \gamma_c + \rho_q + \delta_{j,m} + \varepsilon_{c,q}, \tag{1.2}$$

where q indexes calendar quarters, q_0 denotes the quarter immediately preceding the policy (2017 Q4), and is omitted as the reference period. Each coefficient $\theta_{d,q}$ measures the deviation in PM2.5 for distance bin d in quarter q relative to the omitted quarter (2017 Q4) and the distance bin (40-43 km), and the full set of coefficients is plotted in Figure 1.11.

Figure 1.11 presents the estimated coefficients for selected bins relative to the least exposed bin (42-45 km). Prior to 2018, the estimated coefficients were generally small and statistically indistinguishable from zero, particularly in the more distant bins, supporting the plausibility of the parallel trends assumption by displaying similar pre-trends. Cells in the closest bin (0–3 km) exhibit temporary positive deviations in 2016, coinciding with heightened enforcement of Chinese waste import controls and increased imports in Indonesia, as well as a systematic upward trend leading into the policy window.

Figure 1.11: Event-Study by Distance from Waste Sites

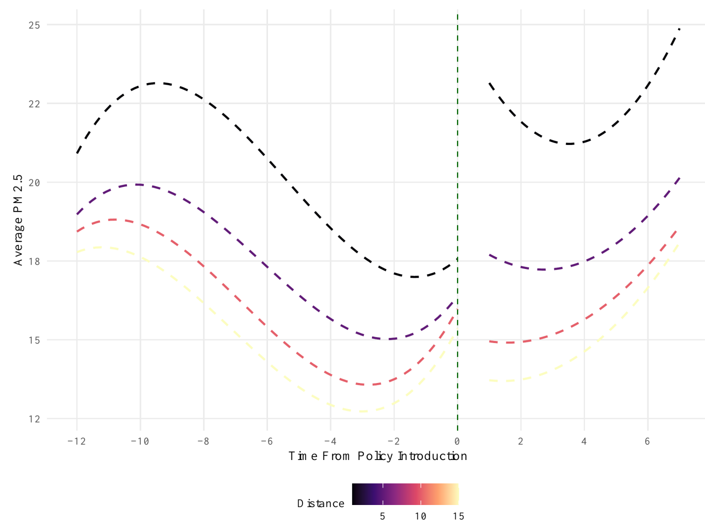


Note: The figure reports estimated coefficients for $PM_{2.5}$ concentrations (μg/m^3) for each time period and distance bin. Estimates are relative to 2017 Q4, the final period before the policy, and the furthest distance bin, consisting of cells located 40–43 km from a waste site. Fire-season months, defined as August through October, are excluded in each year. The shaded region denotes the period during which China implemented stricter environmental enforcement.

Following the implementation of the National Sword policy, the observed trends change. Estimated coefficients for the nearest bin rise sharply from 2018 Q1 onward and remain elevated through 2019, while effects attenuate with distance and are close to zero for the outermost bin. This post-policy divergence is characterized by a persistent increase in $PM_{2.5}$ near waste sites and much smaller changes farther away, which is consistent with intensified waste processing and open burning in response to redirected plastic waste flows.

Visual evidence from the raw data further supports the presence of similar pre-trends. Figure 1.12 shows that the average $PM_{2.5}$ in near and far bins follows similar trajectories in the extended pre-policy period, with no systematic divergence prior to 2018.[1]

Figure 1.12: Average $PM_{2.5}$ Concentrations Over Time



Note: The figure reports quarterly average $PM_{2.5}$ concentrations (μg/m^3) from 2010 Q1 through 2019 Q4. Fire-season months, defined as August through October, are excluded in each year.

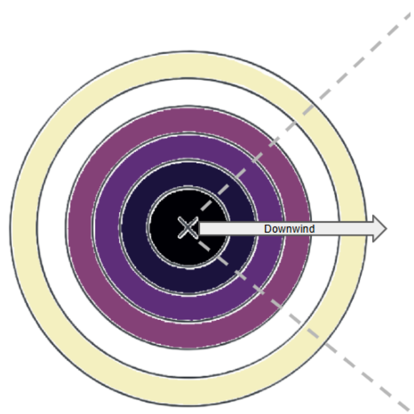
1.4.3 Wind and Triple Difference

Cells located very close to a waste site may differ systematically from cells located farther away in ways unrelated to the policy. To address this concern, wind direction

[1]Trends in the raw data are descriptive and do not control for fixed effects or confounders

is incorporated into the analysis using a triple-difference specification. This approach compares cells that are near and downwind of a waste site to cells that are near and upwind, thereby holding proximity constant while exploiting quasi-random variation in wind exposure, as displayed in Figure 1.13. Because upwind and downwind cells within the same distance band are geographically proximate, they are likely to share similar observable and unobservable characteristics, differing primarily in their exposure to pollution

Figure 1.13: Near-Far and Downwind Triple-Difference Design



Note: Waste sites are denoted by an "X." The triple-difference design compares changes in $PM_{2.5}$ after the policy across nearby and distant cells and across downwind and non-downwind locations.

The identifying assumption is that, in the absence of the policy, pollution trends in downwind and upwind cells within a given distance bin would have evolved similarly. In other words, any differential pollution trends between downwind and upwind cells are assumed to be stable over time and comparable across distance bins.

To integrate wind exposure into the analysis, the following triple-difference specification is estimated:

$$
\begin{aligned}
Pollution_{c,t} = &\sum_{d=1}^{14} \beta_{1,d} \left(Post_t \times \mathbb{1}\{Bin_c = d\}\right) \\
&+ \sum_{d=1}^{14} \beta_{2,d} \left(Wind_{c,t} \times \mathbb{1}\{Bin_c = d\}\right) \\
&+ \sum_{d=1}^{14} \beta_{3,d} \left(Post_t \times Wind_{c,t} \times \mathbb{1}\{Bin_c = d\}\right) \\
&+ \beta_4 \left(Post_t \times Wind_{c,t}\right) \\
&+ \gamma_c + \rho_t + \delta_{j,m} + \varepsilon_{c,t},
\end{aligned} \tag{1.3}
$$

where $Wind_{c,t}$ is an indicator equal to 1 if the cell c is downwind from the waste site in time period t. Downwind exposure is defined as the angular difference between the prevailing wind direction and the waste site's centroid for each 1 km $\times$1 km grid cell. Cells whose centroids fall within $\pm 45^\circ$ of the wind direction are classified as downwind. As previously outlined, d denotes the 3 km distance bins from the nearest waste site, and $d = 15$ (42–45 km) is the omitted reference category. The fixed effects γ_c control for time-invariant cell characteristics, ρ_t absorb common time shocks, and $\delta_{j,m}$ are nearest-site-by-month-of-year fixed effects that flexibly control for site-specific seasonal patterns in pollution.

The coefficients $\beta_{3,d}$ identify the causal effect of the policy at distance bin d by comparing the change in the downwind–upwind pollution gap in bin d to the corresponding change in the reference bin. Formally, $\beta_{3,d}$ captures:

$$
\begin{aligned}
&\left[(PM^{DW} - PM^{UW})_{d,Post} - (PM^{DW} - PM^{UW})_{d,Pre}\right] \\
&\quad - \left[(PM^{DW} - PM^{UW})_{15,Post} - (PM^{DW} - PM^{UW})_{15,Pre}\right].
\end{aligned}
$$

This triple-difference estimator exploits variation across time (pre vs. post), space (near vs. far bins), and wind direction (downwind vs. upwind), netting out contemporaneous wind-related changes observed in the furthest distance band.

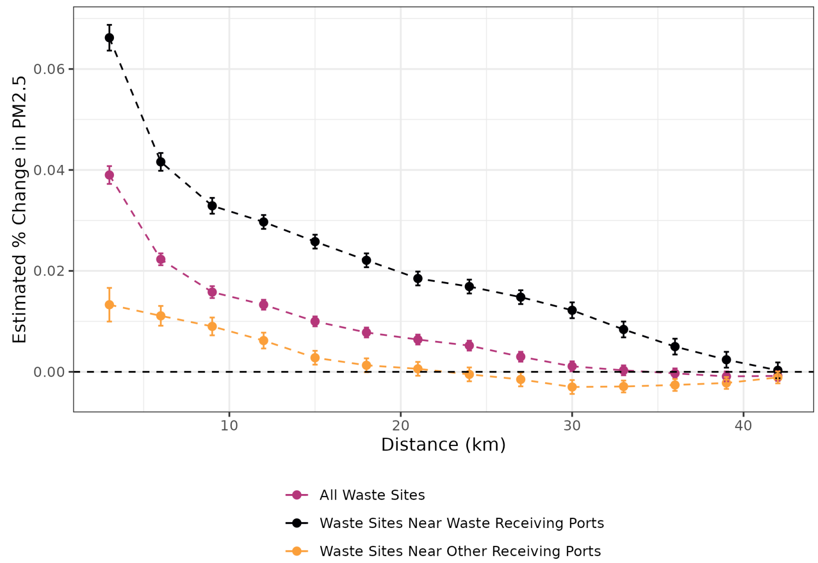
In addition to estimating equation (1.3) on the full sample of waste sites, the sample is also restricted to sites located near ports, and the same specification is re-estimated.

§ 1.5 Results

1.5.1 Difference-in-Difference: Near vs Far

The analysis begins by presenting difference-in-differences estimates of post-policy changes in ambient $PM_{2.5}$ concentrations across distance bins from waste sites. Figure 1.14 plots the estimated treatment effects for each distance bin, with coefficients reported relative to the outermost bin (42–45 km), which serves as the omitted category. The figure illustrates how pollution responses vary spatially with proximity to waste sites.

Figure 1.14: Estimated Policy Effects on $PM_{2.5}$ by Distance from Waste Sites



Note: The figure reports estimated policy coefficients for $PM_{2.5}$ concentrations across alternative distance bins. The fifteenth distance bin, consisting of cells located 42–45 km from a waste site, is the omitted reference category. Fire-season months, defined as August through October, are excluded in each year.

Two patterns become evident. First, the estimated effects are greatest in areas near waste sites and diminish steadily with increased distance. Cells within 0 to 3 km exhibit the largest increases in $PM_{2.5}$ concentrations, coefficients decrease consistently across further distance bins and approach zero beyond approximately 40 km. These results suggest that the fluctuations between bins likely reflect systematic spatial variation in treatment intensity rather than sampling noise.

Second, the magnitude of the estimated effects varies by treatment sample. Pollution increases are greatest for sites near waste-receiving ports, intermediate for the full sample of waste sites, and smallest for sites associated with ports that receive other imports. This may indicate that cells near plastic waste-receiving sites experienced greater impacts following the policy, consistent with the substantial increase in waste imports after the policy change.

Tables 1.3 through 1.5 present the corresponding regression estimates in both level and logarithmic specifications. Baseline $PM_{2.5}$ concentrations range from 14 to 17 $\mu g/m^3$ for the furthest away cells, with higher values observed in cells located closer to waste sites (15 to 22 $\mu g/m^3$). In the nearest distance bin (0 to 3 km), $PM_{2.5}$ concentrations increase by 1 to 6 percent (0.4 to 1.7 $\mu g/m^3$). The effect size rapidly declines with distance, decreasing by more than half within the first 15 km and become indistinguishable from zero in the further bins.

Collectively, these results demonstrate that post-policy pollution increases are highly localized around waste sites and diminish with distance. This spatial pattern is inconsistent with region-wide shocks or unrelated temporal trends, which would likely affect nearby locations similarly. Instead, the observed treatment effects that attenuate with distance from the source indicate that the policy's environmental impacts are geographically constrained rather than spatially uniform.

1.5.2 Triple Difference Specification with Downwind

Tables 1.6 through 1.8 present triple-difference estimates that exploit variation across three dimensions: distance from waste sites, wind direction, and the post-policy period. Table 1.6 reports results for all cells near waste sites. Table 1.7 restricts the sample to cells whose nearest waste site is located near ports that received waste imports, while Table 1.8 focuses on cells whose nearest waste site is near deep-sea ports that did not receive waste.

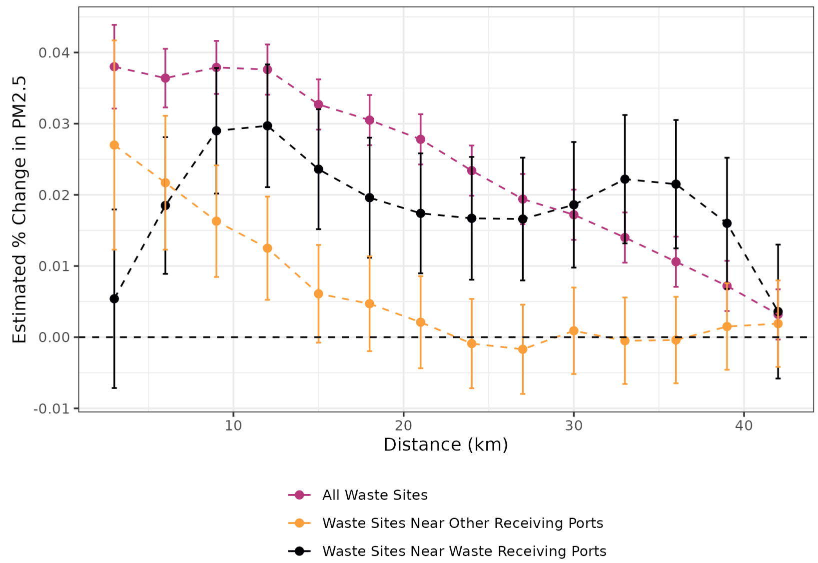
Across specifications, the interaction coefficients between distance bins and the post-policy period demonstrate a clear spatial gradient. Estimated increases in $PM_{2.5}$ concentrations are largest in cells closest to waste sites and decline steadily with distance. For bins sufficiently far from waste sites, the estimates are small and statistically indistinguishable from zero, indicating that policy-induced pollution increases are highly localized.

A comparison across tables reveals systematic differences in magnitude by port type. In Table 1.6, which includes all waste sites, post-policy increases are positive for nearby bins and decline with distance, consistent with the baseline difference-in-differences results. Table 1.7 shows the results restricted to waste sites located near ports that received imported waste, and find that the closest distance bins experience the an increase in $PM_{2.5}$, and statistically significant effects persist over a wider spatial range. These findings indicate that combining proximity to waste sites with exposure to waste-receiving ports resulted in the largest post-policy increases in pollution.

In contrast, Table 1.8, which isolates waste sites near ports that did not receive waste imports, shows markedly smaller and less precisely estimated interaction effects. Although coefficients for nearby bins remain generally positive, their magnitudes are reduced, and statistical significance attenuates more rapidly with distance. This comparison suggests that not all port-adjacent waste sites experienced similar environmental impacts; rather, the largest effects occurred specifically where imported waste flows were likely to be processed.

Figure 1.15 illustrates the triple-difference coefficients by plotting estimated percentage changes in $PM_{2.5}$ across distance bins for the three samples. The figure confirms a consistent decline in treatment effects with distance and demonstrates that cells near waste-receiving ports exhibit the steepest gradients and largest magnitudes. Cells near non-receiving ports display flatter profiles, while estimates for the full sample fall between these two cases.

Figure 1.15: Estimated Policy Effects on $PM_{2.5}$ by Distance from Waste Sites and Downwind Exposure



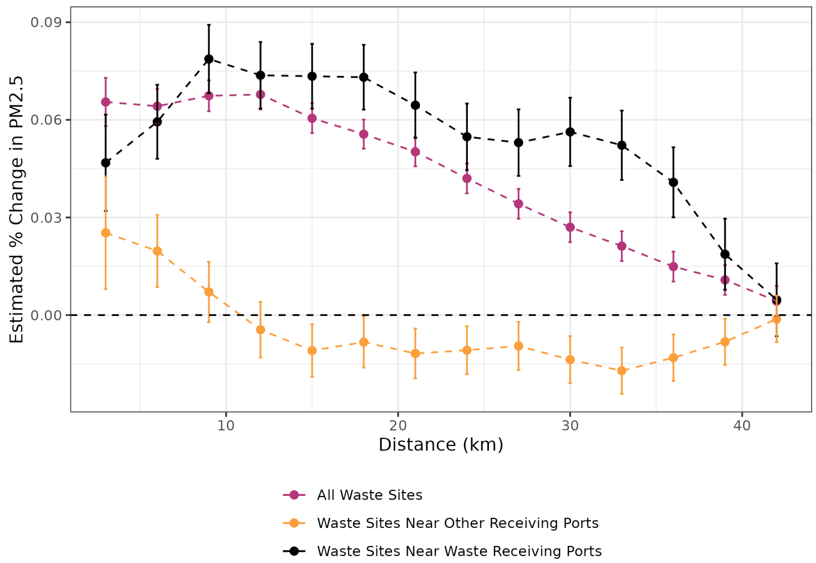
Note: The figure reports triple-difference estimates for $PM_{2.5}$ concentrations across alternative distance bins and downwind exposure. The fifteenth distance bin, consisting of cells located 42–45 km from a waste site, is the omitted reference category. Fire-season months, defined as August through October, are excluded in each year.

Comparing specifications reveals that both the full sample and the non-receiving-port sample exhibit slightly larger percentage increases in $PM_{2.5}$ in the closest distance bins. This may be explained by the fact that when locations are extremely close to a pollution source, exposure is high regardless of wind direction, so the additional effect of being downwind is reduced. In contrast, the pattern observed near waste-receiving ports shows a mild inverted U-shaped relationship with distance, consistent with atmospheric dispersion dynamics. For very near sources, concentration gradients are dominated by proximity; at intermediate distances, wind direction plays a larger role in determining exposure; and at farther distances, pollutants become more diluted.

Taken together, the triple-difference estimates indicate that increases in pollution following the National Sword policy were jointly shaped by local proximity to waste sites, atmospheric transport, and access to import infrastructure. The results therefore support an interpretation in which the environmental evidence is consistent with a mechanism linking trade-driven waste inflows to localized air-quality deterioration through spatial interactions between waste-processing activity and prevailing wind direction. These findings reinforce the interpretation from the difference-in-differences analysis that exposure to imported waste affects air quality primarily in locations that are both geographically close to waste-processing sites and downwind of them.

Lastly, Figure 1.16 plots the effect of the policy for cells that are both downwind and located within each distance bin (difference between $\beta_3 - \beta_2$), relative to cells in the same bin that were downwind during the reference period. This specification isolates the post-policy-change effect on exposure while holding spatial proximity and wind direction constant. The estimates show that downwind cells near waste sites experience statistically significant increases in $PM_{2.5}$ concentrations following the policy, with the largest effects in the nearest-distance bins and a steady decline with distance. The pattern indicates that the policy shock amplified pollution primarily when downwind, rather than uniformly across space. By comparing cells within the same distance bin, these results confirm that the observed increases are not driven solely by noise but instead reflect an interaction between policy-induced waste and downwind exposure.

Figure 1.16: Marginal Effect of the Policy on $PM_{2.5}$ by Distance from Waste Sites and Downwind Exposure



Note: The figure reports the estimated marginal effect of the policy on $PM_{2.5}$ concentrations for nearby, downwind cells across alternative distance bins. The fifteenth distance bin, consisting of cells located 42–45 km from a waste site, is the omitted reference category. Fire-season months, defined as August through October, are excluded in each year.

1.5.3 Back-of-the-envelope Calculation: Infant Mortality

The estimated increases in $PM_{2.5}$ are likely to have significant health implications, particularly for infant health. Fine particulate matter is harmful because it can increase the risk of respiratory and cardiovascular diseases, as well as adverse early-life health outcomes (Jayachandran, 2009; Kan, 2022; Sun et al., 2024; Papadogeorgou et al., 2019; Brunekreef and Holgate, 2002; Chay and Greenstone, 2003) . The WHO air-quality guideline recommends an annual average $PM_{2.5}$ concentration of no more than 5 $\mu g/m^3$ (Weltgesundheitsorganisation and Organization, 2021). In the analysis sample, average $PM_{2.5}$ concentrations remain substantially above this threshold even after excluding the fire-season months. In the main estimates, $PM_{2.5}$ increases by approximately 5–9 percent from a baseline of roughly 15–17 $\mu g/m^3$ during non-fire-season months.[1]

To provide context to the potential magnitude of these effects, a back-of-the-envelope calculation is conducted using existing estimates from the literature on $PM_{2.5}$ and infant mortality. Infant mortality in Indonesia following the policy's implementation was approximately 19 deaths per 1,000 live births (World Bank, 2026). Prior research has found that increases in $PM_{2.5}$ are associated with higher infant mortality (Dong et al., 2025). Specifically, Heft-Neal et al. (2018) estimate that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ increases infant mortality by approximately 9 percent in Africa. This estimate serves as a conservative benchmark, although other studies have reported larger associations between $PM_{2.5}$ exposure and child mortality (Anwar et al., 2021).

Applying this estimate to the observed $PM_{2.5}$ increases implies non-trivial health impacts. For the main estimate of a 1.2 $\mu g/m^3$ increase in $PM_{2.5}$ near waste sites, the implied increase in infant mortality is approximately 1.0 percent. Given a baseline infant mortality rate of 19 deaths per 1,000 live births, this corresponds to roughly 20 additional infant deaths per 100,000 exposed live births. For waste sites located near waste-receiving ports, where the estimated $PM_{2.5}$ increase is approximately 1.7 $\mu g/m^3$, the implied increase in infant mortality is roughly 1.5 percent, or about 28 additional infant deaths per 100,000 exposed live births.

These calculations should be interpreted with caution. While these figures are not direct estimates of the effect of imported waste on infant mortality, they can demonstrate how the estimated changes in $PM_{2.5}$ pollution may affect infant mortality. Ad-

[1] Indonesia experiences high levels of air pollution, in part due to seasonal fires. Excluding August through October reduces the average $PM_{2.5}$ concentration in the estimation sample. As a result, the implied health impacts reported here should be interpreted as conservative with respect to annual exposure.

ditionally, the impact on mortality is calculated using only the closest distance band around waste sites. Therefore, if scaled to a national level, the 28 additional infant deaths per 100,000 would serve as an upper bound of impact. This is because the pollution effect attenuates with distance. However, the number of exposed individuals may increase at further distances, particularly because many newly identified waste sites are located in more densely populated urban areas. As a result, even relatively small increases in $PM_{2.5}$ may have meaningful aggregate consequences.

§ 1.6 Conclusion

The growth in plastic consumption has created a global problem centered around the management and disposal of plastic waste. International trade facilitates the movement of recyclable waste across borders; however, it also raises concerns that environmental harms may be transferred rather than mitigated. This paper examines whether the redirection of plastic waste following China's National Sword policy led to increased local air pollution in Indonesia, a waste-receiving country.

Quantifying these effects is challenging because imported waste is not directly observed after it enters a receiving country. Waste may be recycled, sorted, stored, dumped, or burned, often through both formal and informal networks. Thus, aggregate trade flows provide limited insight into the local environmental impacts of waste imports. The analysis combines high-resolution $PM_{2.5}$ data with waste-site locations, port locations, trade flows, and wind direction to assess changes in pollution around exposed locations following the policy.

The results show that $PM_{2.5}$ concentrations increased near waste sites following the implementation of the National Sword Policy. These increases are concentrated within a few kilometers of waste sites and diminish with distance, suggesting that the observed effects are attributable to localized waste-related activities rather than broader regional changes in air quality. The effects are more pronounced near waste sites located close to ports that receive imported waste, indicating that pollution increases were concentrated in areas most exposed to redirected waste flows. Wind-based estimates further support this interpretation, demonstrating larger post-policy increases in cells located downwind of waste sites.

These findings illustrate how environmental consequences of plastic waste trade can manifest at the local level. National or regional averages may obscure the exposure experienced by communities residing near waste sites, particularly when pollution is concentrated around locations where waste is sorted, accumulated, or burned. The results provide evidence that global waste trade can generate localized environmental costs in receiving countries, especially when imported waste exceeds the capacity of local systems to manage it safely.

More broadly, the analysis suggests that unilateral restrictions are insufficient to address the global plastic waste problem. Policies that reduce waste imports in one country may improve domestic environmental conditions, but they can generate new externalities if displaced waste is redirected to countries with weaker monitoring, enforcement, and disposal capacity. Effective plastic waste governance therefore requires more than transferring waste across borders. It necessitates stronger tracking of international waste flows, enforcement at receiving ports, monitoring of informal processing and burning, and investment in safe waste-management infrastructure in recipient countries.

Ultimately, the global plastic waste crisis cannot be resolved by relocating waste from one jurisdiction to another. Environmental policy should distinguish between genuine reductions in waste generation and the displacement of environmental harms.

Without coordinated regulation and enhanced local capacity, efforts to improve environmental quality in one country may simply transfer pollution to vulnerable communities elsewhere.

Table 1.3: Estimated coefficients for $PM_{2.5}$ Concentration using Difference in Difference Specification for ALL Waste Sites

Dependent Variables:	$PM_{2.5}$ Concentration			$\ln(PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	5.032***			0.2677***		
	(0.0197)			(0.0012)		
3 - 6 km	3.806***			0.2126***		
	(0.0144)			(0.0009)		
6 -9 km	3.222***			0.1848***		
	(0.0129)			(0.0008)		
9 - 12 km	2.739***			0.1620***		
	(0.0123)			(0.0008)		
12 - 15 km	2.372***			0.1416***		
	(0.0119)			(0.0007)		
15 - 18 km	2.013***			0.1208***		
	(0.0118)			(0.0007)		
18 - 21 km	1.651***			0.0991***		
	(0.0118)			(0.0007)		
21 - 24 km	1.365***			0.0821***		
	(0.0117)			(0.0007)		
24 - 27 km	1.098***			0.0652***		
	(0.0118)			(0.0007)		
27 - 30 km	0.9273***			0.0537***		
	(0.0118)			(0.0007)		
30 - 33 km	0.7841***			0.0436***		
	(0.0119)			(0.0007)		
33 - 36 km	0.5806***			0.0300***		
	(0.0120)			(0.0007)		
36 - 39 km	0.3425***			0.0164***		
	(0.0120)			(0.0007)		
39 - 42 km	0.1220***			0.0061***		
	(0.0121)			(0.0007)		
0 - 3 km × Post Policy = 1	1.207***	1.207***	1.207***	0.0390***	0.0390***	0.0390***
	(0.0311)	(0.0247)	(0.0947)	(0.0019)	(0.0009)	(0.0051)
3 - 6 km × Post Policy = 1	0.6541***	0.6541***	0.6541***	0.0223***	0.0223***	0.0223***
	(0.0227)	(0.0136)	(0.0873)	(0.0014)	(0.0006)	(0.0049)
6 - 9 km × Post Policy = 1	0.4547***	0.4547***	0.4547***	0.0158***	0.0158***	0.0158***
	(0.0204)	(0.0109)	(0.0839)	(0.0013)	(0.0006)	(0.0048)
9 - 12 km × Post Policy = 1	0.3718***	0.3718***	0.3718***	0.0133***	0.0133***	0.0133***
	(0.0194)	(0.0099)	(0.0796)	(0.0012)	(0.0005)	(0.0046)
12 - 15 km × Post Policy = 1	0.2811***	0.2811***	0.2811***	0.0100***	0.0100***	0.0100**
	(0.0189)	(0.0094)	(0.0730)	(0.0012)	(0.0005)	(0.0043)
15 - 18 km × Post Policy = 1	0.2157***	0.2157***	0.2157***	0.0078***	0.0078***	0.0078**
	(0.0187)	(0.0091)	(0.0665)	(0.0011)	(0.0005)	(0.0039)
18 - 21 km × Post Policy = 1	0.1660***	0.1660***	0.1660***	0.0064***	0.0064***	0.0064*
	(0.0186)	(0.0091)	(0.0601)	(0.0011)	(0.0005)	(0.0036)
21 - 24 km × Post Policy = 1	0.1188***	0.1188***	0.1188**	0.0052***	0.0052***	0.0052
	(0.0186)	(0.0090)	(0.0538)	(0.0011)	(0.0005)	(0.0032)
24 - 27 km × Post Policy = 1	0.0593***	0.0593***	0.0593	0.0030***	0.0030***	0.0030
	(0.0186)	(0.0089)	(0.0467)	(0.0011)	(0.0005)	(0.0028)
27 - 30 km × Post Policy = 1	0.0227	0.0227**	0.0227	0.0011	0.0011**	0.0011
	(0.0187)	(0.0090)	(0.0398)	(0.0011)	(0.0005)	(0.0024)
30 - 33 km × Post Policy = 1	-0.0032	-0.0032	-0.0032	0.0003	0.0003	0.0003
	(0.0188)	(0.0091)	(0.0328)	(0.0012)	(0.0005)	(0.0020)
33 - 36 km × Post Policy = 1	-0.0183	-0.0183**	-0.0183	-0.0003	-0.0003	-0.0003
	(0.0189)	(0.0092)	(0.0266)	(0.0012)	(0.0005)	(0.0015)
36 - 39 km × Post Policy = 1	-0.0302	-0.0302***	-0.0302	-0.0009	-0.0009	-0.0009
	(0.0190)	(0.0092)	(0.0193)	(0.0012)	(0.0005)	(0.0011)

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Table 1.3 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
39 - 42 km × Post Policy = 1	-0.0169	-0.0169*	-0.0169*	-0.0008	-0.0008	-0.0008
	(0.0191)	(0.0093)	(0.0091)	(0.0012)	(0.0005)	(0.0005)
Post Policy = 1	0.0102			0.0139***		
	(0.0135)			(0.0008)		
Fixed-effects						
id		Yes	Yes		Yes	Yes
time		Yes	Yes		Yes	Yes
X-month			Yes			Yes
Dependent Variables Mean		15.20			2.614	
Observations		438,270			438,270	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 1.4: Estimated coefficients for $PM_{2.5}$ Concentration using Difference in Difference Specification for Waste Sites Near Waste Receiving Ports

Dependent Variables:	$PM_{2.5}$ Concentration			ln($PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	4.083***			0.2190***		
	(0.0313)			(0.0018)		
3 - 6 km	3.114***			0.1788***		
	(0.0244)			(0.0014)		
6 - 9 km	2.666***			0.1571***		
	(0.0225)			(0.0013)		
9 - 12 km	2.161***			0.1339***		
	(0.0217)			(0.0013)		
12 - 15 km	1.862***			0.1166***		
	(0.0214)			(0.0013)		
15 - 18 km	1.634***			0.1027***		
	(0.0213)			(0.0013)		
18 - 21 km	1.320***			0.0838***		
	(0.0215)			(0.0013)		
21 -24 km	1.145***			0.0729***		
	(0.0216)			(0.0013)		
24 - 27 km	1.013***			0.0633***		
	(0.0217)			(0.0013)		
27 - 30 km	1.018***			0.0599***		
	(0.0221)			(0.0013)		
30 - 33 km	1.076***			0.0592***		
	(0.0225)			(0.0013)		
33 - 36 km	0.9082***			0.0453***		
	(0.0229)			(0.0014)		
36 - 39 km	0.5961***			0.0276***		
	(0.0232)			(0.0014)		
39 - 42 km	0.1691***			0.0086***		
	(0.0236)			(0.0014)		
0 - 3 km × Post Policy = 1	1.699***	1.699***	1.699***	0.0662***	0.0662***	0.0662***
	(0.0495)	(0.0351)	(0.1636)	(0.0029)	(0.0013)	(0.0090)
3 - 6 km × Post Policy = 1	0.9404***	0.9404***	0.9404***	0.0416***	0.0416***	0.0416***
	(0.0385)	(0.0179)	(0.1527)	(0.0023)	(0.0009)	(0.0086)
6 - 9 km × Post Policy = 1	0.7146***	0.7146***	0.7146***	0.0329***	0.0329***	0.0329***
	(0.0356)	(0.0141)	(0.1486)	(0.0021)	(0.0008)	(0.0085)
9 - 12 km × Post Policy = 1	0.6377***	0.6376***	0.6376***	0.0298***	0.0297***	0.0297***
	(0.0343)	(0.0129)	(0.1435)	(0.0020)	(0.0007)	(0.0083)
12 - 15 km × Post Policy = 1	0.5408***	0.5408***	0.5408***	0.0258***	0.0258***	0.0258***
	(0.0338)	(0.0123)	(0.1358)	(0.0020)	(0.0007)	(0.0079)
15 - 18 km × Post Policy = 1	0.4601***	0.4601***	0.4601***	0.0221***	0.0221***	0.0221***
	(0.0337)	(0.0121)	(0.1275)	(0.0020)	(0.0007)	(0.0075)
18 - 21 km × Post Policy = 1	0.3728***	0.3728***	0.3728***	0.0185***	0.0185***	0.0185***
	(0.0339)	(0.0121)	(0.1166)	(0.0020)	(0.0007)	(0.0069)
21 -24 km × Post Policy = 1	0.3175***	0.3175***	0.3175***	0.0169***	0.0169***	0.0169***
	(0.0341)	(0.0121)	(0.1052)	(0.0020)	(0.0007)	(0.0063)
24 - 27 km × Post Policy = 1	0.2637***	0.2637***	0.2637***	0.0148***	0.0148***	0.0148***
	(0.0343)	(0.0121)	(0.0946)	(0.0020)	(0.0007)	(0.0057)
27 - 30 km × Post Policy = 1	0.2128***	0.2128***	0.2128***	0.0122***	0.0122***	0.0122**
	(0.0349)	(0.0124)	(0.0811)	(0.0021)	(0.0008)	(0.0049)
30 - 33 km × Post Policy = 1	0.1350***	0.1350***	0.1350**	0.0084***	0.0084***	0.0084**
	(0.0356)	(0.0127)	(0.0649)	(0.0021)	(0.0008)	(0.0039)
33 - 36 km × Post Policy = 1	0.0663*	0.0663***	0.0663	0.0050**	0.0050***	0.0050*
	(0.0362)	(0.0130)	(0.0500)	(0.0021)	(0.0008)	(0.0029)
36 - 39 km × Post Policy = 1	0.0182	0.0182	0.0182	0.0024	0.0024***	0.0024
	(0.0367)	(0.0132)	(0.0377)	(0.0022)	(0.0008)	(0.0020)

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Table 1.4 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
39 - 42 km $\times$ Post Policy = 1	4.75×10^{-5}	4.75×10^{-5}	4.75×10^{-5}	0.0003	0.0003	0.0003
	(0.0372)	(0.0135)	(0.0173)	(0.0022)	(0.0008)	(0.0010)
Post Policy = 1	-0.5725***			-0.0195***		
	(0.0266)			(0.0016)		
Fixed-effects						
id		Yes	Yes		Yes	Yes
time.x		Yes	Yes		Yes	Yes
site_id-month			Yes			Yes
Dependent Variables Mean		17.20			2.712	
Observations		193,818			193,818	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 1.5: Estimated coefficients for $PM_{2.5}$ Concentration using Difference in Difference Specification for Waste Sites Near Non-Waste Receiving Ports

Dependent Variables:	$PM_{2.5}$ Concentration			ln($PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	0.9880***			0.0630***		
	(0.0296)			(0.0020)		
3 - 6 km	0.8800***			0.0580***		
	(0.0189)			(0.0013)		
6 - 9 km	0.8908***			0.0584***		
	(0.0160)			(0.0011)		
9 - 12 km	0.8228***			0.0546***		
	(0.0147)			(0.0010)		
12 - 15 km	0.6644***			0.0448***		
	(0.0140)			(0.0010)		
15 - 18 km	0.5489***			0.0374***		
	(0.0135)			(0.0009)		
18 - 21 km	0.4986***			0.0326***		
	(0.0132)			(0.0009)		
21 -24 km	0.4098***			0.0263***		
	(0.0129)			(0.0009)		
24 - 27 km	0.3057***			0.0188***		
	(0.0127)			(0.0009)		
27 - 30 km	0.2686***			0.0166***		
	(0.0125)			(0.0009)		
30 - 33 km	0.2272***			0.0135***		
	(0.0124)			(0.0008)		
33 - 36 km	0.1524***			0.0087***		
	(0.0124)			(0.0008)		
36 - 39 km	0.0554***			0.0028***		
	(0.0123)			(0.0008)		
39 - 42 km	0.0335***			0.0018**		
	(0.0123)			(0.0008)		
0 - 3 km × Post Policy = 1	0.4315***	0.4315***	0.4315***	0.0133***	0.0133***	0.0133**
	(0.0467)	(0.0386)	(0.1021)	(0.0032)	(0.0017)	(0.0057)
3 - 6 km × Post Policy = 1	0.3581***	0.3581***	0.3581***	0.0111***	0.0111***	0.0111**
	(0.0298)	(0.0220)	(0.0957)	(0.0020)	(0.0010)	(0.0054)
6 - 9 km × Post Policy = 1	0.3006***	0.3006***	0.3006***	0.0090***	0.0090***	0.0090*
	(0.0253)	(0.0177)	(0.0872)	(0.0017)	(0.0009)	(0.0050)
9 - 12 km × Post Policy = 1	0.2068***	0.2068***	0.2068***	0.0062***	0.0062***	0.0062
	(0.0233)	(0.0151)	(0.0781)	(0.0016)	(0.0008)	(0.0045)
12 - 15 km × Post Policy = 1	0.1044***	0.1044***	0.1044	0.0028*	0.0028***	0.0028
	(0.0221)	(0.0135)	(0.0662)	(0.0015)	(0.0007)	(0.0040)
15 - 18 km × Post Policy = 1	0.0578***	0.0578***	0.0578	0.0013	0.0013*	0.0013
	(0.0213)	(0.0126)	(0.0592)	(0.0015)	(0.0007)	(0.0036)
18 - 21 km × Post Policy = 1	0.0303	0.0303**	0.0303	0.0006	0.0006	0.0006
	(0.0208)	(0.0123)	(0.0534)	(0.0014)	(0.0007)	(0.0032)
21 -24 km × Post Policy = 1	-0.0060	-0.0060	-0.0060	-0.0005	-0.0005	-0.0005
	(0.0203)	(0.0120)	(0.0484)	(0.0014)	(0.0007)	(0.0030)
24 - 27 km × Post Policy = 1	-0.0344*	-0.0344***	-0.0344	-0.0015	-0.0015**	-0.0015
	(0.0200)	(0.0118)	(0.0433)	(0.0014)	(0.0007)	(0.0027)
27 - 30 km × Post Policy = 1	-0.0553***	-0.0553***	-0.0553	-0.0030**	-0.0030***	-0.0030
	(0.0198)	(0.0116)	(0.0370)	(0.0013)	(0.0007)	(0.0024)
30 - 33 km × Post Policy = 1	-0.0614***	-0.0614***	-0.0614*	-0.0029**	-0.0029***	-0.0029
	(0.0196)	(0.0115)	(0.0332)	(0.0013)	(0.0006)	(0.0021)
33 - 36 km × Post Policy = 1	-0.0539***	-0.0539***	-0.0539**	-0.0026*	-0.0026***	-0.0026
	(0.0196)	(0.0115)	(0.0268)	(0.0013)	(0.0006)	(0.0016)
36 - 39 km × Post Policy = 1	-0.0462**	-0.0462***	-0.0462**	-0.0022	-0.0022***	-0.0022*
	(0.0195)	(0.0114)	(0.0192)	(0.0013)	(0.0006)	(0.0012)

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Table 1.5 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
39 - 42 km × Post Policy = 1	-0.0211	-0.0211*	-0.0211**	-0.0011	-0.0011*	-0.0011**
	(0.0195)	(0.0114)	(0.0085)	(0.0013)	(0.0006)	(0.0005)
Constant	14.25***			2.569***		
	(0.0087)			(0.0006)		
Post Policy = 1	0.2426***			0.0282***		
	(0.0137)			(0.0009)		
Fixed-effects						
id		Yes	Yes		Yes	Yes
time.x		Yes	Yes		Yes	Yes
site_id-month			Yes			Yes
Dependent Variables Mean		14.25			2.569	
Observations		205,051			205,051	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 1.6: Estimated coefficients for $PM_{2.5}$ Concentration using Triple Difference Specification for ALL Waste Sites

Dependent Variables:	$PM_{2.5}$ Concentration			ln($PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	5.273***			0.2808***		
	(0.0232)			(0.0014)		
3 - 6 km	4.028***			0.2247***		
	(0.0169)			(0.0010)		
6 - 9 km	3.446***			0.1968***		
	(0.0152)			(0.0009)		
9 - 12 km	2.898***			0.1708***		
	(0.0144)			(0.0009)		
12 - 15 km	2.522***			0.1503***		
	(0.0140)			(0.0009)		
15 - 18 km	2.157***			0.1294***		
	(0.0139)			(0.0009)		
18 - 21 km	1.752***			0.1054***		
	(0.0138)			(0.0008)		
21 - 24 km	1.436***			0.0868***		
	(0.0138)			(0.0008)		
24 - 27 km	1.173***			0.0702***		
	(0.0138)			(0.0008)		
27 - 30 km	0.9881***			0.0572***		
	(0.0138)			(0.0008)		
30 - 33 km	0.8162***			0.0448***		
	(0.0139)			(0.0009)		
33 - 36 km	0.5961***			0.0299***		
	(0.0140)			(0.0009)		
36 - 39 km	0.3326***			0.0150***		
	(0.0140)			(0.0009)		
39 - 42 km	0.1256***			0.0060***		
	(0.0141)			(0.0009)		
Downwind = 1	-0.0503***	0.3534***	0.1573	0.0007	0.0250***	0.0149
	(0.0194)	(0.0153)	(0.1916)	(0.0012)	(0.0011)	(0.0126)
0 - 3 km × Downwind = 1	-0.8421***	-0.3567***	-0.2778*	-0.0457***	-0.0275***	-0.0229**
	(0.0438)	(0.0398)	(0.1593)	(0.0027)	(0.0023)	(0.0101)
3 - 6 km × Downwind = 1	-0.7583***	-0.4336***	-0.2834*	-0.0416***	-0.0278***	-0.0202**
	(0.0319)	(0.0261)	(0.1513)	(0.0020)	(0.0017)	(0.0098)
6 - 9 km × Downwind = 1	-0.7593***	-0.5006***	-0.3096**	-0.0410***	-0.0295***	-0.0204**
	(0.0287)	(0.0229)	(0.1462)	(0.0018)	(0.0015)	(0.0095)
9 - 12 km × Downwind = 1	-0.5358***	-0.5106***	-0.3288**	-0.0300***	-0.0302***	-0.0215**
	(0.0273)	(0.0217)	(0.1406)	(0.0017)	(0.0015)	(0.0091)
12 - 15 km × Downwind = 1	-0.5145***	-0.4841***	-0.3262**	-0.0303***	-0.0278***	-0.0205**
	(0.0267)	(0.0213)	(0.1322)	(0.0016)	(0.0015)	(0.0086)
15 - 18 km × Downwind = 1	-0.4962***	-0.4367***	-0.3061**	-0.0301***	-0.0251***	-0.0192**
	(0.0265)	(0.0211)	(0.1249)	(0.0016)	(0.0014)	(0.0081)
18 - 21 km × Downwind = 1	-0.3490***	-0.3665***	-0.2723**	-0.0221***	-0.0224***	-0.0185**
	(0.0264)	(0.0209)	(0.1132)	(0.0016)	(0.0014)	(0.0074)
21 - 24 km × Downwind = 1	-0.2477***	-0.2899***	-0.2263**	-0.0167***	-0.0186***	-0.0163**
	(0.0264)	(0.0210)	(0.1019)	(0.0016)	(0.0015)	(0.0066)
24 - 27 km × Downwind = 1	-0.2707***	-0.2146***	-0.1759*	-0.0181***	-0.0148***	-0.0136**
	(0.0265)	(0.0211)	(0.0907)	(0.0016)	(0.0015)	(0.0058)
27 - 30 km × Downwind = 1	-0.2236***	-0.1491***	-0.1432*	-0.0128***	-0.0098***	-0.0101**
	(0.0267)	(0.0212)	(0.0784)	(0.0016)	(0.0015)	(0.0050)
30 - 33 km × Downwind = 1	-0.1187***	-0.1140***	-0.1271**	-0.0044***	-0.0072***	-0.0082**
	(0.0269)	(0.0213)	(0.0644)	(0.0017)	(0.0015)	(0.0040)
33 - 36 km × Downwind = 1	-0.0576**	-0.0703***	-0.1015*	0.0004	-0.0043***	-0.0058*
	(0.0271)	(0.0214)	(0.0542)	(0.0017)	(0.0015)	(0.0032)

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Table 1.6 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
36 - 39 km × Downwind = 1	0.0374	-0.0587***	-0.0685	0.0052***	-0.0036**	-0.0036
	(0.0272)	(0.0215)	(0.0418)	(0.0017)	(0.0015)	(0.0023)
39 - 42 km × Downwind = 1	-0.0135	-0.0258	-0.0269	0.0003	-0.0011	-0.0010
	(0.0274)	(0.0217)	(0.0203)	(0.0017)	(0.0015)	(0.0012)
0 - 3 km × Post Policy = 1	1.001***	1.035***	1.119***	0.0276***	0.0288***	0.0339***
	(0.0367)	(0.0299)	(0.1115)	(0.0023)	(0.0013)	(0.0060)
3 - 6 km × Post Policy = 1	0.4267***	0.4775***	0.5463***	0.0101***	0.0126***	0.0169***
	(0.0268)	(0.0171)	(0.1027)	(0.0016)	(0.0009)	(0.0058)
6 - 9 km × Post Policy = 1	0.2090***	0.2669***	0.3392***	0.0025*	0.0056***	0.0101*
	(0.0240)	(0.0140)	(0.0993)	(0.0015)	(0.0008)	(0.0056)
9 - 12 km × Post Policy = 1	0.1492***	0.1894***	0.2573***	0.0010	0.0032***	0.0075
	(0.0228)	(0.0128)	(0.0940)	(0.0014)	(0.0007)	(0.0054)
12 - 15 km × Post Policy = 1	0.1001***	0.1277***	0.1855**	-0.0003	0.0013*	0.0050
	(0.0222)	(0.0123)	(0.0865)	(0.0014)	(0.0007)	(0.0050)
15 - 18 km × Post Policy = 1	0.0536**	0.0734***	0.1279	-0.0014	-0.0003	0.0033
	(0.0219)	(0.0120)	(0.0783)	(0.0013)	(0.0007)	(0.0046)
18 - 21 km × Post Policy = 1	0.0267	0.0401***	0.0858	-0.0015	-0.0008	0.0022
	(0.0218)	(0.0119)	(0.0700)	(0.0013)	(0.0007)	(0.0041)
21 - 24 km × Post Policy = 1	-0.0022	0.0160	0.0513	-0.0018	-0.0008	0.0015
	(0.0217)	(0.0118)	(0.0620)	(0.0013)	(0.0007)	(0.0037)
24 - 27 km × Post Policy = 1	-0.0409*	-0.0220*	0.0040	-0.0031**	-0.0020***	-7.36×10^{-5}
	(0.0217)	(0.0118)	(0.0544)	(0.0013)	(0.0007)	(0.0033)
27 - 30 km × Post Policy = 1	-0.0736***	-0.0520***	-0.0321	-0.0048***	-0.0034***	-0.0017
	(0.0218)	(0.0118)	(0.0461)	(0.0013)	(0.0007)	(0.0028)
30 - 33 km × Post Policy = 1	-0.0904***	-0.0673***	-0.0530	-0.0047***	-0.0033***	-0.0021
	(0.0219)	(0.0119)	(0.0368)	(0.0013)	(0.0007)	(0.0023)
33 - 36 km × Post Policy = 1	-0.0905***	-0.0670***	-0.0597**	-0.0044***	-0.0030***	-0.0023
	(0.0221)	(0.0120)	(0.0282)	(0.0014)	(0.0007)	(0.0017)
36 - 39 km × Post Policy = 1	-0.0821***	-0.0616***	-0.0615***	-0.0040***	-0.0027***	-0.0024**
	(0.0222)	(0.0121)	(0.0202)	(0.0014)	(0.0007)	(0.0012)
39 - 42 km × Post Policy = 1	-0.0413*	-0.0335***	-0.0324***	-0.0021	-0.0016**	-0.0015**
	(0.0223)	(0.0122)	(0.0096)	(0.0014)	(0.0007)	(0.0006)
Downwind = 1 × Post Policy = 1	-0.3496***	-0.5403***	-0.2271	-0.0199***	-0.0310***	-0.0108
	(0.0308)	(0.0193)	(0.2233)	(0.0019)	(0.0013)	(0.0144)
0 - 3 km × Downwind = 1 × Post Policy = 1	0.7428***	0.6448***	0.3249	0.0410***	0.0380***	0.0186
	(0.0694)	(0.0604)	(0.2079)	(0.0043)	(0.0030)	(0.0120)
3 - 6 km × Downwind = 1 × Post Policy = 1	0.8136***	0.6585***	0.3920**	0.0437***	0.0364***	0.0197*
	(0.0506)	(0.0367)	(0.1966)	(0.0031)	(0.0021)	(0.0117)
6 - 9 km × Downwind = 1 × Post Policy = 1	0.8722***	0.6954***	0.4170**	0.0471***	0.0379***	0.0205*
	(0.0455)	(0.0315)	(0.1894)	(0.0028)	(0.0019)	(0.0114)
9 - 12 km × Downwind = 1 × Post Policy = 1	0.7942***	0.6761***	0.4130**	0.0440***	0.0376***	0.0210*
	(0.0433)	(0.0292)	(0.1805)	(0.0027)	(0.0018)	(0.0109)
12 - 15 km × Downwind = 1 × Post Policy = 1	0.6548***	0.5770***	0.3499**	0.0372***	0.0327***	0.0183*
	(0.0424)	(0.0280)	(0.1668)	(0.0026)	(0.0018)	(0.0103)
15 - 18 km × Downwind = 1 × Post Policy = 1	0.5901***	0.5384***	0.3232**	0.0333***	0.0305***	0.0164*
	(0.0420)	(0.0273)	(0.1546)	(0.0026)	(0.0018)	(0.0096)
18 - 21 km × Downwind = 1 × Post Policy = 1	0.5144***	0.4822***	0.2976**	0.0294***	0.0278***	0.0155*
	(0.0418)	(0.0271)	(0.1414)	(0.0026)	(0.0018)	(0.0089)
21 - 24 km × Downwind = 1 × Post Policy = 1	0.4535***	0.3997***	0.2537**	0.0263***	0.0234***	0.0136*
	(0.0418)	(0.0270)	(0.1284)	(0.0026)	(0.0018)	(0.0080)
24 - 27 km × Downwind = 1 × Post Policy = 1	0.3803***	0.3191***	0.2106*	0.0232***	0.0194***	0.0115
	(0.0420)	(0.0270)	(0.1125)	(0.0026)	(0.0018)	(0.0070)
27 - 30 km × Downwind = 1 × Post Policy = 1	0.3666***	0.2902***	0.2084**	0.0221***	0.0172***	0.0106*
	(0.0423)	(0.0271)	(0.0963)	(0.0026)	(0.0018)	(0.0060)
30 - 33 km × Downwind = 1 × Post Policy = 1	0.3331***	0.2482***	0.1894**	0.0192***	0.0140***	0.0091*
	(0.0426)	(0.0272)	(0.0812)	(0.0026)	(0.0018)	(0.0049)
33 - 36 km × Downwind = 1 × Post Policy = 1	0.2773***	0.1890***	0.1579**	0.0160***	0.0106***	0.0076*
	(0.0429)	(0.0273)	(0.0675)	(0.0026)	(0.0018)	(0.0040)
36 - 39 km × Downwind = 1 × Post Policy = 1	0.2008***	0.1238***	0.1200**	0.0120***	0.0072***	0.0058**

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Table 1.6 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0432)	(0.0272)	(0.0492)	(0.0027)	(0.0018)	(0.0028)
39 - 42 km $\times$ Downwind = 1 $\times$ Post Policy = 1	0.0949**	0.0653**	0.0596**	0.0052*	0.0032*	0.0026*
	(0.0435)	(0.0272)	(0.0239)	(0.0027)	(0.0018)	(0.0015)
Post Policy = 1	0.1014***			0.0191***		
	(0.0158)			(0.0010)		
Fixed-effects						
id		Yes	Yes		Yes	Yes
time.x		Yes	Yes		Yes	Yes
site_id-month			Yes			Yes
Dependent Variable Mean		15.21			2.614	
Observations		438,270			438,270	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 1.7: Estimated coefficients for $PM_{2.5}$ Concentration using Triple Difference Specification for Waste Sites Near Waste Receiving Ports

Dependent Variables:	$PM_{2.5}$ Concentration			ln($PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	4.441***			0.2321***		
	(0.0372)			(0.0022)		
3 - 6 km	3.490***			0.1936***		
	(0.0291)			(0.0017)		
6 - 9 km	3.102***			0.1753***		
	(0.0269)			(0.0016)		
9 - 12 km	2.546***			0.1503***		
	(0.0259)			(0.0015)		
12 - 15 km	2.261***			0.1348***		
	(0.0255)			(0.0015)		
15 - 18 km	2.039***			0.1221***		
	(0.0254)			(0.0015)		
18 - 21 km	1.666***			0.1008***		
	(0.0255)			(0.0015)		
21 - 24 km	1.431***			0.0867***		
	(0.0257)			(0.0015)		
24 - 27 km	1.281***			0.0761***		
	(0.0258)			(0.0015)		
27 - 30 km	1.275***			0.0722***		
	(0.0262)			(0.0015)		
30 - 33 km	1.286***			0.0687***		
	(0.0267)			(0.0016)		
33 - 36 km	1.071***			0.0517***		
	(0.0271)			(0.0016)		
36 - 39 km	0.6651***			0.0291***		
	(0.0275)			(0.0016)		
39 - 42 km	0.1946***			0.0090***		
	(0.0278)			(0.0016)		
Downwind = 1	-1.026***	0.2470***	0.2246	-0.0749***	0.0058***	0.0146
	(0.0370)	(0.0271)	(0.2738)	(0.0022)	(0.0019)	(0.0188)
0 - 3 km × Downwind = 1	-1.170***	-0.2865***	-0.3761	-0.0414***	-0.0119***	-0.0233
	(0.0684)	(0.0487)	(0.2430)	(0.0040)	(0.0030)	(0.0160)
3 - 6 km × Downwind = 1	-1.109***	-0.4565***	-0.4302*	-0.0409***	-0.0140***	-0.0209
	(0.0529)	(0.0359)	(0.2325)	(0.0031)	(0.0025)	(0.0155)
6 - 9 km × Downwind = 1	-1.265***	-0.5301***	-0.4700**	-0.0497***	-0.0168***	-0.0220
	(0.0489)	(0.0332)	(0.2282)	(0.0029)	(0.0023)	(0.0152)
9 - 12 km × Downwind = 1	-1.103***	-0.5335***	-0.4599**	-0.0440***	-0.0182***	-0.0225
	(0.0472)	(0.0322)	(0.2226)	(0.0028)	(0.0022)	(0.0148)
12 - 15 km × Downwind = 1	-1.150***	-0.5620***	-0.4680**	-0.0498***	-0.0195***	-0.0229
	(0.0465)	(0.0321)	(0.2149)	(0.0027)	(0.0022)	(0.0142)
15 - 18 km × Downwind = 1	-1.168***	-0.5423***	-0.4437**	-0.0535***	-0.0193***	-0.0220
	(0.0464)	(0.0324)	(0.2060)	(0.0027)	(0.0023)	(0.0135)
18 - 21 km × Downwind = 1	-1.001***	-0.4607***	-0.3865**	-0.0471***	-0.0181***	-0.0212*
	(0.0467)	(0.0326)	(0.1922)	(0.0028)	(0.0023)	(0.0126)
21 - 24 km × Downwind = 1	-0.8321***	-0.4073***	-0.3369*	-0.0381***	-0.0169***	-0.0199*
	(0.0471)	(0.0331)	(0.1761)	(0.0028)	(0.0023)	(0.0115)
24 - 27 km × Downwind = 1	-0.7964***	-0.3690***	-0.3040*	-0.0364***	-0.0162***	-0.0190*
	(0.0474)	(0.0339)	(0.1608)	(0.0028)	(0.0024)	(0.0103)
27 - 30 km × Downwind = 1	-0.8075***	-0.2980***	-0.2720*	-0.0377***	-0.0126***	-0.0162*
	(0.0483)	(0.0347)	(0.1403)	(0.0029)	(0.0024)	(0.0089)
30 - 33 km × Downwind = 1	-0.6797***	-0.2675***	-0.2696**	-0.0300***	-0.0121***	-0.0154**
	(0.0493)	(0.0355)	(0.1179)	(0.0029)	(0.0025)	(0.0073)
33 - 36 km × Downwind = 1	-0.5162***	-0.1818***	-0.2201**	-0.0193***	-0.0083***	-0.0120**
	(0.0501)	(0.0362)	(0.1002)	(0.0030)	(0.0025)	(0.0058)

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Table 1.7 *(continued)*

Model:	(1)	(2)	(3)	(4)	(5)	(6)
36 - 39 km × Downwind = 1	-0.1980***	-0.1418***	-0.1629**	-0.0027	-0.0077***	-0.0095**
	(0.0508)	(0.0367)	(0.0827)	(0.0030)	(0.0025)	(0.0044)
39 - 42 km × Downwind = 1	-0.0804	-0.0267	-0.0398	-0.0011	-0.0007	-0.0017
	(0.0517)	(0.0376)	(0.0406)	(0.0031)	(0.0026)	(0.0022)
0 - 3 km × Post Policy = 1	1.548***	1.623***	1.734***	0.0633***	0.0669***	0.0699***
	(0.0588)	(0.0428)	(0.2070)	(0.0035)	(0.0017)	(0.0114)
3 - 6 km × Post Policy = 1	0.6900***	0.8020***	0.8936***	0.0343***	0.0403***	0.0431***
	(0.0461)	(0.0234)	(0.1942)	(0.0027)	(0.0012)	(0.0110)
6 - 9 km × Post Policy = 1	0.4023***	0.5403***	0.6389***	0.0220***	0.0297***	0.0332***
	(0.0426)	(0.0189)	(0.1900)	(0.0025)	(0.0011)	(0.0109)
9 - 12 km × Post Policy = 1	0.3417***	0.4625***	0.5635***	0.0186***	0.0256***	0.0293***
	(0.0411)	(0.0175)	(0.1840)	(0.0024)	(0.0010)	(0.0106)
12 - 15 km × Post Policy = 1	0.2944***	0.3868***	0.4846***	0.0166***	0.0220***	0.0256**
	(0.0404)	(0.0171)	(0.1739)	(0.0024)	(0.0010)	(0.0100)
15 - 18 km × Post Policy = 1	0.2463***	0.3160***	0.4115**	0.0142***	0.0182***	0.0221**
	(0.0403)	(0.0171)	(0.1628)	(0.0024)	(0.0010)	(0.0095)
18 - 21 km × Post Policy = 1	0.1930***	0.2413***	0.3284**	0.0118***	0.0146***	0.0181**
	(0.0406)	(0.0172)	(0.1481)	(0.0024)	(0.0010)	(0.0087)
21 - 24 km × Post Policy = 1	0.1594***	0.2007***	0.2746**	0.0108***	0.0132***	0.0160**
	(0.0408)	(0.0172)	(0.1336)	(0.0024)	(0.0010)	(0.0079)
24 - 27 km × Post Policy = 1	0.1219***	0.1544***	0.2084*	0.0090***	0.0111***	0.0130*
	(0.0410)	(0.0173)	(0.1204)	(0.0024)	(0.0010)	(0.0072)
27 - 30 km × Post Policy = 1	0.0798*	0.1184***	0.1544	0.0063**	0.0090***	0.0102
	(0.0416)	(0.0176)	(0.1032)	(0.0025)	(0.0010)	(0.0062)
30 - 33 km × Post Policy = 1	-0.0086	0.0441**	0.0689	0.0016	0.0051***	0.0060
	(0.0424)	(0.0179)	(0.0806)	(0.0025)	(0.0011)	(0.0050)
33 - 36 km × Post Policy = 1	-0.0659	-0.0103	0.0052	-0.0018	0.0018	0.0025
	(0.0431)	(0.0182)	(0.0589)	(0.0025)	(0.0011)	(0.0036)
36 - 39 km × Post Policy = 1	-0.0792*	-0.0384**	-0.0378	-0.0029	-0.0002	3.58×10^{-5}
	(0.0437)	(0.0185)	(0.0426)	(0.0026)	(0.0011)	(0.0025)
39 - 42 km × Post Policy = 1	-0.0332	-0.0217	-0.0223	-0.0009	-4.07×10^{-5}	-0.0002
	(0.0443)	(0.0187)	(0.0194)	(0.0026)	(0.0011)	(0.0012)
Downwind = 1 × Post Policy = 1	0.2653***	0.0975***	0.0881	0.0321***	0.0240***	0.0134
	(0.0581)	(0.0322)	(0.3617)	(0.0034)	(0.0023)	(0.0243)
0 - 3 km × Downwind = 1 × Post Policy = 1	0.4343***	0.2738***	-0.1111	0.0054	-0.0014	-0.0119
	(0.1081)	(0.0820)	(0.3409)	(0.0064)	(0.0042)	(0.0210)
3 - 6 km × Downwind = 1 × Post Policy = 1	0.7370***	0.4482***	0.1556	0.0185***	0.0034	-0.0047
	(0.0833)	(0.0511)	(0.3250)	(0.0049)	(0.0031)	(0.0203)
6 - 9 km × Downwind = 1 × Post Policy = 1	0.9173***	0.5522***	0.2427	0.0290***	0.0090***	-0.0010
	(0.0770)	(0.0448)	(0.3161)	(0.0045)	(0.0029)	(0.0199)
9 - 12 km × Downwind = 1 × Post Policy = 1	0.8649***	0.5535***	0.2371	0.0297***	0.0118***	0.0014
	(0.0742)	(0.0421)	(0.3032)	(0.0044)	(0.0028)	(0.0193)
12 - 15 km × Downwind = 1 × Post Policy = 1	0.7071***	0.4893***	0.1815	0.0236***	0.0110***	0.0006
	(0.0732)	(0.0408)	(0.2856)	(0.0043)	(0.0028)	(0.0184)
15 - 18 km × Downwind = 1 × Post Policy = 1	0.6079***	0.4579***	0.1578	0.0196***	0.0111***	-0.0002
	(0.0730)	(0.0403)	(0.2678)	(0.0043)	(0.0028)	(0.0174)
18 - 21 km × Downwind = 1 × Post Policy = 1	0.5243***	0.4184***	0.1453	0.0174***	0.0115***	0.0013
	(0.0734)	(0.0403)	(0.2475)	(0.0043)	(0.0028)	(0.0162)
21 - 24 km × Downwind = 1 × Post Policy = 1	0.4783***	0.3722***	0.1409	0.0167***	0.0106***	0.0028
	(0.0739)	(0.0405)	(0.2248)	(0.0044)	(0.0029)	(0.0146)
24 - 27 km × Downwind = 1 × Post Policy = 1	0.4398***	0.3532***	0.1817	0.0166***	0.0111***	0.0058
	(0.0744)	(0.0411)	(0.2035)	(0.0044)	(0.0029)	(0.0132)
27 - 30 km × Downwind = 1 × Post Policy = 1	0.4373***	0.3119***	0.1960	0.0186***	0.0100***	0.0067
	(0.0758)	(0.0424)	(0.1761)	(0.0045)	(0.0030)	(0.0114)
30 - 33 km × Downwind = 1 × Post Policy = 1	0.4812***	0.3035***	0.2235	0.0222***	0.0109***	0.0082
	(0.0774)	(0.0434)	(0.1454)	(0.0046)	(0.0031)	(0.0093)
33 - 36 km × Downwind = 1 × Post Policy = 1	0.4354***	0.2528***	0.2045*	0.0215***	0.0101***	0.0083
	(0.0786)	(0.0441)	(0.1145)	(0.0046)	(0.0031)	(0.0070)
36 - 39 km × Downwind = 1 × Post Policy = 1	0.3094***	0.1864***	0.1854**	0.0160***	0.0082***	0.0077

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Table 1.7 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0797)	(0.0442)	(0.0896)	(0.0047)	(0.0031)	(0.0052)
39 - 42 km × Downwind = 1 × Post Policy = 1	0.1127	0.0709	0.0739*	0.0036	0.0008	0.0016
	(0.0811)	(0.0447)	(0.0431)	(0.0048)	(0.0032)	(0.0026)
Post Policy = 1	-0.6383***			-0.0282***		
	(0.0316)			(0.0019)		
Fixed-effects						
id		Yes	Yes		Yes	Yes
time.x		Yes	Yes		Yes	Yes
site_id-month			Yes			Yes
Dependent Variable Mean		17.50			2.734	
Observations		193,818			193,818	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 1.8: Estimated coefficients for $PM_{2.5}$ Concentration using Triple Difference Specification for Waste Sites Near Non-Waste Receiving Ports

Dependent Variables:	$PM_{2.5}$ Concentration			ln($PM_{2.5}$ Concentration)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
0 - 3 km	0.9043***			0.0634***		
	(0.0339)			(0.0023)		
3 - 6 km	0.7952***			0.0583***		
	(0.0217)			(0.0015)		
6 - 9 km	0.7878***			0.0571***		
	(0.0184)			(0.0013)		
9 - 12 km	0.7006***			0.0516***		
	(0.0169)			(0.0012)		
12 - 15 km	0.5553***			0.0419***		
	(0.0161)			(0.0011)		
15 - 18 km	0.4647***			0.0352***		
	(0.0155)			(0.0011)		
18 - 21 km	0.4131***			0.0299***		
	(0.0152)			(0.0010)		
21 - 24 km	0.3407***			0.0246***		
	(0.0149)			(0.0010)		
24 - 27 km	0.2500***			0.0175***		
	(0.0146)			(0.0010)		
27 - 30 km	0.2044***			0.0136***		
	(0.0145)			(0.0010)		
30 - 33 km	0.1652***			0.0098***		
	(0.0143)			(0.0010)		
33 - 36 km	0.1140***			0.0061***		
	(0.0143)			(0.0010)		
36 - 39 km	0.0270*			0.0007		
	(0.0143)			(0.0010)		
39 - 42 km	0.0258*			0.0012		
	(0.0143)			(0.0010)		
Downwind = 1	0.3713***	0.4651***	0.1006	0.0425***	0.0361***	0.0111
	(0.0198)	(0.0190)	(0.2917)	(0.0013)	(0.0013)	(0.0199)
0 - 3 km × Downwind = 1	0.3791***	0.0723	0.3298*	0.0017	-0.0115***	0.0091
	(0.0690)	(0.0678)	(0.1683)	(0.0047)	(0.0044)	(0.0110)
3 - 6 km × Downwind = 1	0.3864***	0.0642	0.3124*	0.0020	-0.0097***	0.0103
	(0.0439)	(0.0436)	(0.1624)	(0.0030)	(0.0029)	(0.0106)
6 - 9 km × Downwind = 1	0.4678***	0.0790**	0.2792*	0.0092***	-0.0059**	0.0097
	(0.0372)	(0.0375)	(0.1482)	(0.0025)	(0.0025)	(0.0097)
9 - 12 km × Downwind = 1	0.5531***	0.0628*	0.2207	0.0170***	-0.0045*	0.0077
	(0.0342)	(0.0352)	(0.1367)	(0.0023)	(0.0023)	(0.0088)
12 - 15 km × Downwind = 1	0.5030***	0.0761**	0.1528	0.0170***	-0.0019	0.0049
	(0.0325)	(0.0337)	(0.1231)	(0.0022)	(0.0022)	(0.0080)
15 - 18 km × Downwind = 1	0.3872***	0.0662**	0.0986	0.0130***	-0.0013	0.0024
	(0.0313)	(0.0321)	(0.1160)	(0.0021)	(0.0022)	(0.0076)
18 - 21 km × Downwind = 1	0.3772***	0.0937***	0.0850	0.0139***	0.0014	0.0022
	(0.0304)	(0.0311)	(0.1027)	(0.0021)	(0.0021)	(0.0065)
21 - 24 km × Downwind = 1	0.3081***	0.1248***	0.0844	0.0099***	0.0039*	0.0030
	(0.0297)	(0.0302)	(0.0920)	(0.0020)	(0.0021)	(0.0058)
24 - 27 km × Downwind = 1	0.2517***	0.1186***	0.0876	0.0078***	0.0040**	0.0034
	(0.0292)	(0.0296)	(0.0814)	(0.0020)	(0.0020)	(0.0051)
27 - 30 km × Downwind = 1	0.2847***	0.1110***	0.0845	0.0146***	0.0058***	0.0047
	(0.0288)	(0.0288)	(0.0681)	(0.0020)	(0.0020)	(0.0044)
30 - 33 km × Downwind = 1	0.2673***	0.1058***	0.0870	0.0166***	0.0063***	0.0056
	(0.0285)	(0.0282)	(0.0585)	(0.0019)	(0.0020)	(0.0037)
33 - 36 km × Downwind = 1	0.1742***	0.0686**	0.0480	0.0127***	0.0046**	0.0038
	(0.0284)	(0.0278)	(0.0470)	(0.0019)	(0.0019)	(0.0029)

Continued on next page

Table 1.8 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
36 - 39 km × Downwind = 1	0.1265***	0.0267	0.0228	0.0097***	0.0020	0.0023
	(0.0283)	(0.0275)	(0.0334)	(0.0019)	(0.0019)	(0.0020)
39 - 42 km × Downwind = 1	0.0363	-0.0039	-0.0007	0.0031	9.72×10^{-7}	0.0004
	(0.0282)	(0.0272)	(0.0155)	(0.0019)	(0.0019)	(0.0010)
0 - 3 km × Post Policy = 1	0.3399***	0.3540***	0.4067***	0.0061*	0.0069***	0.0108
	(0.0535)	(0.0441)	(0.1233)	(0.0036)	(0.0022)	(0.0071)
3 - 6 km × Post Policy = 1	0.2879***	0.3030***	0.3517***	0.0051**	0.0062***	0.0098
	(0.0341)	(0.0257)	(0.1154)	(0.0023)	(0.0014)	(0.0068)
6 - 9 km × Post Policy = 1	0.2526***	0.2491***	0.2994***	0.0043**	0.0044***	0.0081
	(0.0290)	(0.0212)	(0.1071)	(0.0020)	(0.0012)	(0.0063)
9 - 12 km × Post Policy = 1	0.1676***	0.1541***	0.2055**	0.0024	0.0020*	0.0057
	(0.0266)	(0.0182)	(0.0966)	(0.0018)	(0.0011)	(0.0058)
12 - 15 km × Post Policy = 1	0.0903***	0.0771***	0.1093	0.0004	-3.81×10^{-5}	0.0024
	(0.0253)	(0.0167)	(0.0837)	(0.0017)	(0.0010)	(0.0052)
15 - 18 km × Post Policy = 1	0.0475*	0.0357**	0.0605	-0.0006	-0.0011	0.0009
	(0.0244)	(0.0159)	(0.0744)	(0.0017)	(0.0010)	(0.0046)
18 - 21 km × Post Policy = 1	0.0338	0.0224	0.0399	-0.0005	-0.0009	0.0008
	(0.0239)	(0.0155)	(0.0667)	(0.0016)	(0.0010)	(0.0041)
21 - 24 km × Post Policy = 1	0.0097	0.0052	0.0153	-0.0010	-0.0009	0.0003
	(0.0233)	(0.0152)	(0.0600)	(0.0016)	(0.0009)	(0.0038)
24 - 27 km × Post Policy = 1	-0.0180	-0.0237	-0.0054	-0.0017	-0.0018*	-7.43×10^{-6}
	(0.0230)	(0.0149)	(0.0529)	(0.0016)	(0.0009)	(0.0034)
27 - 30 km × Post Policy = 1	-0.0538**	-0.0629***	-0.0359	-0.0038**	-0.0041***	-0.0017
	(0.0227)	(0.0147)	(0.0446)	(0.0015)	(0.0009)	(0.0030)
30 - 33 km × Post Policy = 1	-0.0595***	-0.0681***	-0.0400	-0.0032**	-0.0036***	-0.0013
	(0.0226)	(0.0146)	(0.0385)	(0.0015)	(0.0009)	(0.0026)
33 - 36 km × Post Policy = 1	-0.0578**	-0.0639***	-0.0430	-0.0029*	-0.0032***	-0.0016
	(0.0225)	(0.0147)	(0.0300)	(0.0015)	(0.0009)	(0.0020)
36 - 39 km × Post Policy = 1	-0.0556**	-0.0582***	-0.0457**	-0.0028*	-0.0029***	-0.0020
	(0.0224)	(0.0146)	(0.0212)	(0.0015)	(0.0009)	(0.0014)
39 - 42 km × Post Policy = 1	-0.0302	-0.0304**	-0.0226**	-0.0017	-0.0017*	-0.0011*
	(0.0225)	(0.0146)	(0.0099)	(0.0015)	(0.0009)	(0.0007)
Downwind = 1 × Post Policy = 1	-0.7095***	-0.7083***	-0.1994	-0.0507***	-0.0516***	-0.0120
	(0.0317)	(0.0234)	(0.3300)	(0.0022)	(0.0015)	(0.0216)
0 - 3 km × Downwind = 1 × Post Policy = 1	0.3543***	0.2829***	0.1009	0.0270***	0.0235***	0.0101
	(0.1098)	(0.1033)	(0.2547)	(0.0075)	(0.0053)	(0.0150)
3 - 6 km × Downwind = 1 × Post Policy = 1	0.2622***	0.1854***	0.0219	0.0217***	0.0169***	0.0050
	(0.0699)	(0.0603)	(0.2413)	(0.0048)	(0.0033)	(0.0145)
6 - 9 km × Downwind = 1 × Post Policy = 1	0.1693***	0.1669***	-0.0002	0.0163***	0.0152***	0.0034
	(0.0594)	(0.0502)	(0.2222)	(0.0040)	(0.0028)	(0.0131)
9 - 12 km × Downwind = 1 × Post Policy = 1	0.1336**	0.1689***	-0.0024	0.0125***	0.0134***	0.0014
	(0.0547)	(0.0451)	(0.2067)	(0.0037)	(0.0025)	(0.0120)
12 - 15 km × Downwind = 1 × Post Policy = 1	0.0179	0.0520	-0.0340	0.0061*	0.0070***	0.0005
	(0.0520)	(0.0409)	(0.1806)	(0.0035)	(0.0024)	(0.0110)
15 - 18 km × Downwind = 1 × Post Policy = 1	0.0037	0.0364	-0.0245	0.0047	0.0056**	0.0008
	(0.0500)	(0.0382)	(0.1627)	(0.0034)	(0.0023)	(0.0100)
18 - 21 km × Downwind = 1 × Post Policy = 1	-0.0424	-0.0101	-0.0509	0.0021	0.0029	-0.0016
	(0.0486)	(0.0369)	(0.1455)	(0.0033)	(0.0022)	(0.0088)
21 - 24 km × Downwind = 1 × Post Policy = 1	-0.0976**	-0.0898**	-0.1012	-0.0009	-0.0017	-0.0044
	(0.0475)	(0.0356)	(0.1313)	(0.0032)	(0.0022)	(0.0078)
24 - 27 km × Downwind = 1 × Post Policy = 1	-0.1032**	-0.0868**	-0.1342	-0.0017	-0.0018	-0.0069
	(0.0467)	(0.0347)	(0.1172)	(0.0032)	(0.0021)	(0.0070)
27 - 30 km × Downwind = 1 × Post Policy = 1	-0.0335	-0.0052	-0.0917	0.0009	0.0018	-0.0061
	(0.0462)	(0.0341)	(0.1024)	(0.0031)	(0.0021)	(0.0061)
30 - 33 km × Downwind = 1 × Post Policy = 1	-0.0260	0.0007	-0.0959	-0.0005	0.0006	-0.0071
	(0.0456)	(0.0336)	(0.0930)	(0.0031)	(0.0021)	(0.0053)
33 - 36 km × Downwind = 1 × Post Policy = 1	-0.0098	0.0099	-0.0541	-0.0004	0.0004	-0.0047
	(0.0455)	(0.0335)	(0.0795)	(0.0031)	(0.0021)	(0.0044)
36 - 39 km × Downwind = 1 × Post Policy = 1	0.0219	0.0268	-0.0080	0.0015	0.0015	-0.0012

Continued on next page

Table 1.8 (continued)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0452)	(0.0333)	(0.0563)	(0.0031)	(0.0021)	(0.0031)
39 - 42 km $\times$ Downwind $=1$ $\times$ Post Policy $=1$	0.0286	0.0271	0.0030	0.0019	0.0017	-8.01×10^{-5}
	(0.0451)	(0.0332)	(0.0243)	(0.0031)	(0.0021)	(0.0015)
Post Policy $=1$	0.4216***	0.4228***	0.2929**	0.0412***	0.0414***	0.0313***
	(0.0158)	(0.0103)	(0.1446)	(0.0011)	(0.0006)	(0.0091)
Fixed-effects						
id		Yes	Yes		Yes	Yes
site_id-month			Yes			Yes
Dependent Variable Mean		14.15			2.558	
Observations		205,051			205,051	

Note: Estimated using equation 3. Bin 40-43km is the reference period and Upwind.
If indicated, models include fixed effects for cell ID, time period, and site-by-month.
***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Chapter 2

Roads to the Market or the Town Hall? New Evidence from India's PMGSY[1]

§ 2.1 Introduction

While global poverty has decreased substantially in recent decades, approximately 700 million people continue to experience extreme poverty, and 79% of these individuals live in rural areas (World Bank, 2024). Poor people in rural areas are often isolated from pathways out of poverty, in part because of a lack of basic infrastructure and connectivity to external markets. Poor road connectivity is often considered a major barrier to poverty reduction and development in rural areas (Banerjee et al., 2020). This has spurred infrastructure investments to improve connectivity and catalyze development in many countries.

We examine how rural road connectivity spurs development in the context of the world's largest rural road construction program, Pradhan Mantri Gram Sadak Yojana (PMGSY) in India. The PMGSY program, launched in 2000, provides all-weather road connectivity to unconnected villages and, to date, has connected more than

[1]This is joint work with Santosh Kumar Gautam (Keough School of Global Affairs, University of Notre Dame), and Ariel Zucker (Department of Economics, University of California Santa Cruz)

170,000 villages at a cost of $45 billion (MORD, 2023). While a growing body of research examines rural roads' impacts on village economies and household welfare (e.g., Aggarwal, 2018; Asher and Novosad, 2020; Chaurey and Le, 2022; Dasgupta et al., 2024; Shamdasani, 2021; Dumas and Játiva, 2024; Gautam et al., 2025), methodological and data constraints limit our understanding of these impacts. In particular, while the program aims to connect villages to a range of hubs – markets, tourist areas, schools, health facilities, and government headquarters – previous work has not examined whether connectivity impacted governance. We evaluate the impacts of this program using unique village-level microdata collected in 267 villages in Uttar Pradesh (UP), with a particular focus on an understudied channel through which roads shape rural development: their effect on government presence, political connectivity, and the quality of public service delivery.

A unique feature of the PMGSY program is that the priority for connecting a given village was determined in part by population size, allowing us to address the usual challenge of endogenous road placement. In particular, road connection plans were made at the district level to prioritize connecting larger populations first. Thus, across districts, unconnected villages of similar size had very different priority rankings depending on how many larger villages in their district were also unconnected. We exploit this variation using an Instrumental Variables (IV) approach to estimate the causal impacts of connectivity through a paved road on economic, social, and institutional outcomes at the village level. We instrument for road connectivity using the village's population rank within all unconnected villages in its district, controlling for population size.

Our empirical strategy is similar in spirit to prior evaluations of PMGSY that exploit the quasi-random variation in the roll-out of the program but differs in important ways. To our knowledge, this study is the first to use variation in the population rank to study the impacts of PMGSY roads. In particular, previous work has exploited national guidelines suggesting that habitations with populations first above 1,000 and then above 500 be prioritized in respective waves of construction.[1] Our approach uses a village's position in the within-district ordering of unconnected villages. Thus, two villages with the same population can have different ranks depending on whether they are located in a district with many or few larger unconnected villages. This allows us to identify the causal effect of PMGSY in a state that did not comply with the aforementioned PMGSY population guidelines.[2]

Furthermore, we use a novel primary village-level survey dataset designed and collected around the PMGSY roll-out years. This dataset has a number of advantages relative to previous work. First, it includes direct information on a wide range of outcomes, including prices, wages, migration patterns, and governance. Second, it includes village-level information on outcomes such as land quality that are only available at the district level in secondary datasets.[3] Finally, we are able to assess the medium-term impacts of roads, as the data were collected 2–3 years after the completion of the road.

We investigate the impacts of roads on agricultural, labor market, and governance

[1]E.g., Asher and Novosad (2020) and Garg et al. (2024) use a fuzzy regression discontinuity design comparing villages across the 1,000 and 500 population cut-offs, Aggarwal (2018) and Aggarwal (2021) use cross-district and -time variation in the fraction of villages reached by the program; and Adukia et al. (2020) and Shamdasani (2021) examine PMGSY roll-out controlling for village and time fixed effects.

[2]Notably, the official program description allowed for exceptions to the population threshold guidelines in order to promote connectivity to administrative, market, educational, health, or tourist centers (NRRDA, 2003). Asher and Novosad (2020) identify six states that did comply with these guidelines, noting that UP "built many [PMGSY] roads but did not follow the rules at all." Specifically, they identify non-compliant states first through conversations with officials at the National Rural Roads Development Agency, and then verify that crossing the 500- or 1,000-person threshold does not sharply increase the probability of receiving a road in these states. UP's non-compliance with the threshold guidance does not threaten the validity of our instrument.

[3]Studies conducted at the district level must assume that the fraction of connected villages in a district is not correlated with changes in the outcome over time.

outcomes. Our central finding is that road connectivity substantially strengthens the local state: we find a 1.1 SD increase in an index of government official visits and police activity, a 0.9 SD increase in political connectivity, higher wages on government construction projects, and lower prices at government-run ration shops[1]; a pattern we interpret as evidence of reduced corruption and improved oversight.

Alongside these governance effects, we extend prior findings on agriculture and labor markets. We confirm that roads shift labor away from agriculture (Asher and Novosad, 2020; Shamdasani, 2021; Garg et al., 2024) without clearly impacting agricultural inputs or yields.[2] At the same time, we find novel evidence that farmers benefit from higher prices while also allowing the development of a more diverse portfolio of village agricultural activities (particularly animal husbandry).

Turning to the labor market, we dive more deeply than previous literature into how the exit from agriculture plays out. Our evidence confirms that the importance of casual labor increases. However, we find that the location of new labor opportunities is almost exclusively within the village. Despite presumably increasing access to local labor markets outside the village, road construction actually decreases short-term migration and casual labor outside the village, with an index of migration declining by 0.8 SD. Moreover, while local labor supply increases, we find no evidence of wage decreases; in fact, point estimates suggest that wages within the village increase across the board,[3] with large and statistically significant impacts on wages in government

[1]This finding is broadly in line with Aggarwal (2018), who finds that aggregated consumer prices decrease. Our results suggest that overall price declines are due in part to local ration shops. We do not see evidence of (non-governmental) consumer price changes at the nearest market, though the point estimate on an index of prices is negative (Table B.6). Most villages in our sample do not report local non-fair shop consumer prices.

[2]Existing evidence on how roads impact agricultural technology adoption and inputs is somewhat mixed:Asher and Novosad (2020) finds null effects, but Shamdasani (2021) find that remote villages which were connected earlier had faster agricultural technology adoption and Aggarwal (2018) find that districts with more connected villages have faster growth in agricultural technology adoption.

[3]Our results are in line with, but noisier than, Garg et al. (2024), which finds that PMGSY

construction projects. Overall, this points to the fact that connectivity to external markets enriches the local economies of connected villages, rather than draining them of workers.

§ 2.2 Rural Roads in India: Pradhan Mantri Gram Sadak Yojana (PMGSY)

The PMGSY is a flagship rural road program launched by the Government of India (GoI) in 2000 with the aim of reducing poverty in unconnected villages. At its inception, around 330,000 of India's 825,000 villages lacked all-weather road connectivity (NRRDA, 2005), and the program initially focused on connecting large unconnected villages to support agrarian market access (NRRDA, 2003). By 2013, most such villages were connected, and the focus shifted to improving and maintaining rural roads. To date, PMGSY has significantly improved rural connectivity in India, with more than 742,000 kilometers of rural roads constructed or upgraded and more than 170,000 habitations connected at an estimated investment of $45 billion (MORD, 2022; MORD, 2023).

We study the initial road-building iteration of the PMGSY road program, now known as PMGSY-I, under which roads linking unconnected villages were sanctioned and constructed in sequential phases from 2000-2013. The villages selected for connectivity in each phase were prioritized in part according to the population size of the village or cluster of villages (habitation), with larger villages receiving higher priority. For example, the earliest phases of construction (2000–2003) aimed to connect all unconnected villages with a 2001 census population of 1,000 or more, with subsequent

increases local agricultural wages in other states of India.

waves targeting villages of 500 or more (by 2007) and eventually 250 or more (until 2013),and official guidelines recommended that preference generally be given to road segments serving larger populations (NRRDA, 2003).

However, population was not the only factor. Official guidelines emphasized completing a "Core Network" connecting villages to basic services. Funds were not available for land acquisition or road repair, making some connections infeasible. Moreover, factors such as political considerations, economic importance, and the type of link route may have influenced prioritization.

Despite this, the population remained the main basis for road allocation (Lehne et al., 2018). Officials prioritized unconnected villages within a district in large part according to their 2001 census population, with larger villages typically given higher priority. The within-district population criteria meant that a village had a higher probability of receiving a PMGSY road over a similar-sized village if there were fewer larger eligible villages within its district. Consequently, a village in a district with many larger unconnected villages was less likely to receive a new road, even when the population size was held constant.

§ 2.3 Sampling and Data

2.3.1 Setting and Sample

To measure the impacts of PMGSY, we surveyed 267 villages in the 14 districts nearest Lucknow,[1] the capital of Uttar Pradesh (UP), in the summer of 2007. UP is India's fourth most populous state with over 200 million people. UP is primarily agrarian

[1]The number of districts in UP expanded from 70 to 75 in 2005. We use the pre-2005 district definitions as PMGSY was targeted using 2001 census information. The 14 districts are Bahraich, Barabanki, Faizabad, Farrukhabad, Gonda, Sultanpur, Hardoi, Kanpur Dehat, Kanpur Nagar, Lakhimpur Kheri, Rai Bareilly, Shahjahanpur, Sitapur, and Unnao.

(65% of the population depends on agriculture) with high poverty (38%) (Agriculture Department, 2020) and had the most unconnected villages before PMGSY (MORD, 2023), making it ideal for studying road connectivity impacts. However, unlike some states, UP did not comply with the population-based threshold rules at all, and thus regression discontinuity-based analyses of PMGSY have excluded it from analysis (Asher and Novosad, 2020).

The sample was chosen to represent two sets of villages with otherwise similar characteristics: those with completed PMGSY roads and those sanctioned for future PMGSY roads but with construction not yet started. To derive our sampling frame, we collected a list of villages that had already been connected or were scheduled for future connectivity between 2003 and 2006 from the PMGSY website (Ministry of Rural Development, 2023). Following PMGSY documentation at the time, we refer to villages sanctioned for future road construction in 2003–2004 as "Phase 3" villages, those in 2004–2005 as "Phase 4" villages, and those in 2005–2006 as "Phase 5" villages. At the time of the survey in 2007, most Phase 3 villages had completed road construction, many Phase 4 villages had begun construction, and most Phase 5 villages had not yet started construction. We excluded Phase 4 villages to avoid biasing our results by comparing villages with complete roads to those in the middle of the construction process. From Phase 3 and Phase 5 villages, we selected all villages within a fairly narrow population range of 950-1,175 people (as reported in the PMGSY program data).[1]

This process led to 302 villages of similar population size, which we aimed to survey. During the survey, 35 of these were dropped, primarily due to incorrect or insufficient identifying information. Of our final sample of 267 villages, 144 were Phase 3

[1]This population band was selected to ensure comparable numbers of Phase 3 and Phase 5 villages on either side of the 1,000 population threshold (the data were collected before we understood that the threshold would not bind in UP) while also accounting for budgetary constraints. Since the population distribution is not uniform, the band is not symmetrical around 1,000. The narrow band further ensures that Phase 3 and Phase 5 villages are fairly similar in population size.

and 123 were Phase 5.[1]

To examine the validity of our instrument, we conduct placebo tests in both the survey sample and in a larger sample of villages. The extended sample is constructed by matching as many Phase 3 and Phase 5 villages from the PMGSY program list to the 2001 census as possible, including villages from all districts in UP and without population restrictions. This yields a larger sample of 1,670 Phase 3 and 1,247 Phase 5 villages.

2.3.2 Data Collection and Processing

We surveyed selected villages using the rapid rural appraisal methodology (RRA), a community-based data collection approach that provides reliable village-level information in a cost-effective manner.(Chambers, 1994).[2] While RRA is less suitable for measuring private household behaviors, it is particularly appropriate when the unit of analysis is the village. It is well suited for collecting village-level information on infrastructure, agricultural activities, prices, wages, migration, governance, and public service delivery (Crawford, 1997), which are generally common knowledge within the community but difficult and costly to measure through household surveys. Responses are generated through structured discussions involving a large number of villagers, allowing individual reporting errors to be corrected through consensus and improving the reliability of village-level measures. The methodology is also highly cost-effective and has been widely used and validated in development research for collecting accurate community-level data (Franzel and Crawford, 1987; Chattopadhyay and Duflo,

[1] We show in Table B.1 that our study sample is quite representative of rural villages in UP in terms of census variables. However, our average village has some marked differences from the average rural village of India at the time, such as being geographically larger, having a larger share of SC and a smaller share of ST villagers, and being closer to a town.

[2] RRA is a field-based survey method to collect data from the local community about village infrastructures and resources.

2004).

Experienced enumerators trained in RRA methodology gathered villagers at a central village facility, such as a temple, school, or community hall. The survey was typically conducted at dusk, when most villagers had completed work. The average meeting included 132 participants, though participation varied substantially across villages.[1] The enumerators first drew a resource map of the village, marking all the roads leading to the village and the details of the homes connected by these roads, to develop a common understanding of the village's population size, boundaries, and connectivity. Subsequently, a structured questionnaire was used to gather information from the villagers. The survey team encouraged participants to respond, and relied on consensus or majority opinions for survey responses.

The survey measured income sources, migration behavior, wages, agricultural outcomes, prices, and government/political activity.[2] The survey also collected data on village connectivity by a motorable road, which serves as the independent variable in our analyses. Specifically, we ask: "Is there a motorable road to the village that a car can travel on?"[3]

Following data collection, we undertake a number of cleaning and processing steps. We group related outcomes from the village survey.[4] We then process outcomes, for example by removing implausible values and computing household shares. Finally,

[1]This represents about 10% of the village population. Meeting size ranged from 25–450 villagers (the distribution is shown in Figure B.6 of Appendix B). Moreover, participants were majority male (75% on average), and outcomes in traditionally male domains may be reported more accurately.

[2]A full list of survey questions used for analysis is in Table B.7 in Appendix B. The few outcomes that reflect household or individual conditions (e.g., migrants per household) may be less accurate.

[3]It is possible that some Phase 3 villages had not yet been connected by 2007 (e.g., because of implementation difficulties) or that some Phase 5 villages had already been connected, e.g., through other programs. Because villagers may consider some roads "motorable" despite not being improved by PMGSY, our results should be interpreted as the impact of moving from a non-motorable road to a PMGSY road (i.e., the impact of new motor connectivity), rather than the impact of improving a motorable road up to PMGSY standards. We compare our survey measure of connectivity to the PMGSY construction phase in Table B.2 of Appendix B.

[4]We exclude relevant outcomes if the survey data contained more than 50 missing entries.

where possible, we create standardized indices of related outcomes that we expect to move directionally together. Indices are computed as the unweighted averages of their standardized components following Kling et al. (2007), where missing component values were imputed to the sample mean of the corresponding component prior to standardization.

We supplement the survey data with the 2001 Census of India, which reports village-level socioeconomic and demographic characteristics prior to the announcement of the PMGSY program. We were able to match 253 of the 267 surveyed villages to census data using name and district.[1] These data serve two purposes: First, we can improve power–and potentially causal identification–by including controls from the 2001 Census in our main analyses. Second, they allow us to conduct placebo tests to confirm that the variation in road construction we exploit does not correlate with preexisting differences between villages reported in the census.

2.3.3 Descriptive Statistics

Table 2.1 provides key summary statistics. Panel A shows selected survey outcomes. Sample villages are primarily agrarian, with 57% of households earning income from their own farms and limited commercial connectivity (0.58 vehicle visits per day on average). Migration is common, averaging 1.16 migrants per household. We further summarize agricultural inputs and outcomes, wages and prices, and government and political presence.

Panel B reports baseline controls from the 2001 census among surveyed villages, including per capita income in the Gram Panchayat (GP), irrigation availability, and

[1] The unit for connectivity under PMGSY is 'habitation', defined as a cluster of populations living in an area, the location of which does not change over time. This often, but not always, corresponds to a census village.

village population. Finally, Panel C reports the endogenous and the instrumental variable used in the analysis. Specifically, we instrument the existence of a motorable road to the village, as measured in the village survey (70% of villages have one). Our instrument is the within-district population rank of the village among all unconnected villages sanctioned for road connection between 2003 and 2006 (i.e., Phase 3, 4, and 5 villages), from smallest to largest. The average population rank of villages in our sample is 76, and ranges from 7 to 192.

§ 2.4 Empirical Strategy

We aim to estimate the causal impact of road connectivity on economic and governance outcomes. However, the potential endogeneity of road placement (before or within the PMGSY program) could lead to biased estimates in an OLS regression of any given outcome on the presence of a motorable road to the village. For instance, if roads were built according to the perceived developmental potential, local officials may have chosen to connect the richer villages first — a common scenario in large infrastructure projects. In this case, the OLS coefficients for the road's impacts on development would be biased upward. To address this source of bias, we employ the conditional IV method described in the next section.

2.4.1 Instrumental Variables Approach

We instrument for motorable road access using within-district population rank among unconnected villages sanctioned for PMGSY roads in 2003–2006. National guidelines instructed district governments to prioritize larger villages first, creating quasi-random variation: among villages of equal size, those in districts with fewer larger uncon-

Table 2.1: Descriptive Statistics for Key Variables

	Summary		
	N	mean	sd
Panel A: Selected Outcome Variables			
Truck/bus/commercial visits per day	267	0.58	2.51
Share of households with primary income from own farm	267	0.57	0.50
Share of households with primary income from casual labor in village	267	0.26	0.44
Share of households with primary income from casual labor outside village	267	0.16	0.36
Agriculture daily wage (male)	265	47.94	10.64
Agriculture daily wage (female)	222	38.22	10.41
Non-government construction daily wage (male)	266	51.08	10.06
Government construction daily wage (male)	249	70.98	18.95
Migrants per household: daily	267	0.40	0.61
Migrants per household: weekly	267	0.16	0.23
Migrants per household: monthly	266	0.21	0.35
Migrants per household: yearly	266	0.39	0.68
Wheat price (INR/quintal)	259	910.33	69.51
Rice price (INR/quintal)	207	599.61	94.83
Rice yield (quintal/acre)	208	12.19	4.85
Wheat yield (quintal/acre)	259	11.75	5.63
Share of households that use chemical/fertilizer/pesticide	252	0.91	0.15
Share of households with motorized agriculture equipment	265	0.15	0.15
Village has milk cooperative	267	0.10	0.30
Village has dairy/goat rearing	266	0.09	0.28
Village has poultry farm	258	0.02	0.14
Kerosene price at fair shop	266	10.98	0.58
Rice price at fair shop	259	6.18	1.47
Wheat price at fair shop	254	5.00	1.05
Police visits last 12 months	265	36.92	64.18
Government official visits last 12 months	267	70.62	100.16
Campaign visits/events last 12 months	267	5.06	4.18
Share households receiving Hindi paper	262	0.01	0.02
Panel B: Control Variables			
Per capita panchayat income	104	72.90	98.80
Electricity for agriculture	45	1.00	0.00
Share cultivated area irrigated	194	0.76	0.25
Distance to nearest town (km)	247	12.04	10.17
Census population (thousands)	251	1.76	1.61
Panel C: Endogenous and Instrumental Variables			
Motorable road to village for cars	267	0.70	0.46
Population rank (small to large)	267	75.63	41.06

Note: Descriptive statistics for a selection of variables used in the analysis among the sample of surveyed villages. Panel A shows a selection of outcome variables constructed from the village survey data. Panel B shows the variables we include as controls from the 2001 Census of India. Panel C shows the endogenous variable, which we collect in the village survey, and the instrumental variable, which is constructed as the within-district PMGSY population rank among all Phase 3, 4, and 5 villages.

nected villages were connected earlier.

We estimate the following first-stage equation:

$$ROAD_{vd} = \alpha_0 + \alpha_1 RANK_{vd} + \alpha_2 POPULATION_{vd} + \gamma X_{vd} + \nu_{vd} \tag{2.1}$$

Where $ROAD_{vd}$ is an indicator variable for whether the village v is connected to a motorable road, $RANK_{vd}$ is rank of village v among unconnected villages in district d, $POPULATION_{vd}$ is the village population as measured in the 2001 census, and X_{vd} are village controls from the 2001 census (per-capita GP income, agricultural electricity, fraction of irrigated land, distance to the nearest town, and indicators for missing values).

In the second stage, we regress village-level outcomes of interest Y_{vd} on the predicted value of $ROAD_{vd}$ from Equation (2.1) and the same covariates:

$$Y_{vd} = \delta_0 + \delta_1 \widehat{ROAD}_{vd} + \delta_2 POPULATION_{vd} + \eta X_{vd} + \varepsilon_{vd} \tag{2.2}$$

2.4.2 Identifying Assumptions

Two key conditions must be satisfied for the instrument ($RANK_{vd}$) to be valid: relevance and exogeneity.[1] The relevance condition implies that village rank must predict road construction in the village, and is testable. The exogeneity condition implies that, conditional on the included covariates, the within-district population rank of unconnected villages is related to village outcomes only through the additional likelihood of road connectivity.

A key concern is that villages with larger populations will have a higher rank, and

[1]The third condition, monotonicity, implies that having larger within-district population rank never decreases the village's priority for road connectivity, which seems likely to hold.

larger villages will also tend to have different outcomes for a number of reasons. We allay this concern by controlling for the village population. We measure population using the 2001 census, rather than the PMGSY program data, for two reasons. First, the PMGSY population numbers were potentially manipulable by program officials (e.g., by grouping habitations together or not in order to generate support for a particular road or not), leading to endogeneity concerns. Second, surveyed villages were selected to be within a narrow band of PMGSY population (as described in Section 2.3.1), so PMGSY population is similar among our sample by design. However, our results are robust to including PMGSY population instead of census population, and to including nonlinear population controls.[1]

A second concern is that population rank could predict outcomes through other policies. This might appear especially concerning for other policies targeted on population. For example, the Total Sanitation Campaign (TSC) used population thresholds to target prizes to village chairmen for achieving "open defecation free" status (NGP in Hindi initials) beginning in 2005 (Spears, 2012), with a discontinuity in prize size at populations of 1,000.[2] Other infrastructure and programs, like Aganwadi (health care) Centers and ASHA (community health) workers, have density targets (such as 1 per 800 individuals). However, any link between our instrument and other population-based policies is substantially weakened by three facts. First, our instrument is population rank only among unconnected villages sanctioned for a PMGSY road between 2003 and 2006. Other policies would have impacted a different set of villages, with

[1]Results controlling for PMGSY population are shown in Section B.3 of Appendix B; other specifications are not shown.

[2]We are not concerned that the TSC is driving our results for other reasons. First, the NGP prize is a relatively small program: in its full run from 2005-12, only 2% of villages in UP received the prize (Kapur and Chowdhury, 2012), and fewer than 1% had received the prize by 2007. Second, despite the established link between sanitation and primary education attendance (Adukia, 2017) which could eventually shift labor markets, there is limited scope for sanitation to affect outcomes of employment, wages, or governance in only 1–2 years.

prioritization muddled by other program-specific priorities.[1] Second, our instrument is a rank variable controlling for population. Thus, we explicitly control for any continuous differences according to population that the other population-based policies we have identified (such as Aganwadi placement) rely on.

Finally, to support excludability, we conduct placebo tests examining whether rank predicts pre-program (2001 census) outcomes. If rank were confounded with factors driving development aside from roads, it would likely predict development outcomes recorded in the census. The absence of differences would further support the validity of the exclusion restriction.[2]

§ 2.5 Results

In this section, we present empirical findings that illustrate local-level adjustments following the introduction of PMGSY roads. We first examine economic outcomes that situate our study into the existing literature on PMGSY rural roads. Agricultural workers benefit from higher output prices, while those transitioning out of agriculture find better-paying jobs in local casual labor. We then examine outcomes that have received less attention in prior work: governance, political connectivity, and local service delivery. Road connectivity boosts government engagement, as seen through increased visits by government officials, and more frequent police patrols. Villagers enjoy lower prices in government-supported shops and higher wages in government-supported construction. Together, these outcomes highlight the diverse economic, social, and politi-

[1] E.g., the TSC did not exclude connected villages, but was available to any rural village with open defecation.

[2] An additional strategy would be to test if rank predicts post-program (2011 census) outcomes that we expect should not be impacted by road access. However, given the potential far-reaching impacts of road connectivity, we are not sure of outcomes that are theoretically isolated from impacts on a 4-year timescale.

cal transformations brought about by improved rural connectivity.

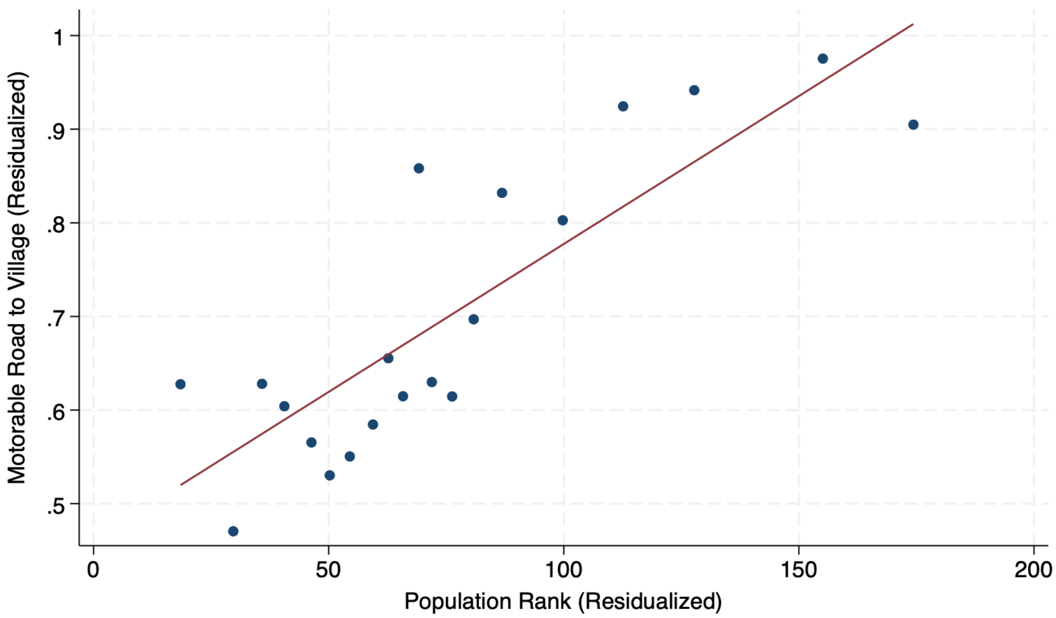
2.5.1 First Stage

Before analyzing downstream outcomes on markets and governance, we first establish the relevance of our instrument. The binscatter of our first-stage variation demonstrates that there is a remarkably linear relationship between rank and the probability of receiving a road, conditional on included census controls (Figure 2.1). The coefficient of 0.003 implies that moving one place higher in the within-district population ranking increases the probability of having a motorable road by 0.3 percentage points. While this one-rank change is small in magnitude, it is balanced by the substantial variation in rank: a one-standard-deviation increase in rank corresponds to a roughly 12 pp increase in the likelihood of road connectivity. Most importantly for our analysis, the first-stage relationship is strong, with a Kleibergen–Paap F-statistic of 16.7 (Panel A of Table B.4).

We next show suggestive evidence that motorable roads improved the connectivity of villages, the key mechanism through which we expect roads to impact village outcomes. The best available proxy for connectivity in our survey data is the volume of commercial vehicles (like trucks and buses). A caveat is that by far the most common forms of transportation for key village activities are bicycling and walking, while motorized transit is incredibly rare (Table B.3 in Appendix B). Because the presence of commercial vehicles is extremely rare and skewed in our sample (daily vehicle visits are reported to be exactly zero for 225 of 267 villages), this outcome is noisy and unlikely to comprehensively capture road connectivity.

Nonetheless, the 2SLS results in Panel B of Table B.4 show suggestive evidence that connecting villages with a motorable road substantially increases the volume of

Figure 2.1: First Stage: Population Rank Predicts Motorable Road



Note: This figure shows a bin-scatter plot of the relationship between the within-district population rank and our first-stage prediction of an indicator of whether a village had a motorable road at the time of the survey (village population and other controls described in equation 2.1 are partialled out). The sample includes the 267 surveyed villages.

commercial vehicles passing through each day; the coefficient is positive (1.472) but not statistically significant. The point estimate implies that a motorable road connecting the village raises commercial vehicle traffic by about 1.5 additional truck, bus, and commercial vehicle visits per day. This result suggests that the program meaningfully enhanced village road utilization—the channel through which road access would affect economic and governance outcomes.

2.5.2 Effects on the Labor Market

We next turn to 2SLS estimates of the impacts of rural roads on labor markets in Table 2.2.

Panel A shows that road connectivity causes villagers to shift from earning income primarily from their own farms to casual labor inside the village, suggesting that it supports the growth of local industries. Specifically, improved road connectivity reduces the share of villages where the primary source of income in the village overall is on villagers' own farms by a statistically significant 48.7 percentage points (pp) (column 1).[1] Roads appear to dramatically expand the primacy of income from casual labor. While this point estimate is very large, a caveat is that the size of this change may primarily reflect a large mass of villages that, without roads, would rank the primacy of own-farm agriculture only just above a form of casual labor.[2] Interestingly, we find that the location of this income-generating casual labor is primarily within the newly connected village: the primacy of casual labor *within* the village as an income

[1]Reduced-form binscatters of this and other key outcomes against rank are shown in Section B.1 of Appendix B.

[2]Respondents ranked the three most important village livelihood sources; we code indicators for the top-ranked sources (see Table B.7). The large point estimate reflects a shift in villages ranking of own-farm activity from the first to the second or third most important source. Because the outcome is a nonlinear aggregate, our point estimate is not directly comparable to existing estimates of how roads shift average household-level income. Our results could be generated from small or large household-level shifts in underlying income sources.

source increases by 39.8 pp relative to a sample mean of 26% (column 2), while there is essentially no change in the primacy of casual labor outside the village (column 3). Questions about the share of households participating in casual labor inside and outside the village further support this conclusion. Roads lead to a statistically significant 24.8 pp decline in the share of households in casual labor both in and out of the village (column 6), offset by a statistically insignificant increase in the share of households in casual labor within the village of 19.6 pp (column 4).[1]

Panel B shows the impact of road connectivity on wages. The point estimates are positive, but are imprecisely estimated due to large standard errors. For example, road access increases the male wage index by 0.45 SD (column 1), consistent with a moderate improvement in men's wages, but the estimate is noisy.

Panel C examines how road connectivity impacts migration, and provides further evidence that rural roads support local economic development. The impact of roads on migration is theoretically ambiguous: while roads may increase connectivity to higher-wage labor markets, they also may increase the marginal product of local labor. We find that roads decrease our index of household migration by 0.83 SD, significant at the 5% level (column 1). Impacts are most pronounced for daily migrants, which fall by 0.65 migrants per household following road connectivity, though this estimate is noisy (column 2). However, point estimates for longer-term migration are negative across the board (columns 3–5). This decline in migration aligns with increased employment opportunities outside agriculture, higher wages in local economy, and (as we show in the next section) increased agricultural prices.

In summary, labor market dynamics shift following road construction. Earnings move away from agriculture toward casual labor and out-migration decreases as local

[1]The share of households participating in casual labor only outside the village is largely unchanged (column 5).

Table 2.2: 2SLS Estimates of the Impacts of Roads on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Main Source of Income in Village			Share of Households in Casual Labor		
	Own Farm	Casual Labor in Village	Casual Labor out of Village	In Village	Out of Village	Both in and out of village
Panel A: Labor Outcomes						
Motorable Road to Village	-0.487***	0.398***	0.119	0.196	0.020	-0.248**
	(0.160)	(0.131)	(0.115)	(0.128)	(0.091)	(0.113)
Dependent Variable Mean	0.57	0.26	0.16	0.28	0.34	0.36
Observations	267	267	267	267	267	267
		Male Wages				
	Wage Index: Male	Agriculture	Construction	Female Wages: Agriculture		
Panel B: Wages						
Motorable Road to Village	0.449	3.450	6.685	7.877		
	(0.722)	(6.745)	(9.392)	(4.897)		
Dependent Variable Mean	0.09	47.94	51.08	38.22		
Observations	267	265	266	222		
		Migrants per Household				
	Migration Share Index	Daily	Weekly	Monthly	Yearly	
Panel C: Migration Outcomes						
Motorable Road to Village	-0.835**	-0.645*	-0.052	-0.240	-0.520	
	(0.402)	(0.351)	(0.062)	(0.162)	(0.364)	
Dependent Variable Mean	0.03	0.40	0.16	0.21	0.39	
Observations	267	267	267	266	266	

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

job opportunities improve, leading to a significant decline in daily commutes in search of jobs. The patterns in our occupational and income source findings accord with previous work finding that road connectivity leads to a decreased dependence on agricultural income and a turn toward casual labor (Asher and Novosad, 2020; Shamdasani, 2021). However, to our knowledge, we present the first evidence that additional casual labor opportunities are concentrated within the village, and the first evidence that roads decrease out-migration.

2.5.3 Effects on Agricultural Development

Given that labor shifts away from own-farm agriculture following road construction, a natural question is whether this is a result of increased alternative opportunities or somehow due to a decrease in the return to farming. This question is particularly important in light of the dependence on agriculture for the majority of villages in UP. In Table 2.3, we assess how roads impact agricultural inputs and diversification, yields, and prices.

Our results suggest that roads may actually increase the returns to agriculture. In Panel A, we first show evidence that road construction increases the price fetched for staple crops: an index of rice and wheat farm-gate prices increasing by 1.3 SD (column 1). One may expect a rise in yields along with the higher prices fetched, but we do not see any changes in yields: the coefficient estimate on our index of rice and wheat yields is -0.02 SD, though it is somewhat imprecisely estimated (column 4). Our result is consistent with Asher and Novosad (2020), who find precisely no impact on satellite-based measures of yield. However, their measures conflate yield reductions from decreased cultivation with any increases on still-cultivated land. We find that even yields on still-cultivated land do not increase.

We also find evidence of a broadening of agricultural pursuits beyond staple crop farming in Panel B, with roads leading to a moderate but statistically significant increase in an index of agricultural diversification (column 1). Turning to the index components, we find that dairy and goat rearing are present in 26 pp more villages following road construction (column 3), and milk cooperatives are present in 19 pp more villages (column 2), though this impact is not statistically significant. The prevalence of poultry farms appears unchanged (column 4).

Finally, in Panel C we examine whether roads impact agricultural inputs. We do not find any evidence of changes in the outcomes we measure, which include the fraction of farms using chemical fertilizer and/or pesticides (column 2), the use of motorized farm equipment (column 3), and visits from fertilizer companies (column 4). However, our measures are quite coarse, and we do not have measures of the use of high-yield seed varieties, which are a key agricultural input in this setting.

Taken together, the results suggest that roads reduce transaction costs in agricultural markets, perhaps especially for highly perishable goods like milk, and enhance agricultural diversification and profitability. Our results provide, to our knowledge, the first evidence from India that road connectivity increases output prices for agricultural staples, which are a key input to farmer welfare.[1] On the other hand, the fact that roads increased agricultural diversification toward animal husbandry aligns with previous work showing that PMGSY roads led to crop diversification beyond traditional cereals (Shamdasani, 2021).

2.5.4 Effects on Corruption, Local Governance, and Political Connectivity

Our final set of results indicate that, beyond their economic effects, rural roads improve governance and social institutions. Villages with new roads experience a greater presence of government officials, more frequent police patrols, and both a reduction in fair price shop (FPS) prices and increase in government wages.

Panel A of Table 2.4 shows that prices for staple goods at government-supported FPS decrease, while wages paid for government-supported labor increase following

[1] Shamdasani (2021) do not find statistically significant impacts of PMGSY on rice and wheat prices measured in the Rural Economic & Demographic Survey. (Khandker et al., 2009) find impacts of road construction on output prices in Bangladesh.

Table 2.3: 2SLS Estimates of the Impacts of Roads on Agricultural Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
		Prices in INR/Quintal			Yields in Quintal/Acre	
	Price Index	Wheat	Rice	Yields Index	Wheat	Rice
Panel A: Agricultural Prices & Yields						
Motorable Road to Village	1.316***	24.151	250.151***	-0.018	1.083	-1.016
	(0.293)	(38.152)	(54.067)	(0.472)	(2.583)	(2.612)
Dependent Variable Mean	0.14	910.33	599.61	-0.01	11.75	12.19
Observations	267	259	207	267	259	208
	Farm Diversification Index	Milk Coop in Village	Dairy or Goat Rearing in Village	Poultry Farm in Village		
Panel B: Agricultural Diversification						
Motorable Road to Village	0.468***	0.186	0.255**	-0.034		
	(0.164)	(0.133)	(0.104)	(0.043)		
Dependent Variable Mean	-0.02	0.10	0.09	0.02		
Observations	267	267	266	258		
	Farm Input Index	Fraction using Chemical/ Fertilizer/ Pesticide	Fraction with Motorized Agricultural Equipment	Fertilizer Company Visited at least once in Past Year		
Panel C: Farm Input Use						
Motorable Road to Village	-0.120	-0.007	-0.002	-0.162		
	(0.188)	(0.082)	(0.123)	(0.168)		
Dependent Variable Mean	-0.01	0.91	0.15	0.26		
Observations	267	252	265	267		

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

road construction. The 0.43 SD decrease in an index of FPS prices (column 1) is driven primarily by a *Rs.* 0.7 decrease in the price of wheat (column 2), but the point estimates for rice and kerosene prices are also negative (columns 3 and 4). At the same time, we find that daily wages in government construction projects, which provide jobs guaranteed through the Mahatma Gandhi National Rural Employment Guarantee Act (NREGA), increase by *Rs.* 39.2.

These results are surprising since FPS prices and government construction wages are set centrally. However, overcharging in FPS shops and underpayment for NREGA work are common (Jadhav et al., 2022; Parashar, 2025; Niehaus and Sukhtankar, 2013). We thus interpret our results as suggesting that road connectivity reduces corruption in both these programs: FPS overcharging and NREGA underpayment both decreased.

Why might roads decrease corruption? One potential explanation is that, as transportation costs decreased, and providers of government services demanded less overhead to cover their costs. Another explanation is that accountability to local officials increased as road connectivity allowed for greater oversight. While our data do not allow us to decisively confirm or rule out either of these channels, we find evidence that roads increased both local civil service and political activity, which are consistent with increased oversight.

Specifically, Panel B of Table 2.4 explores how road connectivity affects the presence of local government officials. We find that an index of local government presence increases by 1.1 SD (column 1). This result is primarily driven by two types of officials: police and lekhpal, or revenue officials. In particular, we find that police make more than 92 additional visits per year, including 43 more patrols, following road construction (columns 2 and 3), and lekhpals visit 49 more times per year (column 7). While not statistically significant, point estimates also suggest an additional 30 visits per year from village development officers (column 6). We don't see evidence of substantially increased governance by more central officials, such as district collectors and block development officers (columns 4 and 5, respectively), though the point estimates are positive and substantial compared to the average rate of visits from such officials in our sample.

Finally, we find some evidence that roads increase political engagement. In Panel C, we find that an index of political connectivity increased by 0.9 SD (column 1). While none of the individual index components are statistically significant, the biggest driver is the additional 2.7 campaign visits per year (column 2). Thus, it is plausible that political accountability improved along with civil service presence in the wake of road connectivity.

Overall, our results present novel evidence that road construction leads not only to improved market access, but also to improved government access and accountability. The delivery of core social programs, such as food rations and guaranteed employment, improves.

Table 2.4: 2SLS Estimates of the Impacts of Roads on Governance Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Fair Shop Prices					
	Fair Shop Price Index	Wheat	Rice	Kerosene	Male Wages: Government Construction		
Panel A: Government Prices and Wages							
Motorable Road to Village	-0.434*	-0.684*	-0.073	-0.396	39.195***		
	(0.241)	(0.362)	(0.317)	(0.451)	(14.272)		
Dependent Variable Mean	-0.03	5.00	6.18	10.98	70.98		
Observations	267	254	259	266	249		
		Police Activity in Past 12 Months		Government Official Visits in Past 12 Months			
	Civil Services Index	Police Visits	Police Patrolling	Collector	BDO	VDO	Lekhpal
Panel B: Civil Service Connectivity							
Motorable Road to Village	1.133***	91.699**	42.925***	0.031	0.540	30.154	48.926***
	(0.214)	(41.168)	(7.375)	(0.137)	(0.561)	(22.588)	(13.894)
Dependent Variable Mean	0.21	36.92	8.94	0.06	0.73	42.11	27.72
Observations	267	267	267	266	267	267	267
	Political Connectivity Index	Campaign Visits in Past 12 Months	Campaign Events in Past 12 Months	Share of Households Receiving Hindi Newspaper			
Panel C: Political Connectivity							
Motorable Road to Village	0.933*	2.650	0.034	0.001			
	(0.518)	(2.790)	(0.246)	(0.006)			
Dependent Variable Mean	0.12	4.76	0.29	0.01			
Observations	267	267	267	262			

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

2.5.5 Placebo Results

As discussed in Section 2.4.2, we test whether road connectivity in our survey period (instrumented by rank) predicts 2001 census outcomes to support excludability. We conduct this test in two samples: first in the 253 survey villages that we are able to match with census data, and then in all 2,917 Phase 3 and Phase 5 villages in UP matched with census data. In the latter sample, we proxy for the endogenous outcome of whether a given village had a motorable road in 2007 (which we only know for surveyed villages) with an indicator for being a Phase 3 village.

Table B.5, Panel A reports the results of the placebo analysis examining the effects of roads on pre-program (2001 census) outcomes. We do not see any evidence that, in 2001, the higher-ranked villages in our sample were more likely to have a mud or paved road connection, other transport connection, newspaper access, more forested area, more cultivated area, access to agricultural electricity, maternal & child or primary health centers. We find, however, that higher-ranked villages are *less* likely to have post or phone communication facilities (column 3) or a primary school (column 9) prior to the PMGSY program. Thus, the better outcomes we witness in these villages in 2007 are unlikely to be driven by pre-existing advantages in infrastructure or services.

Moreover, the differences according to village rank fade in the expanded sample of villages, suggesting that even the differences we see in our survey sample are not due to systematic targeting of facilities according to village rank at the level of state policy. Panel B shows placebo results for census outcomes related to road connectivity and agricultural and infrastructure development. The sample is more than ten times as large, yet all but one of the 2SLS coefficients are statistically insignificant. We do see that, statewide, higher-ranked villages are more likely to have a primary school (column 9). Thus, our instrument may not be excludable for educational outcomes. Overall, this table provides strong evidence that future road placement does not correlate strongly with advantageous preexisting village conditions either in our sample or in the rest of UP, helping to address concerns about endogenous road placement and the excludability of the instrument.

§ 2.6 Conclusion

The role of road infrastructure in improving rural livelihoods is a persistent question in economic development. Given the centrality of road infrastructure in market and social connections, many countries have implemented policies to improve rural road networks. However, evaluating the effectiveness of these large-scale road projects remains challenging due to limited data availability and concerns over endogenous road placement, especially in developing countries. We aim to further understanding of the impacts of rural roads by estimating the short-term impacts of the world's largest rural road construction program, PMGSY, in India.

To address potential endogeneity in road placement, we instrument the road placement by within-district population rank, thereby estimating the causal impacts of road connectivity on village-level outcomes. While not the subject of our paper, this strategy has promise for other administrative datasets that have been used to evaluate the impact of PMGSY around population cut-offs. In particular, it could allow researchers to understand how PMGSY impacts outcomes for villages away from these cut-offs.

We presents several interesting findings about the multifaceted impacts of rural roads on rural development. We contribute to the existing literature on the agricultural and employment impacts of PMGSY by offering a more nuanced view on how roads impact sectoral transformation away from agriculture. At the same time, we find that roads influence village welfare not only through market activity, but also through government activity and oversight.

Specifically, we find that while rural connectivity led to an improvement in agricultural diversification and higher output prices, villagers turn even more toward casual labor, presumably where improvements in productivity outweigh the gains in agriculture. However, the casual labor markets that villagers turn to are primarily within the connected village, and villagers are less likely to undertake daily commutes to find work despite the better road access to nearby labor markets. Moreover, roads increase government activity—with more visits by politicians, police, and civil servants—and improve the delivery of government services.

Chapter 3

Rural Roads and Child Health: Evidence from India's PMGSY[1]

§ 3.1 Introduction

Despite the proven benefits of basic child health services, access to care remains limited in many rural areas of low- and middle-income countries (WHO, 2015). One of the reasons for this is physical connectivity: poor transport infrastructure increases the time and monetary costs of accessing essential services, reducing utilization even where facilities formally exist (Aggarwal, 2021).

Rural roads have the potential to improve health through several channels. The most direct mechanism is enhanced access to formal care; roads can facilitate household travel to health centers, hospitals, and other providers. Existing evidence from India's rural road program highlights this pathway, demonstrating that better connectivity increases institutional antenatal care, facility deliveries, vaccination, and other child health investments (Aggarwal, 2021; Dasgupta et al., 2024). Roads may also improve health by enabling health services to reach villages more effectively. Enhanced

[1]This is joint work with Santosh Kumar Gautam (Keough School of Global Affairs, University of Notre Dame), and Ariel Zucker (Department of Economics, University of California Santa Cruz)

connectivity may increase health-worker visits, improving access without increasing institutional health-care utilization.

Additionally, roads can produce countervailing effects through increased pollution, changes in labor markets, or alterations in the timing and location of births (Aggarwal, 2021; Garg et al., 2024). Consistent with this ambiguity, prior evidence on the impacts of roads on child health is mixed: studies have documented reductions in infant mortality in some areas (Dasgupta et al., 2024), but increases in others (Aggarwal, 2021; Garg et al., 2024). Understanding the channels through which roads influence child health is therefore crucial for assessing the net effects of rural infrastructure.

This paper studies the effect of rural road connectivity on child health in the context of India's Pradhan Mantri Gram Sadak Yojana (PMGSY). We use novel village-level survey data collected in 2007 from 267 villages in Uttar Pradesh, shortly after the completion of early PMGSY roads. The dataset includes self-reported measures of child mortality, access to health workers, home births, and travel time. This enables us to assess not only whether roads influence child survival, but also whether these effects occur through increased travel to formal facilities or through enhanced village-level access to health services.

Identifying the causal impact of road connectivity is challenging due to the fact that road placement is endogenous to local development. We address this issue by employing an instrumental-variables strategy based on PMGSY rollout rules. Within districts, villages with higher population rank among unconnected villages were more likely to receive road connections earlier. We use the within-district population rank as an instrument for whether a village had a motorable road at the time of the survey, controlling for village population and pre-program census characteristics.

We find that road connectivity significantly improves child health outcomes. The presence of a motorable road reduces reported under-five mortality by 5.0 percentage points (pp). Road access also improves community health worker access: an index of health worker access increases by 0.50 standard deviations, driven by significant improvements in the likelihood of having an Auxiliary Nurse Midwife (ANM) worker in or near the village and in the frequency of health worker visits.[1]

The mechanism we observe differs from that found in the existing literature. We do not find any evidence of an increased use of health facilities as in Aggarwal (2021). Effects on travel time to facilities are imprecise, and villagers report an increase in the proportion of children born at home. Although self-reported village-level measures should be interpreted with caution, the pattern suggests an alternative pathway: roads may improve child health not only by facilitating access to health services but also by enabling frontline health workers to reach remote communities.

§ 3.2 Background and Data

The PMGSY program is a rural infrastructure program launched by the Government of India in 2000 to provide all-weather road connectivity to unconnected rural habitations. The program has substantially expanded rural connectivity in India (O.M.M.A.S, 2023; Ministry of Rural Development, 2023, 2022).

To evaluate the impacts of PMGSY, we conducted a village survey in 2007 across 14 districts in Uttar Pradesh (UP). UP is India's most populous state, with a 65% agrarian workforce; it provides a critical setting for this study, particularly as it initially had the nation's largest concentration of unconnected villages (Agriculture Department, 2020). To minimize unobserved heterogeneity and ensure comparability between the

[1]ANMs are frontline female health workers providing maternal and child health services through Sub-Centres, the lowest tier of India's rural public health system, typically serving about 5,000 people in rural areas.

treatment and comparison groups, we restricted our sample to a narrow population bandwidth. Specifically, we selected villages with populations between 950 and 1,175 residents. This restriction yielded an initial pool of 302 villages spread across 14 districts. After excluding villages with incomplete or inaccurate administrative records, the final analytical sample consists of 267 villages. This includes 144 Phase 3 (connected) villages and 123 Phase 5 (not yet connected) villages. The identification strategy relies on comparing villages sanctioned at different stages of PMGSY implementation. Villages sanctioned in 2003–2004 (Phase 3) had completed construction by the survey date, whereas those sanctioned in 2005–2006 (Phase 5) had not yet begun construction. Phase 4 villages were excluded to avoid the confounding effects of ongoing construction.

The survey employed a participatory rapid rural appraisal methodology (RRA). Enumerators gathered villagers at a central location and collected information through a structured village meeting rather than individual interviews; thus, the survey measures are community-reported village-level aggregates. The survey collected data on child mortality, access to community health workers, and access to health facilities. Child mortality outcomes are calculated from raw data on the number of children (under 5 and under 1) and the number of child deaths in the last year (under 5 and under 1) in the village; similarly, home birth rates are calculated from raw data on home births in the past year and the number of children under 1. The remainder of our outcomes are directly reported. Summary statisitcs for surveyed villages can be found in Table 3.1

We supplement survey data with 2001 Census records to capture village characteristics before PMGSY implementation, successfully matching 253 of 267 villages (95%). These pre-program data provide baseline controls and allow us to examine whether future road placement is correlated with pre-existing village characteristics that might drive the differences in health outcomes we document.

Table 3.1: Descriptive Statistics

	Summary		
	N	mean	sd
Panel A: Outcome Variables			
Under 5 Mortality	266	0.03	0.03
Under 1 Mortality	267	0.20	0.21
ANM in own or nearby village	267	0.42	0.49
Dai in own or nearby village	267	0.31	0.46
Number of health worker visits last year	267	0.86	5.10
Share of children born at home last year	267	0.73	0.30
Minutes to reach care: complicated delivery	267	112.70	62.73
Minutes to reach care: injections	267	35.95	33.78
Minutes to reach care: TB Treatment	267	143.93	95.08
Attendance of primary school aged boys (1 - 6 Likert scale)	265	4.79	1.17
Attendance of primary school aged girls (1 - 6 Likert scale)	265	4.78	1.19
Village has primary school	267	0.84	0.37
Fraction of teachers absent on an average day	266	0.12	0.20
Number of days school closed early last week	267	0.78	1.72
Days mid-day meal served in school during the last week	256	5.13	1.74
Motorable road to village for cars	267	0.70	0.46
Panel B: 2001 Census of India			
Per capita panchayat income	104	72.90	98.80
Electricity for agriculture	251	0.18	0.38
Share cultivated area irrigated	194	0.76	0.25
Distance to nearest town (km)	247	12.04	10.17
Census population (thousands)	251	1.76	1.61
Village has medical facility	251	0.33	0.47
Village has health center	251	0.05	0.21
Village has community health worker	251	0.22	0.41
Village has private medical practitioner	251	0.04	0.21
Village has education facility	251	0.86	0.34

Note: Descriptive statistics for a selection of variables used in the analysis among the sample of surveyed villages. Panel A shows a selection of outcome variables constructed from the village survey data. Panel B shows the variables we include as controls from the 2001 Census of India. Dai is a community-based traditional birth attendant who has received basic training in safe delivery practices and maternal care and primarily assists with home deliveries and is not part of India's formal public health workforce.

§ 3.3 Methodology

A central concern in evaluating infrastructure investments is endogenous road placement: villages that receive roads may differ systematically from those that do not. We address this issue by using an instrumental-variables approach based on PMGSY rollout rules. Under PMGSY, villages were prioritized for road construction in part by population size, with larger unconnected villages within a district more likely to be connected earlier. We therefore instrument road connectivity using a village's within-district population rank among unconnected villages scheduled for PMGSY construction. Conditional on village population and pre-program census characteristics, this rank generates variation in the likelihood of receiving a motorable road by the time of the survey. Villages with high ranks within a district were more likely to receive a motorable road under the program, compared to comparable-sized but lower-ranked villages in other districts.

Specifically, we estimate the following first-stage equation:

$$ROAD_{vd} = \alpha_0 + \alpha_1 RANK_{vd} + \alpha_2 POP_{vd} + \gamma X_{vd} + \nu_{vd}, \tag{3.1}$$

where $ROAD_{vd}$ is an indicator equal to one if village v in district d had a motorable road at the time of the survey; $RANK_{vd}$ is the village's within-district population rank; POP_{vd} is the village population from the 2001 Census; and X_{vd} is a vector of pre-program census controls.[1]

[1] Controls include an indicator for agricultural electricity, a maternal/child welfare center present in the village, any health center or sub center present in the village, community health worker present in the village, and registered private medical practitioner present in the village, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included.

The second-stage equation is:

$$Y_{vd} = \beta_0 + \beta_1 \widehat{ROAD}_{vd} + \beta_2 POPvd + \delta X_{vd} + \varepsilon_{vd}, \tag{3.2}$$

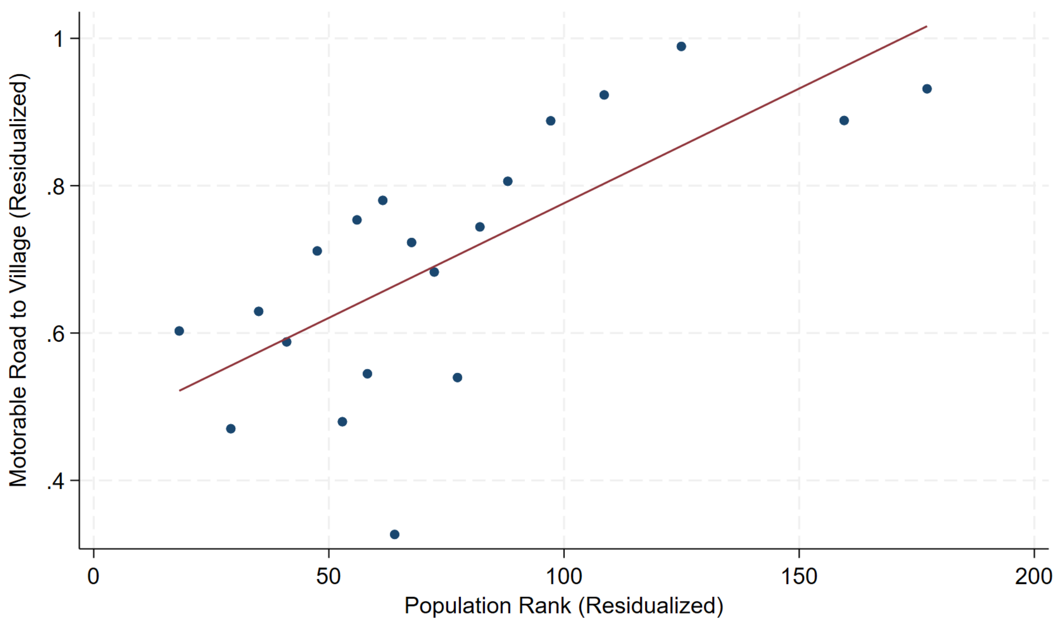
where Y_{vd} denotes a village-level child health outcome. The coefficient of interest is β_1, which captures the effect of motorable road connectivity for villages whose road status was shifted by their position in the within-district population ranking. Standard errors are clustered at the district level.

The identifying assumption is that, conditional on village population and baseline census characteristics, within-district population rank affects child health only through its effect on road connectivity. A valid instrument must satisfy two conditions: relevance and exogeneity (Angrist and Pischke, 2009). The relevance condition requires that within-district population rank strongly predicts road connectivity and is directly testable. The exogeneity condition requires that, conditional on the included covariates, within-district population rank affects child health only through its effect on road connectivity. Although the exclusion restriction cannot be tested directly, several features of the research design support its plausibility. First, the instrument is based on the within-district population ranking among PMGSY-eligible villages rather than the population norms/thresholds (one ANM per 3000-5000 people in rural areas) that could have been used to allocate other government programs. Second, our specifications control for village population and a rich set of pre-program census characteristics, including baseline health infrastructure, socioeconomic conditions, and geographic characteristics, thereby accounting for observable differences that may be correlated with road placement. Finally, we examine instrument relevance and present placebo regressions using pre-program census variables. These results are reported in the following section.

§ 3.4 Results and Discussion

The first-stage relationship is strong: within-district population rank significantly increases the probability of motorable road access by 0.3 pp (Table 3.2; Figure 3.1); first-stage instrument F-statistics exceed 10, minimizing weak instrument concerns (Angrist and Pischke, 2009).[1] We also examine the exclusion restriction using placebo regressions on pre-program census outcomes; we include a set of relevant pre-program village characteristics to improve the plausibility of this assumption (Table 3.3).

Figure 3.1: First-Stage: Population Rank Predicts Motorable Road



Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and an indicator of whether a village had a motorable road at the time of the survey. The figure shows the raw data underlying our first stage. We include census population and other relevant controls outlined in the first stage equation. The sample includes the 267 surveyed villages.

[1]The rank has a mean of 75.6 and a standard deviation of 41.1. Given the estimated first-stage coefficient of 0.003, a one-standard-deviation increase in population rank predicts a 12.3 pp increase in the probability that a village has a motorable road (0.003×41.1=0.123).

Table 3.2: First Stage Estimate and Impacts of Roads on Child Health (2SLS Estimates)

	(1)	(2)	(3)	(4)	(5)
	Motorable Road to Village				
Panel A: First stage					
Population rank (small to large)	0.003***				
	(0.001)				
F-statistics					
Cragg–Donald F	22.02				
Kleibergen–Paap F	18.74				
Dependent Variable Mean	0.70				
Observations	267				
	Child Mortality Index	Under-five Mortality	Infant Mortality		
Panel B: Child Mortality					
Motorable Road to Village	-1.125**	-0.050***	-0.111		
	(0.523)	(0.016)	(0.095)		
F-statistics					
Cragg–Donald F	22.02	21.50	22.02		
Kleibergen–Paap F	18.74	17.95	18.74		
Dependent Variable Mean	-0.00	0.03	0.19		
Observations	267	266	267		
	Health Worker Access Index	ANM in Own or Nearby Village	Dai in Own or Nearby Village	Number of Health Worker Visits Last Year	
Panel C: Community Health Worker Access					
Motorable Road to Village	0.502**	0.572**	-0.090	4.014***	
	(0.240)	(0.272)	(0.201)	(1.509)	
F-statistics					
Cragg–Donald F	22.02	22.02	22.02	22.02	
Kleibergen–Paap F	18.74	18.74	18.74	18.74	
Dependent Variable Mean	0.00	0.44	0.26	1.20	
Observations	267	267	267	267	
			Minutes to Reach Care:		
	Facility Access Index	Share of Children Born at Home Last Year	Complicated Delivery	Injections	TB Treatment
Panel D: Health Facility Access					
Motorable road to village	0.073	0.232**	-7.542	-10.442	64.423
	(0.464)	(0.118)	(47.342)	(13.913)	(71.476)
F-statistics					
Cragg–Donald F	22.02	22.02	22.02	22.02	22.02
Kleibergen–Paap F	18.74	18.74	18.74	18.74	18.74
Dependent Variable Mean	0.00	0.73	118.81	33.10	139.31
Observations	267	267	267	267	267

Note: This table shows estimates of β_1 from Equation (3.2) for various outcomes. Controls include an indicator for agricultural electricity, and if a Maternal/Child Welfare Center is present in the village, if any health center or sub centers are present in the village, if there is a community health worker present in the village, and if there is a registered private medical practitioner present in the village, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. The dependent variable mean is for unconnected villages that do not have a road. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 3.2 reports 2SLS estimates of the effect of motorable road connectivity on child health and access to health services. Panel B shows that road connectivity significantly improves child survival. A motorable road reduces an index of under-5 and infant mortality by 1.13 standard deviations, driven by a 5.0 pp reduction in under-5 mortality. The estimated effect on infant mortality is also large and negative, but it is less precisely measured. Although the mortality measures are self-reported village aggregates, the pattern provides evidence that rural road connectivity improved child health outcomes.

Panel C assesses access to community health workers. Road connectivity increases the health worker access index by 0.50 standard deviations. The likelihood that an ANM is available in the village or nearby rises by 57.2 pp, and the number of health worker visits in the previous year increases by 4.01 visits. These findings indicate that roads enhanced the capacity of health services to reach villages. This interpretation is consistent with other unpublished work suggesting that PMGSY increased health care utilization through improvements in supply-side access, including health worker presence, health camps, and health-related awareness (Banerjee and Sachdeva, 2015).

Panel D examines whether the observed mortality effects appear to operate through improved access to formal health facilities. We find limited evidence supporting this channel. The impact of roads on an index of facility access is almost exactly zero. The estimated effects on travel time for complicated deliveries, injections, and tuberculosis treatment go in different directions but are imprecise. However, road connectivity increases the reported proportion of children born at home by 23.2 pp.

The fact that we find reductions in under-five mortality is consistent with evidence from Dasgupta et al. (2024), which also documents improvements in child survival following PMGSY, although they contrast with studies reporting adverse mortality effects in other settings (Aggarwal, 2021; Garg et al., 2024). Specifically, Dasgupta et al. (2024) find that road access reduced infant mortality by 1.7-1.9 pp, with improved access to health facilities (breastfeeding and immunization increased). On the other hand, Aggarwal (2021) observes an increase in infant mortality, despite finding that road construction increased institutional antenatal care, facility delivery, and vaccination rates. The study shows an increase of approximately 25 infant deaths per 1,000 live births (equivalent to a 2.5 pp increase in the probability of infant death) among male infants. The paper suggests that this might be explained by more high-risk babies making it to term but would not survive the first year of life. Similarly, Garg et al. (2024) find that PMGSY roads increased agricultural fires and particulate pollution, raising infant mortality in downwind villages by 0.3 pp and null effects in upwind villages.

Like Dasgupta et al. (2024), we find reductions in child mortality, but do not find evidence that the effects are driven by increased facility use or institutional delivery; if anything, we see these reductions despite a turn toward home birth. Previous work showing that early movements toward hospital delivery among rural mothers in India had no detectable effect on child mortality (Powell-Jackson et al., 2015), perhaps due to poor facility quality, can help us rationalize these diverse results. Broad increases in institutional delivery and care are neither necessary nor sufficient to improve infant health in rural areas. Improvements in preventive health care, often delivered by community health workers (ANM/Dai), provide another channel. Instead, our results point to an alternative mechanism: improved road connectivity increases the presence of frontline health workers, particularly ANMs, who provide essential preventive maternal and newborn care within villages. By improving access to antenatal care, skilled birth attendance, postnatal visits, and timely referrals, these community-based providers may have made home deliveries safer and improved newborn survival. Our findings therefore suggest that rural roads can improve child health not only by bringing mothers to health facilities but also by bringing essential health services to mothers.

Overall, much of the existing literature on road connectivity and health emphasizes an outward-mobility channel, whereby roads improve health by enabling households to travel to formal providers. Our results instead highlight a complementary inward-service channel, in which roads may improve child survival by facilitating the reach of frontline health workers (ANM/Dai) and basic services directly to remote villages. This distinction is significant because formal facilities may remain inaccessible even after road construction, particularly in rural settings (Kumar et al., 2014). In these contexts, the health benefits of roads may depend not only on household mobility to hospitals, but also on the extent to which public health systems leverage improved connectivity to expand village-level outreach. Strengthening village-level outreach through ANMs and trained dais may therefore be an important pathway through which transport infrastructure translates into improved child survival.

Table 3.3: 2SLS estimates of the impacts of roads on pre-program (placebo) outcomes

	(1)	(2)	(3)	(4)
	Present in Village:			
	Maternal/Child Welfare Center	Health Centers	Community Health Workers	Private Health Workers
Health Outcomes and Facilities				
Motorable Road to Village	0.101	-0.076	-0.435**	0.056
	(0.077)	(0.058)	(0.181)	(0.103)
F-statistics				
Cragg–Donald F	20.38	20.38	20.38	20.38
Kleibergen–Paap F	15.52	15.52	15.52	15.52
Dependent Variable Mean	0.17	0.07	0.22	0.01
Observations	251	251	251	251

Note: The table shows the 2SLS estimates of β_1 from Equation (3.2) for various village-level health outcomes collected in the 2001 census, prior to the announcement of the PMGSY program. "Maternal/Child Welfare Center" is an indicator for having a maternal and child welfare center; and "Health Center" is an indicator for having a primary health center or sub-center; "Community Health Worker" is an indicator for having community health workers present in the village; "Private Health Worker" is an indicator for having private health workers available the village. Controls include an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census. The sample of villages consists of the subset of survey sample villages that could be matched with 2001 census data. Standard errors clustered by district are in parentheses.***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

§ 3.5 Conclusion

This paper provides evidence that improved road connectivity in rural Uttar Pradesh has improved child health outcomes. Using village-level survey data and an instrumental-variables approach based on within-district population rank in the PMGSY rollout, we find that motorable road access reduced under-five mortality and enhanced access to frontline health workers. The findings suggest significant child health gains in villages that received direct road connections.

The mechanism identified in this study differs from the existing published literature linking roads to health outcomes. We do not find that mortality reductions were primarily driven by reduced travel time to formal health facilities or increased rates of institutional delivery. Instead, the results indicate that improved roads may enhance child health by enabling ANMs and other health workers to visit remote villages more frequently. Rural roads may therefore complement public health systems not only by increasing household mobility but also by expanding the reach of community health workers into the village.

A Chapter 1 Appendix

§ A.1 Waste Sites by Country

Table A.1 presents the number of waste sites identified in China and other major waste-receiving countries, along with the proportion of sites first identified after the implementation of the National Sword policy. In China, the relatively small share of newly identified sites aligns with the policy's objective of reducing the visible presence of imported waste. Although this pattern does not conclusively indicate the removal of existing sites, it suggests a deceleration in the emergence of new waste accumulations following the tightening of China's import restrictions.

Conversely, the proportion of post-policy sites is substantially higher in several countries that received redirected waste flows after 2018. This trend aligns with the broader reorganization of the global waste trade described in the previous section, where waste previously shipped to China was diverted to other lower- and middle-income countries. Malaysia has the largest share of newly identified sites, with 48 percent first appearing after the policy. Indonesia, Thailand, and the Philippines also report high post-policy shares, at 33 percent, 31 percent, and 28 percent, respectively. These countries were among the primary destinations affected by the redirection of waste flows following the National Sword Policy. This may suggest that new waste sites reflect increases in local accumulation driven by imports. India represents an exception to this trend, with a lower share of new sites despite being a significant waste-receiving country.

The cross-country patterns in Table A.1 offer descriptive evidence that changes in observed waste-site formation are broadly consistent with the post-2018 redirection of global waste flows. However, the table does not measure the full extent of waste activity, as the data only show when new sites are first identified and do not capture the disappearance of existing sites. Despite this limitation, the higher share of newly identified sites in several receiving countries suggests that the National Sword policy was associated not only with changes in trade flows but also with shifts in the spatial distribution of visible waste accumulation.

Table A.1: Waste Sites Observed China's National Sword Policy

	Total sites	Post-Policy New Sites
China	415	18
India	690	18
Indonesia	373	122
Malaysia	103	49
Philippines	190	53
Thailand	158	49

Note: Post-policy sites are waste sites first observed after January 2018. The share of new sites is calculated as post-policy sites divided by total observed sites in each country.

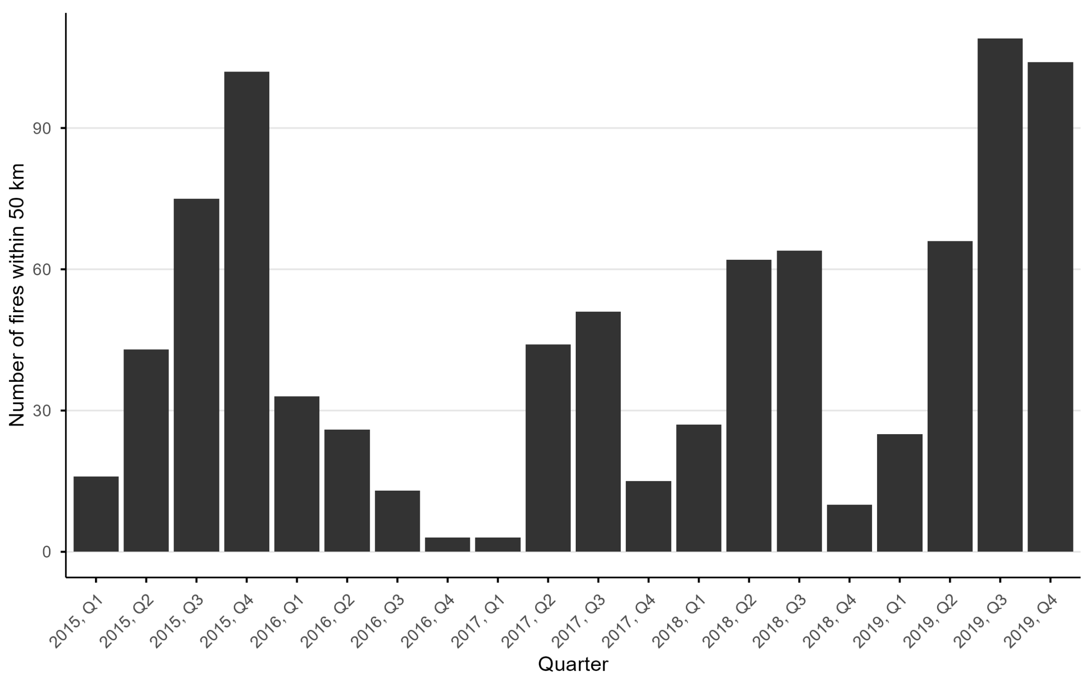
§ A.2 Fire Presence

To show how changes in waste-site activity are accompanied by changes in local burning, this analysis provides descriptive information using burned-area data from the Copernicus Climate Change Service, which provides satellite-derived fire-burned area observations from 2001 to the present (Copernicus Climate Change Service, 2019). These data are reported on a $0.25° \times 0.25°$ grid, corresponding to approximately 25 km × 25 km cells. For each waste site, the analysis identifies whether fire-data grid cells contain burn markers within a 50 km radius. Consistent with the main pollution analysis, the fire season months of August through October are excluded. Excluding these months enables the descriptive analysis to focus on fire activity outside the peak burning season, where observed fires near waste sites may provide more informative evidence of local waste-related burning.

Figure A.1 plots the number of fires near waste sites over time. The end of 2015 shows relatively high fire presence, followed by declines in 2016 and 2017. After the implementation of the National Sword policy, however, fire presence near waste sites increased again. This timing broadly follows the increase in waste imports documented in the trade data, suggesting that areas near waste sites experienced more burning during the period when redirected waste flows increased.

These patterns should be interpreted as descriptive rather than causal. The burned-area data show whether fire activity is observed near waste sites, but they do not identify the source of the fire or distinguish waste burning from other forms of local burning. Nevertheless, the increase in nearby fire activity after 2018 is consistent with the mechanism that greater waste accumulation and processing pressures may have increased local burning around waste sites.

Figure A.1: Quarterly Fire Presence in Indonesia



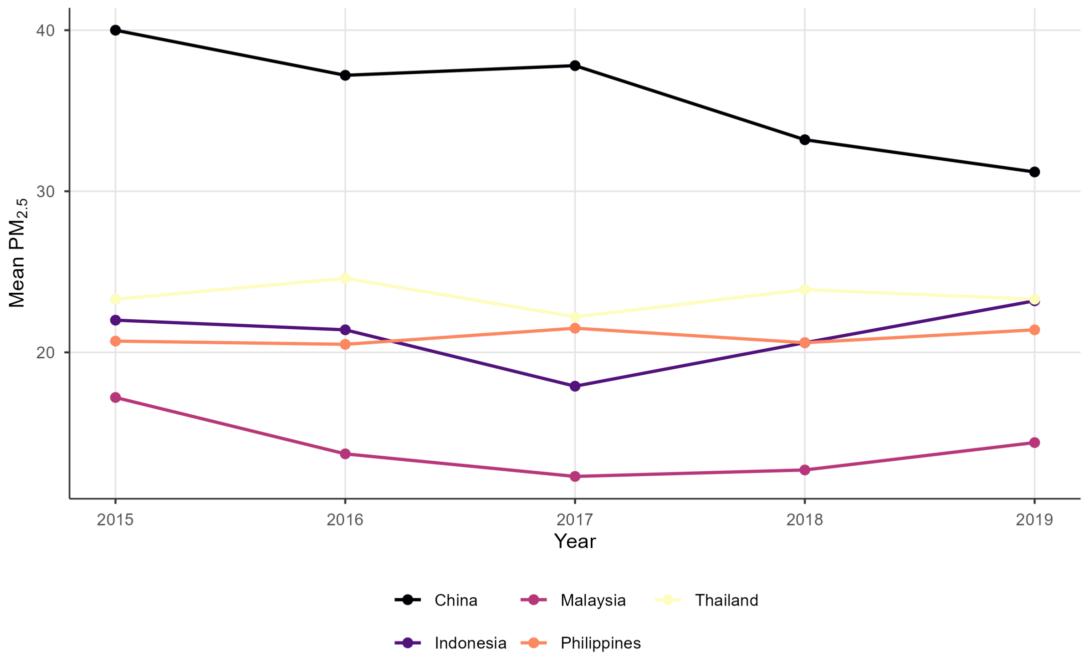
Note: Sum of cells with fire area burned within 50km of waste site.

§ A.3 Pollution Levels by Country

Environmental policies, including China's National Sword policy, aim to mitigate environmental harm in the implementing country. However, without reductions in underlying waste generation or improvements in waste management, such policies may shift environmental burdens to other regions rather than eliminate them. In the absence of international coordination and sufficient waste-management capacity in recipient countries, the externalities targeted by the policy may be transferred across national borders.

Figure A.2 shows descriptive evidence supporting this concern. The figure displays average $PM_{2.5}$ concentrations within 50 kilometers of waste sites identified by Global Plastic Watch in China and several countries that received redirected waste flows following the policy's implementation (Minderoo Foundation, 2023). Pollution levels in China declined after 2017, consistent with the intended domestic effect; in contrast, several recipient countries showed increases in average $PM_{2.5}$ concentrations near waste sites following the policy. This trend is particularly pronounced in Indonesia and Malaysia. These countries also account for a large share of newly identified post-policy waste sites, indicating that increased waste-site activity may be linked to higher local pollution exposure.

Figure A.2: Annual PM2.5 Pollution Concentration by Country



Note: Average pollution each year without using fire season.

B Chapter 2 Appendix

Table B.1: Village Characteristics of Study Sample, Uttar Pradesh, and All India

	Study sample	Uttar Pradesh	India
Panel A: Demographics			
Census population (thousands)	1.76 (1.61)	1.69 (14.76)	1.72 (29.72)
Number of households	285.58 (266.26)	261.33 (2470.61)	324.47 (6017.71)
Village area (hectares)	249.28 (349.26)	221.82 (866.25)	438.19 (941.31)
Share female	0.47 (0.04)	0.48 (0.04)	0.49 (0.04)
Share Scheduled Caste	0.25 (0.15)	0.24 (0.21)	0.17 (0.20)
Share Scheduled Tribe	0.00 (0.00)	0.00 (0.03)	0.19 (0.33)
Panel B: Education and Health Services			
Primary school in village	0.85 (0.36)	0.68 (0.46)	0.79 (0.41)
Middle school in village	0.18 (0.39)	0.18 (0.39)	0.28 (0.45)
Secondary school in village	0.04 (0.20)	0.04 (0.20)	0.11 (0.31)
Health center/sub-center in village	0.05 (0.21)	0.05 (0.22)	0.15 (0.36)
Registered medical practitioner present	0.04 (0.20)	0.07 (0.25)	0.08 (0.28)
Community health worker present	0.21 (0.41)	0.16 (0.36)	0.13 (0.34)
Panel C: Infrastructure and Connectivity			
Approach road is mud or paved	0.92 (0.27)	0.94 (0.23)	0.93 (0.26)
Distance to nearest town (km)	12.04 (10.17)	9.92 (9.23)	23.45 (25.46)
Electricity for agriculture	1.00 (0.00)	0.34 (0.47)	0.40 (0.49)
Panel D: Panchayat and Agriculture			
Per capita panchayat income	72.90 (98.80)	153.82 (12147.33)	300.13 (50794.26)
Share cultivated area irrigated	0.76 (0.25)	0.79 (0.29)	0.41 (0.38)
Share area forested	0.03 (0.08)	0.15 (11.81)	0.11 (6.54)
Share cultivated area irrigated by groundwater	0.44 (0.45)	0.52 (3.57)	0.18 (1.67)
N	253	98,544	593,799
P-value		< 0.001	< 0.001

Note: This table summarizes how characteristics of rural villages in our sample compare to all of UP and India. Data are from the 2001 India Census pulled from (Asher et al., 2019). Column 1 includes villages in our study sample, column 2 includes rural villages in all of UP, and column 3 includes rural villages in all of India. We report standard deviations in parentheses. The p-values reported are for F-tests of whether the listed village characteristics jointly predict inclusion in the study sample relative to the all-UP and all-India comparison samples, respectively.

Table B.2: Survey-Based Road Indicator Corresponds with PMGSY Data

	Motorable Road to Village		
	No	**Yes**	**Total**
Phase 3 Village			
No	72	51	123
Yes	8	136	144
Total	80	187	267

Note: This table tabulates our preferred indicator for road connectivity, whether the village has a motorable road, against whether the village was sanctioned for PMGSY road construction during phase 3 (vs. phase 5). Nearly all phase 3 villages report having a motorable road at the time of the survey, while the majority of phase 5 villages do not.

Table B.3: Primary Modes of Transport for Village Activities

	Injections		Secondary School		Sell Milk		All Factories		Polling Station	
	N	%	N	%	N	%	N	%	N	%
Bicycle	121	45.7	157	59.7	11	57.9	21	77.8	5	2.6
On Foot	112	42.3	93	35.4	0	0.0	3	11.1	186	97.4
Horse/Bullock Cart/Tractor	19	7.2	0	0.0	1	5.3	0	0.0	0	0.0
Rickshaw	6	2.3	0	0.0	2	10.5	0	0.0	0	0.0
Jeep/Truck/Van/Car	5	1.9	4	1.5	4	21.1	0	0.0	0	0.0
Public Transport (Bus/Train)	1	0.4	8	3.0	1	5.3	3	11.1	0	0.0
Other	1	0.4	1	0.4	0	0.0	0	0.0	0	0.0
Total	265		263		19		27		191	

Note: This table reports village-level RRA responses on the primary transport mode used for selected activities from our survey sample. Totals vary across columns because transport-mode questions were asked only when the activity was relevant or reported in the village.

Table B.4: First Stage and 2SLS Estimates of the Impacts of Roads on Commercial Transport

	(1)
	Motorable Road to Village
Panel A: First stage	
Population rank (small to large)	0.003***
	(0.001)
F-statistics	
Cragg–Donald F	22.04
Kleibergen–Paap F	16.73
Dependent Variable Mean	0.70
Observations	267
	Number of Vehicles Visiting Each Day
Panel B: 2SLS Estimates on Commercial Transport	
Motorable Road to Village	1.472
	(0.980)
Dependent Variable Mean	0.58
Observations	267

Note: Panel A shows the estimate of α_1 from the first-stage Equation (2.1), and Panel B shows the 2SLS estimates of δ_1 from Equation (2.2) for the outcome of the number of daily trucks, buses, and other commercial vehicles visiting the village each day. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table B.5: 2SLS Estimates of the Impacts of Roads on Pre-Program Outcomes (Placebo)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Has Mud or Paved Road	Receives Newspaper/ Magazine	Post/ Telegraph/ Phone Facilities	Share of Area Forested	Share of Cultivated Area Irrigated	Electricity for Agriculture	Maternal/ Child Welfare Center	Primary Health Center	Primary School
Panel A: Survey Sample (Surveyed Villages)									
Motorable Road to Village	-0.061	-0.103	-0.323**	0.015	0.099	-0.181	0.051	-0.069	-0.310***
	(0.237)	(0.247)	(0.138)	(0.030)	(0.204)	(0.213)	(0.090)	(0.056)	(0.116)
F-statistics									
Cragg-Donald					18.84				
Kleibergen-Paap					13.25				
Census Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.92	0.24	0.44	0.03	0.58	0.22	0.15	0.05	0.85
Observations	247	247	247	198	206	206	249	249	249
Panel B: Extended Sample (All Rural UP)									
Phase 3 Village	-0.054	-0.074	0.039	0.026	0.063	-0.159	0.101	-0.065	0.450**
	(0.092)	(0.180)	(0.210)	(0.049)	(0.149)	(0.204)	(0.095)	(0.063)	(0.196)
F-statistics									
Cragg-Donald					48.93				
Kleibergen-Paap					7.64				
Census Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.92	0.23	0.34	0.03	0.61	0.33	0.08	0.04	0.78
Observations	2879	2879	2879	2450	2159	2159	2917	2917	2917

Note: The table shows the 2SLS estimates of δ_1 from Equation (2.2) for various village-level outcomes collected in the 2001 Census, prior to the announcement of the PMGSY program. "Post/Telegraph/Phone Facilities" is an indicator for having any of these facilities; "Electricity for Agriculture" is an indicator for having access to agricultural electricity feeders; "Maternal/Child Welfare Center" is an indicator for having a maternal and child welfare center; and "Primary Health Center" is an indicator for having a primary health center or sub-center. The sample of villages consists of the subset of survey sample villages that could be matched with 2001 census data in Panel A, and all Phase 3 and Phase 5 villages in UP that could be matched with 2001 census data in Panel B. When not the outcome itself, controls include an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census population. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table B.6: 2SLS Estimates of the Impacts of Roads on Other Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Nearest Market Prices					
	Nearest Market Price Index	Wheat	Rice	Arhar Dal	Masoor Dal	Moong Dal	Kerosene
Panel A: Nearest Market Prices							
Motorable Road to Village	-0.047	1.121***	-0.311	-0.883	-3.132	-6.799*	-0.432
	(0.297)	(0.412)	(1.018)	(1.015)	(2.390)	(3.962)	(3.089)
Dependent Variable Mean	-0.02	9.73	10.81	40.59	37.31	50.34	28.64
Observations	267	266	267	266	259	257	239

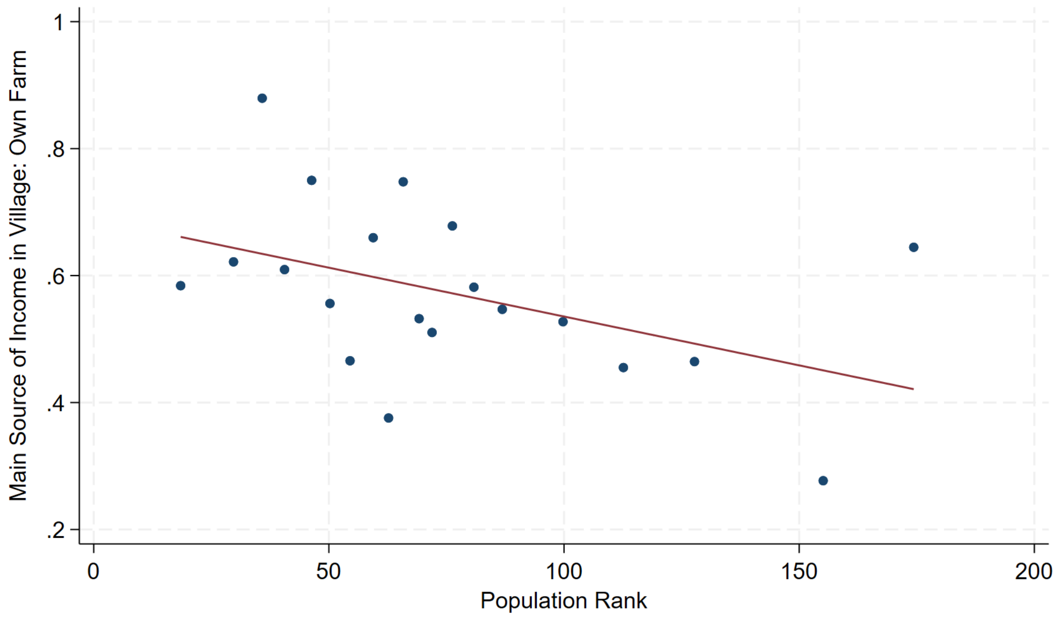
	Number Married in Past 12 Months		Average Age Married		
	Boys	Girls	Boys	Girls	Weddings With Band
Panel B: Weddings					
Motorable Road to Village	-3.627**	-1.114	0.698	-0.162	4.069***
	(1.575)	(2.278)	(2.045)	(2.009)	(1.384)
Dependent Variable Mean	7.01	7.27	19.98	17.99	1.61
Observations	267	267	266	266	266

	Fruit/Vegetable Seller Comes to Village
Panel C: Village Retail	
Motorable Road to Village	0.149
	(0.159)
Dependent Variable Mean	0.56
Observations	266

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, distance to the nearest town, and village population as measured in the 2001 census; indicators for missing census values of each control are also included. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

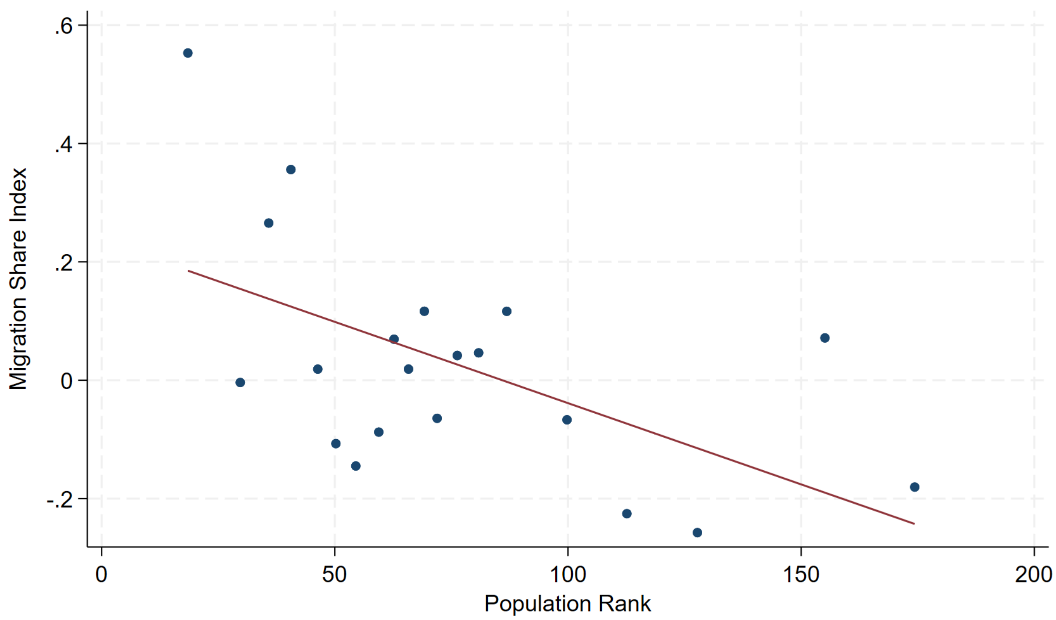
§ B.1 Reduced Form: Population Rank Predicts Key Outcomes

Figure B.1: Reduced Form: Primary Village Income Source is Own Farm



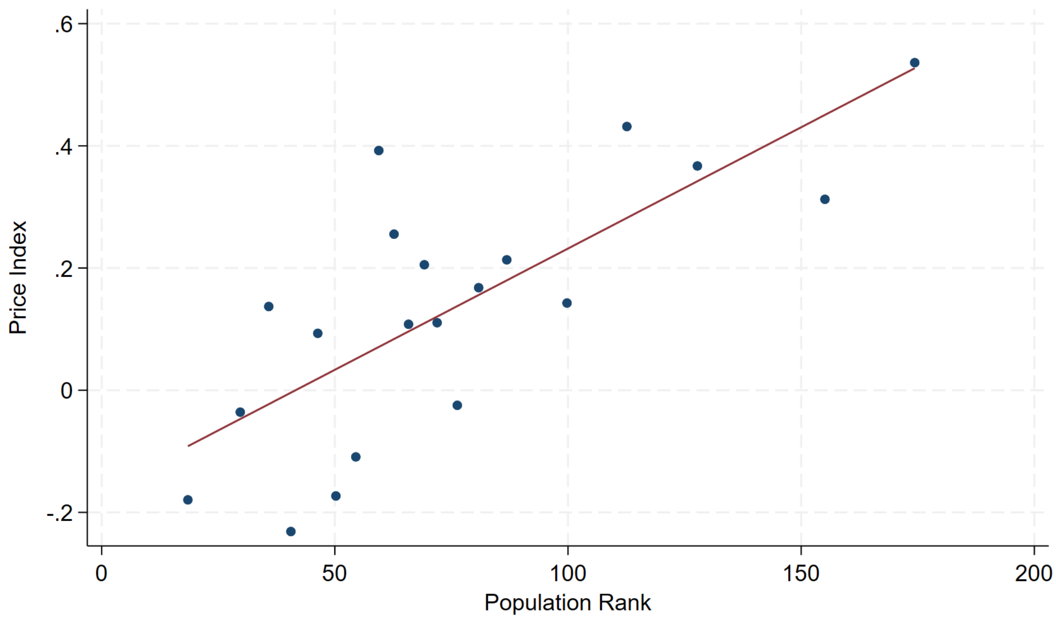
Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and an indicator of whether households ranked own farm as the primary source of income. We include census population and other relevant controls outlined in the regression equation. The sample includes the 267 surveyed villages.

Figure B.2: Reduced form: Migration Share Index



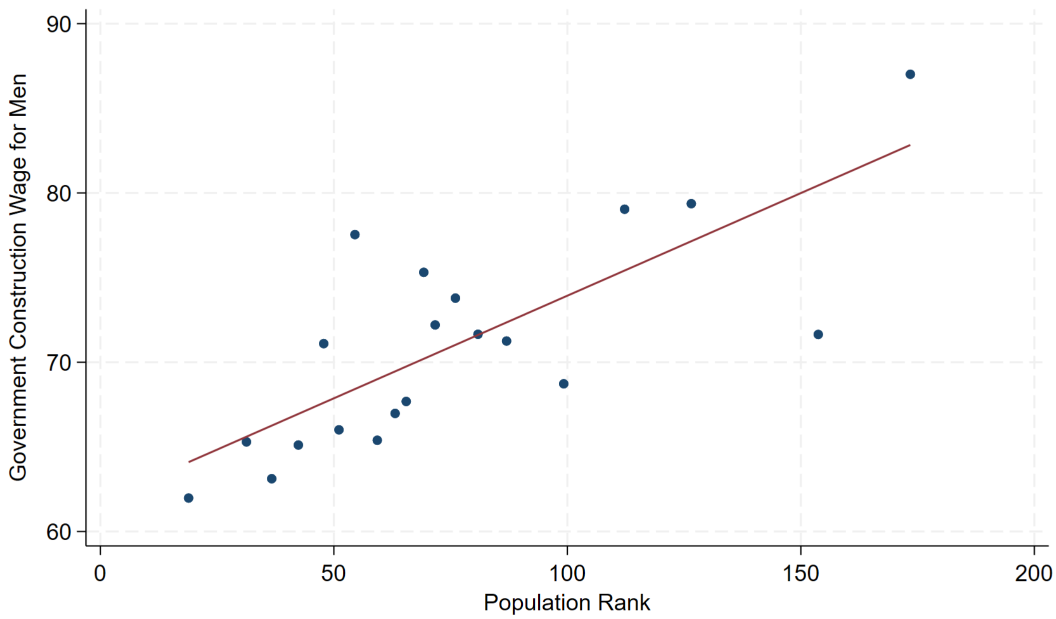
Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and the migration share index (as shown through an index comprised of the migrants per household who partake in daily, weekly, monthly, and yearly migration). We include census population and other relevant controls outlined in the regression equation. The sample includes the 267 surveyed villages.

Figure B.3: Reduced Form: Agriculture Price iIndex



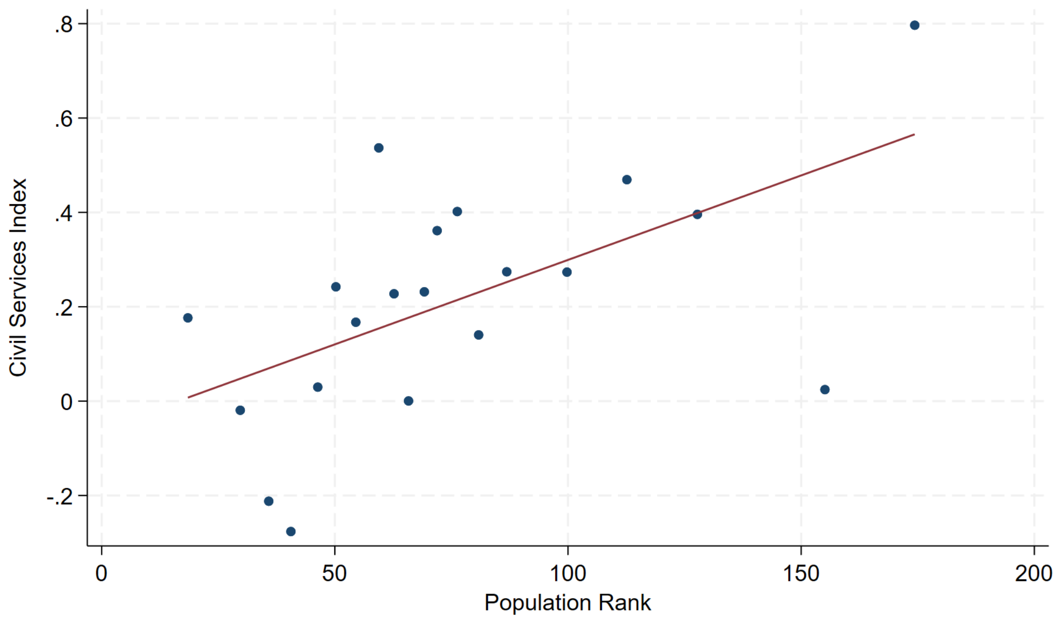
Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and the price index (an index comprised of wheat and rice prices in INR/quintal). We include census population and other relevant controls outlined in the regression equation. The sample includes the 267 surveyed villages.

Figure B.4: Reduced Form: Government Construction Wages (Males)



Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and daily male government construction wages. We include census population and other relevant controls outlined in the regression equation. The sample includes the 267 surveyed villages.

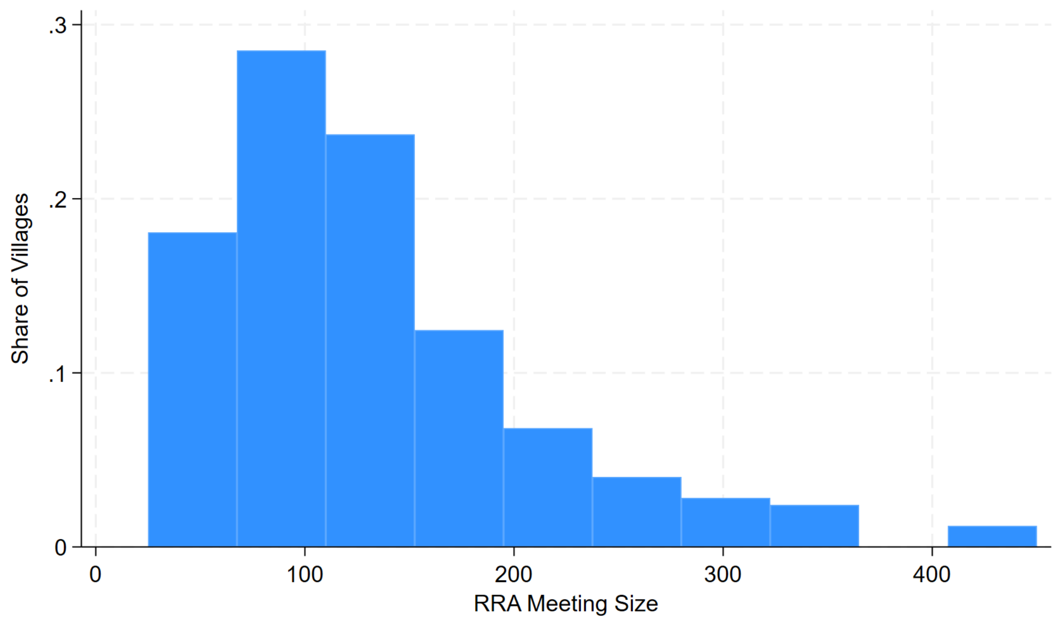
Figure B.5: Reduced Form: Civil Service Index



Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and civil service index (an index comprised of police activity and government official visits over the past 12 months). We include census population and other relevant controls outlined in the regression equation. The sample includes the 267 surveyed villages.

§ B.2 Survey and Outcome Details

Figure B.6: Distribution of Number of RRA Respondents in Each Village



Note: This figure shows a histogram of the number of respondents present during the RRA meeting for each village. The median meeting size is 110 and the mean is 132.

Table B.7: Variable Definitions From Survey and Census

Reference Table and Panel	Outcome Name	Survey Question and Construction
Table 2, Panel A	Main source of income in village: Own Farm	Indicator = 1 if own farm selected as main source of income.
	Main source of income in village: Casual Labor in Village	Indicator = 1 if casual labor (farm and non-farm) in the village is selected as main source of income.
	Main source of income in village: Casual Labor Outside Village	Indicator = 1 if casual labor (farm and non-farm) out of the village is selected as main source of income.
	Share of HHs in Casual Labor: In Village	Proportion of households working in casual labor in the village.
	Share of HHs in Casual Labor: Out of Village	Proportion of households working in casual labor out of the village.
	Share of HHs in Casual Labor: In and Out of Village	Proportion of households working in casual labor in and out of the village.
Table 2, Panel B	Wage Index: Male	Composite index of the daily male agriculture and construction wages. Standardized to mean of 0 and standard deviation of 1.
	Male Wages: Agriculture	The daily male agricultural wage (INR/day) in the village for non-government work.
	Male Wages: Construction	The daily male construction wage (INR/day) in the village for non-government work.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
	Female Agricultural Wage	The daily female agricultural wage (INR/day) in the village for non-government work.
Table 2, Panel C	Migration Share Index	Composite index of the migrants per household who travel daily, weekly, monthly, and yearly. Standardized to mean of 0 and standard deviation of 1.
	Migrants per HH: Daily	Number of daily migrants reported in the village divided by the total number of households in the village.
	Migrants per HH: Weekly	Number of weekly migrants reported in the village divided by the total number of households in the village.
	Migrants per HH: Monthly	Number of monthly migrants reported in the village divided by the total number of households in the village.
	Migrants per HH: Yearly	Number of yearly migrants reported in the village divided by the total number of households in the village.
Table 3, Panel A	Price Index	Composite index of the agricultural price of wheat, rice. Standardized to mean of 0 and standard deviation of 1.
	Agricultural Wheat Price in INR/Quintal	The price of wheat (INR/quintal) today.
	Agricultural Rice Price in INR/Quintal	The price of rice (INR/quintal) today.
	Yields Index	Composite index of the yield wheat, rice. Standardized to mean of 0 and standard deviation of 1.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
	Agricultural Wheat Yields in Quintal/acre	The average yield of wheat (quintal/acre).
	Agricultural Rice Yields in Quintal/acre	The average yield of rice (quintal/acre).
Table 3, Panel B	Farm Diversification Index	Composite index of if there is milk coop, dairy or goat rearing, and poultry farm in the village. Standardized to mean of 0 and standard deviation of 1.
	Milk Coop in Village	Indicator = 1 if the village has a milk cooperative; 0 otherwise.
	Dairy or Goat Rearing in Village	Indicator = 1 if the village has daity or goat rearing 0 otherwise.
	Poultry Farm in Village	Indicator = 1 if the village has a poultry farm; 0 otherwise.
Table 3, Panel C	Farm Input Index	Composite index for the chemical/fertilizer/pesticide share, agriculture equipment, and fertilizer company visiting village. Standardized to mean of 0 and standard deviation of 1.
	Fraction using Chemical/Fertilizer /Pesticide	The number of households that use chemical fertilizers/pesticides dvided by the total number of households in the village.
	Fraction with Motorized Agriculture Equipment	The number of households that use motorized agricultural equipment divided by the total number of households in the village.
	Fertilizer Company Visited at least once in Past Year	Indicator = 1 if the village has a fertilizer company representative visit at least once in the last 12 months; 0 otherwise.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
Table 4, Panel A	Fair Price Shop Price Index	Composite index for the prices of wheat, rice, and kerosene at fair price shops. Standardized to mean of 0 and standard deviation of 1.
	Wheat Price in Fair Price Shops	The price (INR) of wheat at fair price shops.
	Rice Price in Fair Price Shops	The price (INR) of rice at fair price shops.
	Kerosene Price in Fair Price Shops	The price (INR) of kerosene at fair price shops.
	Government Construction Wage for Men	The daily male construction wage (INR/day) in the village for government work.
Table 4, Panel B	Civil Services Index	Composite index for the number of visits by police, police patrolling, collector, BDO, VDO, and Lekhpal. Standardized to mean of 0 and standard deviation of 1.
	Police Visits in Past 12 Months	Number of police visits in the village over the last 12 months.
	Police Patrolling in Past 12 Months	Number of police patrols in the village over the last 12 months (election and non-election periods).
	Collector Visits in Past 12 Months	Number of collector visits in the village over the last 12 months.
	BDO Visits in Past 12 Months	Number of BDO visits in the village over the last 12 months.
	VDO Visits in Past 12 Months	Number of VDO visits in the village over the last 12 months.
	Lekhpal Visits in Past 12 Months	Number of Lekhpal visits in the village over the last 12 months.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
Table 4, Panel C	Political Connectivity Index	Composite index for campaign visits, events, and newspaper access. Standardized to mean of 0 and standard deviation of 1.
	Campaign Visits in Past 12 Months	Total number of campaign visits during election period in village, across all parties.
	Campaign Events in Past 12 Months	Total number of campaign events during election period in village, across all parties.
	Share of HHs Receiving Hindi Newspaper	The number of households receiving hindi newspapers dviided by the total number of households in the village.
Table A.4, Panel A	Motorable Road to Village	Indicator = 1 if there a motorable road to the village that a car can travel on; 0 otherwise.
Table A.4, Panel B	Number of commercial vehicles visiting each day	Direct count for the number of daily trucks, buses, and other commercial vehicles visiting the village each day.
Table A.5 (2001 Census Outcomes)	Village has Mud or Paved Road	Indicator = 1 if the village has a mud or paved road; 0 otherwise.
	Village Receives Newspaper/-Magazine	Indicator = 1 if the village recieves newspaper/magazines; 0 otherwise.
	Village has Post/Telegraph/-Phone Facilities	Indicator = 1 if the village has post, telegraph or phone facilities; 0 otherwise.
	Fraction of Forested Area in Village	Fraction of total village area having forest area.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
	Fraction of Cultivated Area Irrigated in Village	Fraction of total village area having irrigated area.
	Electricity for Agriculture	Indicator = 1 if the village has power supply for electricity for agriculture; 0 otherwise.
	Medical Facilities Present in Village	Indicator = 1 if the village has a medical facility; 0 otherwise.
	Health Centers Present in Village	Indicator = 1 if the village has a health center; 0 otherwise.
	Primary School Present in Village	Indicator = 1 if the village has primary school; 0 otherwise.
Table A.6, Panel A	Nearest Market Price Index	Composite index of the prices for wheat, rice, arhar dal, masoor dal, moong dal, and kerosene at nearest markets. Standardized to mean of 0 and standard deviation of 1.
	Wheat Price at Nearest Market	The price (INR) of wheat at the nearest market.
	Rice Price at Nearest Market	The price (INR) of rice at the nearest market.
	Arhar Dal Price at Nearest Market	The price (INR) of arhar dal at the nearest market.
	Masoor Dal Price at Nearest Market	The price (INR) of masoor dal at the nearest market.
	Moong Dal Price at Nearest Market	The price (INR) of moong dal at the nearest market.

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Table B.7 continued from previous page

Reference Table and Panel	Outcome Name	Survey Question and Construction
	Kerosene Price at Nearest Market	The price (INR) of kerosene at the nearest market.
Table A.6, Panel B	Number of Boys Married in Last 12 Months	Number of boys from the village who got married in the last 12 months.
	Number of Girls Married in Last 12 Months	Number of girls from the village who got married in the last 12 months.
	Average Age of Boys Married	The average age of marriage for boys in your village in the last 12 months.
	Average Age of Girls Married	The average age of marriage for girls in your village in the last 12 months.
	Weddings with Band	Number of marriages that included a musical band.
Table A.6, Panel C	Fruit/Vegetable Seller Comes to Village	Indicator = 1 if the village has fruit/vegetable seller from another village come to your village to sell vegetables/fruits; 0 otherwise.

Note: This table reports definitions for the outcome variables used in the analysis, including their data sources, underlying survey questions, and construction.

§ B.3 Robustness Checks

2SLS Controlling for PMGSY Population in Place of Census Population

In this section, we estimate the relationship between having a motorable road and our key outcomes using the same 2SLS regression as equation 2.2 except we measure village population with PMGSY program data.

Table B.8: Estimates of the Impacts of Roads on Connection to the Outside World

	(1) Motorable Road to Village
Panel A: First stage	
Population rank (small to large)	0.003***
	(0.001)
F-statistics	
Cragg–Donald F	22.28
Kleibergen–Paap F	15.39
Dependent Variable Mean	0.70
Observations	267
	Number of Vehicles Visiting Each Day
Panel B: 2SLS Estimates on Commercial Transport	
Motorable Road to Village	1.661*
	(0.871)
Dependent Variable Mean	0.58
Observations	267

Note: Panel A shows the estimate of α_1 from the first-stage Equation (2.1), and Panel B shows the 2SLS estimates of δ_1 from Equation (2.2) for the outcome of the number of daily trucks, buses, and other commercial vehicles visiting the village each day. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, and distance to the nearest town as measured in the 2001 census; indicators for missing census values of each control; and village population as measured in the PMGSY program data. The sample consists of villages from which primary survey data were collected. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table B.9: Estimates of the Impacts of Roads on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Main Source of Income in Village			Share of Households in Casual Labor		
	Own Farm	Casual Labor in Village	Casual Labor out of Village	In Village	Out of Village	Both in and out of village
Panel A: Labor Outcomes						
Motorable Road to Village	-0.518***	0.394***	0.148	0.184	0.015	-0.239**
	(0.182)	(0.140)	(0.124)	(0.130)	(0.078)	(0.112)
Dependent Variable Mean	0.57	0.26	0.16	0.28	0.34	0.36
Observations	267	267	267	267	267	267
		Male Wages				
	Wage Index: Male	Agriculture	Construction	Female Wages: Agriculture		
Panel B: Wages						
Motorable Road to Village	0.468	3.980	6.525	7.120		
	(0.728)	(6.968)	(9.287)	(5.093)		
Dependent Variable Mean	0.09	47.94	51.08	38.22		
Observations	267	265	266	222		
		Migrants per Household				
	Migration Share Index	Daily	Weekly	Monthly	Yearly	
Panel C: Migration Outcomes						
Motorable Road to Village	-0.797**	-0.580*	-0.053	-0.242	-0.514	
	(0.367)	(0.308)	(0.064)	(0.174)	(0.351)	
Dependent Variable Mean	0.03	0.40	0.16	0.21	0.39	
Observations	267	267	267	266	266	

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, and distance to the nearest town as measured in the 2001 census; indicators for missing census values of each control; and village population as measured in the PMGSY program data. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Table B.10: Estimates of the Impacts of Roads on Agricultural Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
		Prices in INR/Quintal			Yields in Quintal/Acre	
	Price Index	Wheat	Rice	Yields Index	Wheat	Rice
Panel A: Agricultural Prices & Yields						
Motorable Road to Village	1.358***	29.955	250.334***	0.004	1.276	-1.036
	(0.319)	(42.258)	(54.706)	(0.450)	(2.555)	(2.483)
Dependent Variable Mean	0.14	910.33	599.61	-0.01	11.75	12.19
Observations	267	259	207	267	259	208
	Farm Diversification Index	Milk Coop in Village	Dairy or Goat Rearing in Village	Poultry Farm in Village		
Panel B: Agricultural Diversification						
Motorable Road to Village	0.455***	0.210*	0.222**	-0.031		
	(0.150)	(0.119)	(0.087)	(0.041)		
Dependent Variable Mean	-0.02	0.10	0.09	0.02		
Observations	267	267	266	258		
	Farm Input Index	Fraction using Chemical/ Fertilizer/ Pesticide	Fraction with Motorized Agricultural Equipment	Fertilizer Company Visited at least once in Past Year		
Panel C: Farm Input Use						
Motorable Road to Village	-0.114	-0.015	-0.006	-0.129		
	(0.200)	(0.073)	(0.135)	(0.148)		
Dependent Variable Mean	-0.01	0.91	0.15	0.26		
Observations	267	252	265	267		

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, and distance to the nearest town as measured in the 2001 census; indicators for missing census values of each control; and village population as measured in the PMGSY program data. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

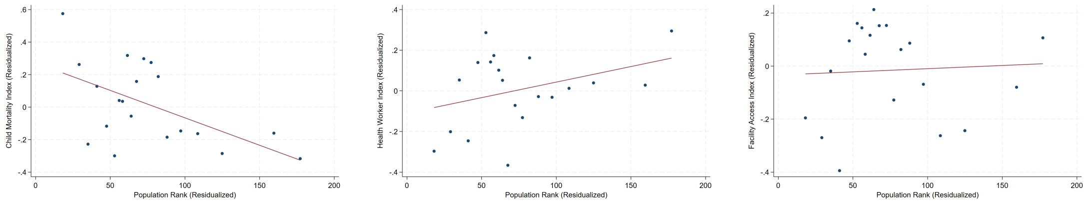
Table B.11: Estimates of the Impacts of Roads on Governance Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Fair Shop Prices					
	Fair Shop Price Index	Wheat	Rice	Kerosene	Male Wages: Government Construction		
Panel A: Government Prices and Wages							
Motorable Road to Village	-0.421*	-0.603	-0.024	-0.429	37.925***		
	(0.238)	(0.379)	(0.277)	(0.495)	(14.670)		
Dependent Variable Mean	-0.03	5.00	6.18	10.98	70.98		
Observations	267	254	259	266	249		
		Police Activity in Past 12 Months		Government Official Visits in Past 12 Months			
	Civil Services Index	Police Visits	Police Patrolling	Collector	BDO	VDO	Lekhpal
Panel B: Civil Service Connectivity							
Motorable Road to Village	1.105***	88.461**	40.193***	0.043	0.318	30.231	48.699***
	(0.212)	(41.561)	(7.033)	(0.141)	(0.536)	(19.952)	(14.408)
Dependent Variable Mean	0.21	36.92	8.94	0.06	0.73	42.11	27.72
Observations	267	267	267	266	267	267	267
	Political Connectivity Index	Campaign Visits in Past 12 Months	Campaign Events in Past 12 Months	Share of Households Receiving Hindi Newspaper			
Panel C: Political Connectivity							
Motorable Road to Village	0.891*	2.821	-0.056	0.005			
	(0.539)	(2.772)	(0.185)	(0.004)			
Dependent Variable Mean	0.12	4.76	0.29	0.01			
Observations	267	267	267	262			

Note: This table shows estimates of δ_1 from Equation (2.2) for various outcomes. Controls include per capita GP income, an indicator for agricultural electricity, fraction of irrigated land, and distance to the nearest town as measured in the 2001 census; indicators for missing census values of each control; and village population as measured in the PMGSY program data. The sample consists of villages from which primary survey data were collected. Indices are computed as the unweighted averages of their standardized components; missing component values are imputed to the sample mean of the corresponding component prior to standardization. Regressions with index outcomes additionally include indicators for missing values of each component. Standard errors clustered by district are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

C Chapter 3 Appendix

Figure C.1: Reduced Form Bin Scatter Plots for Key Outcomes



Note: This figure shows a residual bin-scatter plot of the relationship between the within-district population rank and key health outcomes. The panels show the relationship between population rank and child mortality (left), health worker access (center), and facility access (right) with census population and other controls outlined in the estimating equation partialed out. The sample includes the 267 surveyed villages.

Table C.1: Variable Definitions From Survey and Census

Reference Table and Panel	Outcome Name	Data Source	Survey Question and Construction
Table 2, Panel A	Motorable Road to Village	Survey	Indicator = 1 if there is a motorable road to the village that a car can travel on; 0 otherwise.
Table 2, Panel B	Child mortality index	Survey	Composite index from under-five mortality and under-one mortality. Standardized to mean of 0 and standard deviation of 1.
	Under-five mortality	Survey	Response for the number of children under age 5 who died in the last 12 months divided by the response for the number of children under age 5 in the village.
	Under-one mortality	Survey	Response for the number of children under age 1 who died in the last 12 months divided by the response for the number of children under one in the village in the last 12 months.
Table 2, Panel C	Health worker access index	Survey	Composite index from ANM availability, trained dai availability, and health worker visits. Standardized to a mean of 0 and a standard deviation of 1.
	ANM in own or nearby village	Survey	Indicator = 1 if there is an ANM in the village; 0 otherwise.
	Dai in own or nearby village	Survey	Indicator = 1 if there is a trained dai in the village; 0 otherwise.

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Table C.1 continued from previous page

Reference Table and Panel	Outcome Name	Data Source	Survey Question and Construction
	Number of health worker visits last year	Survey	Direct count for the reported times has a health worker visited the village in the last 12 months.
Table 2, Panel D	Facility access index	Survey	Composite index of home birth share and travel times to care for complicated delivery, injections, and TB treatment. Standardized to mean of 0 and standard deviation of 1.
	Share of children born at home last year	Survey	Response for the number of births that took place at home divided by the number of children born in the village in the last 12 months.
	Minutes to reach care: complicated delivery	Survey	Reported time it takes to reach care for complicated delivery using the usual mode/source of care.
	Minutes to reach care: injections	Survey	Reported time it takes to reach care for injections using the usual mode/source of care.
	Minutes to reach care: TB treatment	Survey	Reported time it takes to reach care for TB treatment using the usual mode/source of care.
Table 3	Maternal/Child Welfare Center	Census	Indicator = 1 if the village has a maternal and child welfare center; 0 otherwise.
	Health Centers	Census	Indicator = 1 if the village has any health centers; 0 otherwise.

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Table C.1 continued from previous page

Reference Table and Panel	Outcome Name	Data Source	Survey Question and Construction
	Community Health Worker	Census	Indicator = 1 if the village has community health workers; 0 otherwise.
	Private Health Worker	Census	Indicator = 1 if the village has private health workers; 0 otherwise.

Note: This table reports definitions for the outcome variables used in the analysis, including their data sources, underlying survey questions, and construction.

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