Citizen Training and the Urban Waste Footprint

Swati Dhingra* and Stephen Machin*

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* *Department of Economics and Centre for Economic Performance, London School of Economics*

Abstract

Diversion of waste away from and targeting zero waste to landfills are sustainability policy aims around the world, especially in developing countries where waste segregation rates are low. A large-scale field experiment in Patna, India, trained citizens in waste segregation practices, recycling mechanics and environmental literacy. Training changed behaviour through direct causal effects, alongside spatial and temporal spillovers. Cumulated economic and environmental benefits were double digit multiples of costs, and the intervention made greenhouse gas emissions savings of over a quarter of household emissions from landfilled waste. Citizen training reduced the urban waste footprint to promote global climate change mitigation.

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1. Introduction

Managing the environmental footprint of rapid urbanisation is central to the United Nations' Sustainable Development Goals, the Global Goals of making cities and human settlements sustainable with responsible consumption and production. Inadequate waste management accelerates climate change and drives the widespread pollution of groundwater, soil, and aquatic ecosystems, ultimately threatening biodiversity and public health.[1] Financially, waste management often constitutes the largest single item in municipal budgets. Despite this expenditure, municipal systems remain heavily reliant on landfills, which generate compounding fiscal, environmental, and public-health costs (Kaza et al. 2018; Matheson 2019).[2] Consequently, diversion of waste away from and targeting zero waste to landfills have emerged as key policy objectives for local and national governments worldwide.[3]

Promoting source segregation and recycling is a fundamental prerequisite for mitigating the urban waste footprint.[4] Separating waste at the point of generation—for households, manufacturing facilities, and institutional entities—enables more waste to be diverted from landfills, thereby suppressing associated methane emissions. Source segregation enhances the overall efficiency of municipal waste management systems by optimising material recovery rates for recycling and increasing the caloric value and efficiency of waste-to-energy incineration.

High recycling rates in many advanced economies are primarily driven by high rates of source segregation, which yield cleaner waste-stream fractions optimal for recycling and recovery (UNEP 2015). Emerging economies—including Brazil, China, India, and the Philippines—have enacted legislative frameworks to divert refuse from landfills through mandatory source-segregation policies. However, despite the fact that source segregation represents a low cost strategy for mitigating urban waste footprints (UNEP 2015), public adoption is low in many developing countries. This implementation gap raises a fundamental question for environmental policy: can governments induce self-enforcing pro-environmental behaviour in economies characterised by weak monitoring and limited enforcement capacity?

Ameliorating low rates of source segregation is a critical, yet understudied, environmental challenge. Credible empirical evidence on mechanisms to optimise waste efficiency, minimize landfilling, and enhance environmental sustainability remains scarce (Bryan et al. 2020). While mitigating methane emissions from waste is widely recognised as a premier negative-cost opportunity for climate change mitigation, local implementation remains obstructed because municipal governments frequently lack the capacity to monitor compliance or effectively enforce Pigouvian policies (Glennerster and Jayachandran 2023; Bryan et al. 2025). Furthermore, literature addressing waste management in developing-world cities is thin, despite extensive observational data studies establishing correlations between unmanaged waste,

[1] See, for example, Vergara and Tchobanoglous (2012), Jambeck et al. (2015), Abelson (1985), Brender et al. (2011).
[2] Lavigne et al. (2014), Yang et al. (2018), https://www.hindustantimes.com/india-news/massive-inferno-at-bhalswa-landfill-in-north-delhi-4th-landfill-fire-in-a-month-101650992868377.html
[3] The US Environmental Protection Agency (EPA) has a target of 75 percent of waste to be diverted away from landfills by 2030. The European Union Landfill Directive seeks to reduce methane emissions by prohibiting organic matter from landfills. The Global Methane Initiative has zero landfilling of degradable wastes as a priority project.
[4] https://www.bbva.com/en/sustainability/5-best-recycling-practices-from-around-the-world/, https://www.epa.gov/transforming-waste-tool/contracting-best-practices-source-separation-requirement-or-preference, https://publications.parliament.uk/pa/cm200102/cmselect/cmenvfru/659/65904.htm

disease, and degraded urban environments (Bryan et al. 2020). More broadly, a growing body of research emphasises the centrality of local environmental amenities to urban productivity, structural development, and human welfare; yet, causal evidence evaluating household responses to targeted environmental interventions remains highly limited (Bryan et al. 2020, Balboni and Shapiro 2025). This paper provides novel causal evidence to bridge this gap, investigating whether enhancing household productivity in waste management can successfully mitigate the economic and social damages of the urban waste footprint.

The question is addressed in a large-scale field experiment studying whether citizen training can generate self-enforcing pro-environmental behaviour. Conducted in 2021/22 in collaboration with the Patna municipal administration in India, the intervention provided practical, hands-on training to citizens in waste segregation practices, recycling mechanics and environmental literacy. A randomised, staggered-rollout research design was set up across a large sample of households clustered along established municipal waste-collection routes. Experimental estimates derived from primary observational waste data reveal a significant causal effect of the training on waste segregation. Specifically, the intervention increased source-segregation rates among treated households by 4.5 to 6.1 percentage points, representing a substantial expansion relative to the 10 percent baseline rate.

A central contribution of this study is demonstrating that these already big direct treatment effects substantially understate the total impact of the intervention. Because pro-environmental behaviours diffuse across proximate networks, the citizen training generated sizable spillovers to untreated households—reflecting how localised knowledge spillovers can drive dynamic interactions across urban space (for more general discussion of local spillovers see Redding 2023). Exploiting the staggered spatial variation in treatment assignment induced by the experimental randomisation, these spillovers are estimated using spatial discontinuity designs, econometric gravity formulations, and spatial decay models. The empirical results confirm that positive, statistically significant spatial spillovers magnify the returns from the intervention. Accounting for these localised externalities raises the total segregation improvement to 12 percentage points, effectively more than doubling the baseline rate within the experimental timeline.

These behavioural externalities extend beyond spatial dimensions to exhibit significant temporal spillovers. Rather than tapering off, source segregation rates rose further following the conclusion of the full rollout. By the time the final cohort of households completed training, the aggregate segregation rate reached 29 percent. This shift persisted further over the longer term, as corroborated by a subsequent follow-up wave. Over the entire study period, the aggregate source-segregation rate expanded by over 200 percent, rising from a baseline of approximately 10 percent at the outset to 32 percent in the follow-up evaluation eight months post-intervention.

From a fiscal and environmental perspective, the citizen training intervention proves to be highly cost-effective and welfare-enhancing. Merely accounting for the reduced municipal expenditure on landfilling allows the intervention to break even in less than 18 months, yielding a standalone benefit-cost ratio (BCR) between 2.8 and 3.3. When integrating the societal value of mitigated methane emissions—monetised at prevailing carbon credit prices—the BCR escalates to between 7.9 and 8.4 within the experimental window. Incorporating the compounding returns from temporal spillovers further drives the intervention comfortably into double-digit benefit-cost ratios. Empirically, the increased source segregation

reduced household greenhouse gas emissions by 26.5 percent, dropping from 274.2 kg to 201.5 kg of CO2e per household annually. Extrapolating these parameters to urban India implies potential aggregate emissions savings exceeding 6.5 million tonnes of CO2e per year, which underscores scope of low-cost behavioural interventions for climate change mitigation.[5]

This paper contributes directly to the literature on the economics of waste and urban environmental externalities (see Kinnaman 2009, Fullerton 2024). While existing empirical evidence is heavily concentrated in high-income nations, we provide large-scale causal evidence from a rapidly expanding, developing-country city where municipal waste challenges are acutely severe. We demonstrate that community-based education generates substantial, persistent improvements in source segregation without relying on continuous external enforcement. The results demonstrate that citizen-led interventions can deliver immediate environmental benefits to localised urban communities, while simultaneously offering a negative cost strategy to curb landfill-driven emissions.

These findings speak directly to a central challenge in environmental economics and public policy: how regulatory authorities can achieve critical ecological objectives when monitoring and enforcement are prohibitively costly or logistically infeasible (see Jayachandran 2022). We demonstrate that citizen training can generate self-enforcing behavioural adaptations that effectively substitute, at least in part, for conventional regulatory oversight. This decentralised mechanism is particularly relevant in contexts with constrained state capacity, where top-down regulation frameworks frequently fracture during implementation. Consequently, this paper complements the broader literature examining the welfare impacts of environmental information and interventions (Allcott and Rogers 2014; Barwick et al. 2024). Crucially, the results reveal that human capital investments extending beyond passive information disclosure to provide intensive, actionable training can catalyse shifts in long-run environmental behaviour.

More broadly, in terms of methodological contribution, this study pushes forward on an expanding literature exploring the intersections of spatial interactions, structural urban development, and environmental externalities (Balboni and Shapiro 2025, Bryan et al. 2025). By leveraging experimental variation with granular data on waste disposal and urban geography, it shows that behavioural mitigation responses propagate dynamically through localised neighbourhood spillovers. These externalities substantially amplify the aggregate returns of the intervention. Accounting for these network effects materially increases the policy's cost-effectiveness relative to standard frameworks that treat households as independent decision-makers. This localised amplification is particularly crucial in dense developing world cities, as costly infrastructure investments are conventionally required to alleviate the environmental and congestion disamenities associated with density (see Duranton and Puga 2020, McCulloch et al. 2025).

The rest of the paper is organised as follows. Section 2 contextualises the citizen training intervention within the broader waste-management literature, reconciling empirical evidence from advanced economies with the institutional realities of waste systems in India and the specific setting in Patna. Section 3 outlines the research design and presents an initial descriptive analysis of the data. Section 4 establishes the baseline causal experimental findings. Section 5 evaluates spatial and temporal externalities, leveraging

[5] Urban population in 2021 from https://niua.in/intranet/sites/default/files/2802.pdf.

Patna's natural and built environment geography alongside econometric gravity and spatial decay models to identify localized spillovers. Section 6 synthesises these various empirical estimates to reconcile their relative magnitudes, and presents a cost-benefit valuation of the intervention in terms of fiscal costs and environmental returns. Finally, Section 7 offers concluding remarks.

2. Waste Management, Related Literature and Study Context

Waste Management

A long tradition in environmental economics, surveyed in Fisher and Peterson (1976), Kinnaman and Fullerton (2000) and Fullerton and Kinnaman (2024), considers waste material as a by-product of consumption. While consumption raises household welfare, the waste material it generates that is disposed of (without proper management) adds to the stock of dumped or landfilled waste in the economy. This creates a disutility for everyone. Alternatively, household waste material can be adequately managed - such as through separation into biodegradable and non-degradable waste to increase recyclability and reduce the need for landfilling. But to do so, waste management both requires household time and effort and reduces resources available to spend on welfare-increasing activities of consumption or leisure. A household's waste production function entails choosing the optimal level of consumption commensurate with by-products to be disposed of or recycled with a time cost of effort.

The literature considers various policy tools, typically Pigouvian taxes, to address externalities from waste disposal to induce socially optimal allocations. Most work focuses on incentives and enforcement. By contrast, this paper studies whether improving households' ability to manage waste can increase compliance with environmental objectives. It studies a policy tool directly aimed at the effort cost of waste management. When households lack practical skills, compliance often fractures due to high behavioural effort costs, space constraints, and entrenched disposal habits—even when general environmental awareness is high. This study asks a highly practical real-world policy question: can investing in citizens' waste-management skills, rather than relying solely on price incentives or enforcement, deliver meaningful environmental gains?

Citizen training is modelled as a labour productivity or technology shifter that enables waste to be managed more efficiently. By reducing the effort required to sort waste correctly, training increases the productivity of waste-management activities and lowers the effective cost of compliance with segregation policies. A formal exposition is given in a model in the Appendix. This underpins the research design and setup of the experimental intervention that produce the empirical findings of this paper.

Over and above the individual household dimensions of citizen training, scope for community education and collective action to improve waste management, and public services more generally, features in early work in economics and psychology (e.g. Moore and Lowenstein 2004). More recently, empirical work highlights a role for education and community connectedness, going beyond information provision, to influence pro-environmental outcomes (see the Ballard et al. 2024 survey and Bhattacharya et al. 2024 for a rare developing country application).[6] Yet causal evidence on the effectiveness of citizen and community

[6] See, *inter alia*, Bernstad et al. (2013), Briguglio (2016) and Carlsson et al. (2021).

training and education remains thin on the ground, even in countries with advanced waste systems that allocate large public budgets to it (see Briguglio 2016 for a survey).

The bulk of existing research has primarily examined the role of prices, incentives, and recycling policies in high-income economies,[7] where waste streams, treatment technologies, and regulatory capacity differ markedly from those in developing countries. There are commonalities, but by and large the waste-management challenge is fundamentally different in developing countries because the focus in advanced economies is often on non-biodegradable waste, whereas preventing biodegradable waste from entering landfills is a central challenge in lower-income settings (Briguglio 2016). More than half of the waste in low- and middle-income countries is food or green waste that does not need to be sent to landfills and that generates methane emissions when it ends up decomposing in landfills (UNESCAP 2015, Meys et al. 2021, Glennerster and Jayachandran 2023). Moreover, the organic material contains a high moisture content and has low calorific value, limiting the viability of incineration and waste-to-energy plants without costly pre-treatment (UNEP 2010, World Bank 2005, Asian Development Bank 2011). Even Shanghai, with its most 'internationally standard' waste stream (a higher fraction of plastics and papers and less moisture), had a waste composition that could barely burn on its own before it implemented mandatory segregation-at-source laws that substantially reduced methane emissions (Zhang et al. 2023).

Segregation of waste, for example into "dry waste" that can be reused or recycled such as paper or plastic bottles, and "wet waste" such as food waste that is biodegradable, reduces amounts that need to be landfilled and increases the efficiency of alternative treatment technologies, such as recycling and waste-to-energy (Kumar et al. 2017, Ahluwalia and Patel 2018). Because these alternatives are often technologically or financially constrained in developing countries, segregation-at-source becomes a critical margin for improving waste management efficiency. Achieving high levels of segregation requires active participation by households. At the same time, monitoring household waste practices is difficult and enforcement costly (Garg et al. 2018, Kaza et al. 2018). Consequently, evidence on waste interventions in developing countries is sparse, with existing studies finding limited impacts of recycling campaigns (Chong et al. 2015; Nepal et al. 2023) or focusing on highly educated populations (Wadehra and Mishra 2018). Evaluating these interventions is further complicated by measurement challenges. Measurement often has to come from self-reported accounts which are not always reliable due to dumping by generators and collectors and lack of awareness of waste management (Ahluwalia and Patel 2018). Further, self-reported desire and willingness to pay need not translate into actual improvements in waste management (Basistha et al. 2024, Fuhrmann-Riebel et al. 2024, Kayamo 2022). These limitations make it difficult to assess whether training changes actual waste management, a gap that the present study addresses using direct observations of household waste disposal.

Waste in India

Most of the world's growth in waste is expected to occur in developing countries, especially in South Asia, where 85 percent of waste is mismanaged compared to less than half on average across all countries (Kaza et al. 2018). Waste generation per capita in India is similar to many low and lower middle-

[7] For example, Smith 1972, Fullerton and Kinnaman 1996, Levinson 1999, Greenstone and Gallagher 2008, Kinnaman 2006, Viscusi et al. 2011, Gamper-Rabindran and Timmins 2011, Currie et al. 2011, 2015, Salz 2022

income countries, at about 0.5 kilograms a day per person. Population growth and economic development in the country have been associated with greater volumes of municipal waste and methane emissions from inadequate disposal (Singh et al. 2018). Globally, India is the third largest emitter of methane, making up a quarter of methane emissions from landfills (see, *inter alia*, Kumar and Sharma 2014, Siddiqui et al. 2011).[8] This problem is expected to increase over the next two decades with proper disposal of growing urban waste estimated to require an area equivalent to the size of three megacities (Chennai, Hyderabad and Mumbai combined). Most Indian cities already spend 10 to 50 percent of their budgets on solid waste management, with smaller cities spending higher shares.[9] Consequently, waste and reducing the load on landfills with the aim of zero landfill have become a key policy focus at all levels of government.

Since 2000, India has adopted legislation requiring municipalities to collect and process waste. Over 90 percent of municipal waste is collected, but of that only about one third is processed (Centre for Science and Environment 2021). Various waste processing methods have been tried, largely proving unsuccessful due to low calorific value of waste that makes incineration unviable, and challenges in the operation and maintenance of landfills and processing plants (Singh et al. 2018, Planning Commission 2021). Traditionally, much of biodegradable waste was recycled when lifestyles were more rural and waste streams were more plastic/chemical-free. An informal network of waste workers still provides important services of collecting and recycling waste items with some resale value (such as metals and newspapers). Additionally, waste pickers recover some material in landfills and dumps, but the value and recyclability of recovered items is compromised. The bulk of waste ends up in landfills, or other waste dumps, as unsegregated waste containing a mixture of biodegradable, non-degradable, inert and hazardous waste.

Waste in the City of Patna

The intervention was conducted in collaboration with the city government of the Patna Municipal Corporation. Patna is the capital city of Bihar, one of the lowest-income states in India, with a per capita GDP of approximately Indian Rupees ₹1,06,000 (or about $1,737 in 2015).[10] Patna district had a population of 5.8 million in the 2011 census, with over 40 percent residing in urban areas and 1.7 million in the City of Patna. It is the fifth fastest growing city in India, with a decadal growth rate of 23 percent in the census.

Patna was named the dirtiest of 47 cities in the 2020 survey of Indian cities.[11] The City budgeted revenue and capital expenditures amounting to ₹15.27 billion (=7.46+7.81 or $2.07 billion) in 2021-22.[12] Of this, ₹2.57 billion (17 percent of revenue and capital expenditures) was spent on solid waste management, the largest single budget item. There were additional sizable expenditures on composting facilities and plastic processing plants reported separately under air pollution control expenses. To benchmark, the budgeted spending on roads and drains for the same period was 7 percent. Only the revenue expenditure heading of salaries, wages and pensions comes close to the amount for solid waste management - at just over 17 percent and including costs of waste management staff (numbers are not broken down by job

[8] https://www.bloomberg.com/features/2022-methane-landfills-south-asia-climate-health-hazard/
[9] https://mohua.gov.in/upload/uploadfiles/files/Part2.pdf; Hanrahan et al. (2006)
[10] From https://patna.nic.in/economy/ and converted to US dollars from World Bank market exchange rate data https://databank.worldbank.org/embed/Exchange-rates-new-LCU-(2015-2023)/id/24d7ded9.
[11] https://ss2023.sbmurban.org/assets/pdf/ss2020_report.pdf
[12] Patna Municipal Corporation Budget 2021-22 available at https://www.pmc.bihar.gov.in/budget.aspx.

characteristics). Patna received ₹11.28 billion as grants from the state and national governments. Of this, ₹4.08 billion was solely for solid waste management, with another billion for various waste and sewage projects. To compare, roads and drains made up ₹1.25 billion.

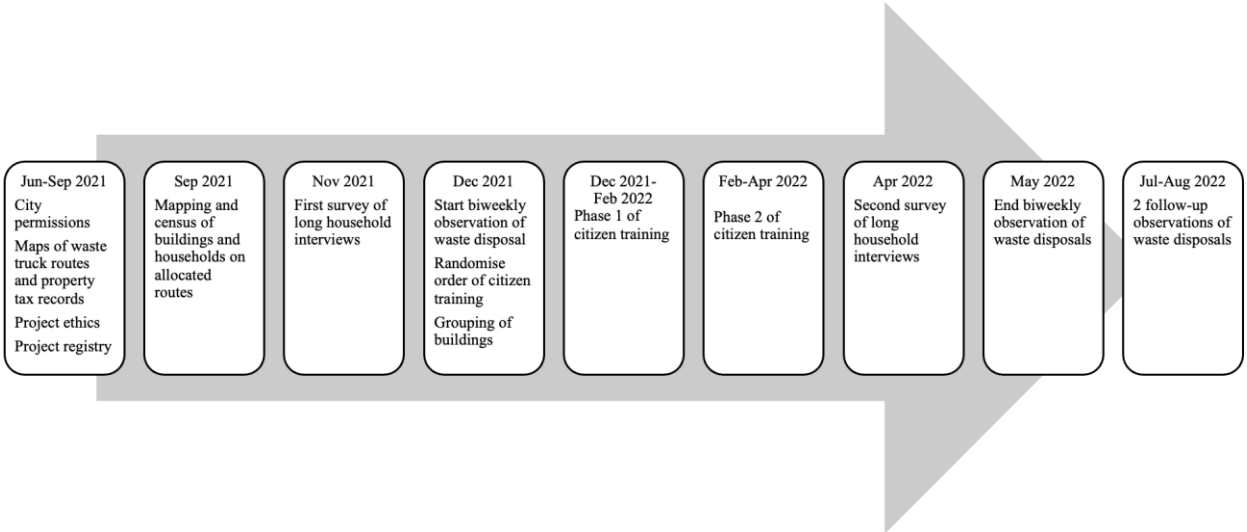
As in many urban areas of India, door-to-door waste collection is provided to resident households (at a mandatory fee of ₹360, or US $4.87, per year) by the city government. The vehicle, typically a waste truck or a handcart in congested areas, moves through a designated route at a certain time each morning to collect waste. The vehicle is operated by two members, a driver and a helper, who play loud music to alert residents of their presence in the area. The vehicle waits for a few minutes at each stop every few metres on its route. Households bring their waste to the vehicle for disposal. The vehicle moves slowly as people typically come on foot from nearby buildings to throw their waste into the truck.

Figure A1 (Panel A) in the Appendix shows a photo of the waste truck and its two main compartments - green for wet waste, blue for dry waste. It also has a separate smaller compartment/container for domestic hazardous waste (a small yellow bin attached to the back of the vehicle). The driver and helper are instructed by the government to not handle waste and residents must empty out their bins or dispose of their bags into the truck compartments. The vehicle takes the same route every morning, then deposits waste at the nearest transfer point, from where it is transported by compactors to waste processing units or landfills (located just outside of the city, shown in Figure A1 Panel B). The vehicle route was designed by the city government at least as far back as 2019 to optimise the amount of fuel consumed during its transit. Vehicle routes remained fixed throughout the study period. An example of the central part of the city and the distinct waste truck route boundaries is in Figure A1 Panel C.[13]

3. Experimental Design and Descriptive Analysis

Timeline and Household Census

The timeline starts from permissions agreed about allocation of intervention areas with the city government in June 2021, with the full sequence as follows (and in Appendix Table A1):



[13] Collection services are provided daily, as is usual across India, because of weather leading to quick putrefaction of organic matter and related problems such as pest infestations.

In July 2021, a month from the start, access was granted to waste truck routes maps and the roster of property tax records on city residents.[14] Also in July, the project received ethics approval and initial project registration occurred in early September.[15] Later that month the mapping and census of buildings and households took place and the first household baseline surveys began. The experiment implementation and data collection of waste observations by enumerators ran from December 2021 to April 2022 in two phases. A second household survey began in April 2022 once full treatment coverage had occurred. Data collection of waste observations continued to May, with a final follow up in August 2022.

The full enumeration census and household survey was undertaken several months prior to the experiment, in July 2021. The enumeration team used detailed maps and building counts to determine both how a full baseline pre-intervention survey of households was to be undertaken and how the randomised experiment structure could be set up. As tax records may not be fully complete through omissions and exclusions, the enumeration team walked door to door along each truck route to determine the geography of the buildings and the number of households residing in them. This enumerator census turned out to be vital, not least because the city has grown very significantly since the last official population census was conducted in 2011, and therefore that the number of households actually living in a building differed from city administrative records.[16] Once complete we ended up with a more comprehensive and up to date census to underpin the experiment and survey work.

Census enumerators recorded the number of family members in each residential building. They observed if waste in the residences was stored in bins/bags, or had been disposed of in the open, by the doorstep or elsewhere outside the building. There were four key Census features:

i) coverage - 10,434 households, 4,202 residences, 57,743 urban citizens;

ii) location - on or near waste truck route (4,135 of 4,202 residences, or 97.7%);[17]

iii) disposal - the vast majority (9,948 households, or 97.6%, on the truck route) stored their waste in bins/bags that were disposed of in the waste truck.[18]

iv) segregation - in the census, household survey and observation data, around one in ten of disposers segregated their waste or reported doing so (as we discuss later in more detail).

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[14] Intervention areas were selected by the city government based on a requirement of covering the city centre and the location of the city's composting facility. The areas reflect two important components of the city's waste chain. It covers dense central-city neighbourhoods and the area around the city's composting facility, where segregated wet waste can feasibly be processed downstream, linking household segregation to actual waste-processing infrastructure. A memorandum of understanding was signed with LSE to mandate citizen training for all households in these areas.

[15] Compared to the census registry, 39 buildings with 123 households that are in a commercial area are excluded for the analysis (but not the intervention) because of differences in waste collection across residential and commercial areas. Details of the experiment registry and protocols are in an online appendix.

[16] One issue was that GPS or mapping applications did not always work correctly in dense built-up locations. Enumerators therefore also sketched on streets and buildings that were missing on maps of the areas and recorded the number of distinct households that were residing in each building.

[17] Defined as within 450 metres of a waste truck collection point. Over half of households reported the truck stops right in front of their house and the rest report walking less than an average of 5.5 minutes away to dispose of their waste. At a usual walking speed of 3 miles per hour, the average walking distance is 450 metres. Several urban studies find local spillovers and externalities within cities decay and fade away beyond distances of 450 to 500 metres (Arzaghi and Henderson 2008, Rossi-Hansberg et al. 2010 and Ahlfeldt et al. 2015 - see Redding's 2023 review).

[18] Among the 2.3 percent of households neither on or near a waste truck route, disposals of waste took place mostly (98.7%) in designated areas, which is in line with the census enumerators' recording of 97.5 percent of buildings that do not have waste dumps near them, as they have access to municipal waste collection and cleaning.

Experimental Design

The training covered all households and the experimental delivery of citizen training design had staggered timing across groups of buildings running from mid-December 2021 to mid-April 2022. The staggered cluster design was adopted for several reasons. First, for reasons of fairness and equity, we (and the Patna government) wanted to guarantee that all households in intervention areas received citizen training. Second, the staggered design enables causal inference via a dynamic treatment-control design where not yet treated clusters serve as a control group for already treated clusters. Third, splitting into two geographically matched halves in a chessboard style configuration (white squares trained first, matched black squares after) ensures treatment-control comparisons are made across clusters similar in characteristics due to geographical sorting (Adukia et al. 2023, Bharathi et al. 2022). Fourth, the matched cluster approach enables spillovers and scaling up among households to be studied. This is important in a setting where spillovers may arise from citizen interactions, a feature explicitly incorporated into the research design. Fifth, and also related to spillovers, the design is combined with geographical features of the city, such as boundary discontinuities based on the natural and built city environment that prevent citizen communication and hence spatial spillovers to control groups.

The enumeration team's geocoded information was used to create 38 groups of an average size of just over 100 contiguous buildings. Building groups were numbered from east to west and north to south on a map, with the grouping designed to ensure geographical spread and enable the chessboard structure of odd numbered (white) in phase 1 and even numbered (black) squares in phase 2. A bi-weekly staggered timing of treatment was randomised for first phase delivery of treatments to white squares and, once complete, matched black square units received the intervention in an analogous second phase.[19]

The chessboard style set up is visually presented in Figure 1, also including 5 pre-intervention periods of data collection. The first data collection for all building clusters took place on 2 December 2021 (time period -5 on the Figure). In all, five pre-treatment data collections occurred prior to the first citizen training intervention (time period 0) delivered on 16 December 2021. Thereafter data collection occurred bi-weekly, with treatments sequentially administered across odd numbered white squares, and then even numbered black squares of building clusters, until the last, 38th, group received training on 18 April 2021 (time period 37).[20] The close gap between treatments is designed to be small enough for fairness among early and late-treated clusters after the end of the intervention, and to reduce spillovers within treated households in a cluster. Overall, the intervention period had 38 days of data collection across all clusters, hence the 38×38 structure of treatment group by time of the Figure.[21]

Once all households had received training – after treatment time period 37 - data collection continued to record waste observations for all clusters on a bi-weekly basis until 31 May 2021. A second

[19] A randomised order of the intervention came from drawing their unique numbers blindly from an urn without replacement by the authors to keep it separate from the training and enumeration teams.

[20] Panels A and B of Figure A2 in the Appendix provide a visual summary of the treatment process through a map that zooms in on one waste truck route in the city centre to show the order of the start of citizen training for different buildings in phases 1 and 2, marked by white and black shading respectively.

[21] In practice, overlap did occur on the start date of groups across waste truck routes, and so the experiment contains 31 unique treatment dates rather than the 38 in the theoretical chessboard in Figure 1. There were periodic breaks in the training schedule for New Year's holiday, the festival of Holi, and the festival of Ram Navami.

household survey was also conducted at the end of all treatments and recorded longer interviews with households. Enumerators followed up two months after the last waste observation to undertake two more data collections (between 27 July and 8 August 2022).

Citizen Training

A detailed and extensive citizen training programme was administered to every household within a group on its randomised start date and in subsequent days. Door-to-door visits were undertaken by two members of the intervention team to train citizens in the group. The main waste manager in a household was given the training and revisits occurred if the person was not available. The same pair of training providers visited a group repeatedly until every household had been covered for delivery of the training.

Training pairs first showed a letter of introduction from Patna Municipal Corporation. They then asked about the primary waste manager of the household (or households in close vicinity) and proceeded with the training. The protocol was designed to provide structured learning materials and undertake active practice sessions to develop skills for practical waste management. Training content included information on the landfill outside Patna and its operation mode and functioning; information on health and environmental impacts on the community of landfilling and open dumping; demonstrations on reducing, segregating, reusing and recycling mechanics; and practice sessions for segregation and home composting.

Team members trained citizens through instruction demonstrations and active practice in segregating waste using the waste bins/bags present in the household. This was followed by a teach-in setting up bins for segregation and composting using the equipment of the training providers and the disposal facilities of the households. Citizens were left with documents on different types of waste for reference, on the landfill outside Patna and were given a phone number. The phone line was fielded by the training staff to answer any queries regarding waste and segregation. Households were also encouraged to call the training team if they wanted any help in setting up their bins or their own home composting kits. An example of some sample material used in the training and education activity is depicted in Figure 2, with additional examples in Figures A3 and A4 of the Appendix.[22]

Outcomes and Measurement

A challenge facing waste studies in developing country settings is a near total lack of reliable or representative data. Existing studies are mostly small scale and low public awareness can make self-reported waste outcome information inaccurate or unreliable (see Wadehra and Mishra's 2018 pioneering study of waste management). Additionally, in an interview undertaken before the experiment with Shivani Wadehra about her work reinforced this issue. Even in a highly educated neighbourhood of Delhi, many residents were unaware that wet waste and dry waste referred to the properties of the waste as opposed to that of the material from which the waste was generated.[23] An interview quote stated: "Many residents thought they were segregating-at-source because they were selling a few valuable metal items to informal sector recyclers

[22] Drivers and helpers (sitting in the trucks) were not involved in citizen training, but were informed of the programme. Waste workers are often from socioeconomically disadvantaged backgrounds and, in practice, have little authority in enforcing waste management rules.

[23] Wet and dry waste are common terms in waste management, referring broadly to biodegradable and non-biodegradable waste.

even when they were mixing up the bulk of their waste in the truck. Even residents, who were diligently segregating all of their waste, categorised an empty plastic milk packet as wet waste."

Several design features ensured a large scale representative data collection which counters possible mismeasurement or difficulty of collection of waste outcome measures. First, the data collection and the intervention are, to our knowledge, much larger in scale and sample than the existing body of environmental work studying waste in developing countries. On possible mismeasurement due to low public awareness, a pair of trained enumerators walked alongside each waste truck twice a week to ensure accurate recording. The enumerators collected distinct measures of waste segregation. A first measure, and the primary measure used in the empirical analysis, recorded the number of disposers of waste and whether their waste was segregated into wet waste and dry waste. This provided a measure of the share of disposers in a building cluster that disposed of segregated waste into the truck. If disposers were segregating their waste, they would typically carry at least two bags/bins and enumerators were able to view the content of the waste when the disposer tipped it into the truck compartments. Enumerators stationed at collection points directly observed households emptying their bins or bags into the waste truck compartments and weighed wet and dry waste separately. Crucially, waste is classified as "mixed" if materials are not properly separated upon visual inspection by enumerators, even when households nominally use different containers. The measure therefore reflects effective quality of source segregation rather than self-reported behaviour or mere possession of multiple bins, reducing concern that estimated treatment effects are driven by superficial compliance, rather than meaningful changes in waste sorting practice.

This main waste segregation metric from the observation data can be triangulated and cross-validated with the census and household survey data and with other measures of waste segregation. The share of waste volume that is segregated was measured as enumerators had weighing scales with a hook to record the volume of dry, wet and unsegregated waste disposed of in the waste truck (see one of the photos, the one shown on the far left, of enumerator activities in Figure A5).[24] Waste volume is recorded with the bin weight before going into the truck and then the bin weight is recorded separately after the waste has been removed as there are no standardised bins/bags. Households can generate all three types of waste – dry, wet and unsegregated and the volumes of all three are considered later as measures of waste segregation.

Longer interviews on waste practices were conducted separately through surveys undertaken before and after the full intervention. Information was collected on whether the household segregated their waste, whether they disposed of their waste through the municipal waste collection services, the number of separate bins/bags of waste in the household and the volumes of dry, wet and unsegregated waste in the bins of the household (where it could be readily measured by the surveyors). These are self-reported measures that provide valuable and informative validation checks on the observation and census data.

To collect the main waste measures, enumerators walked with the waste truck to record their waste observations for household disposers. A disposer can be assigned to a residential building cluster because

[24] Because there are only two compartments in the truck and three possible types of waste streams – dry, wet and unsegregated, enumerators noted that waste drivers and helpers tended to compartmentalise wet and dry either within one compartment by leaving some gap between them or by accumulating the dry waste in bags in which they were disposed of (and often hanging them separately outside the two compartments).

clusters of buildings (as opposed to an individual building) can be visually identified as separate from the next cluster of buildings when viewed by enumerators during disposal into the truck. On average, a building cluster comprises about five to six buildings. Visual identification ensured that disposer numbers per cluster of buildings were accurately recorded, even though the enumerators could not precisely see which building within the cluster the disposer belonged to. If needed, enumerators verified the residential locations of disposers to assign their building clusters. If a group of households disposed of their waste together, such as an apartment complex with centralised bins, it would typically be recorded as one disposing household (unless they explicitly stated being from multiple households). Enumerators were trained for three weeks before the data collection started to enable them to record data at speed.[25]

Enumerators recorded the GPS (or approximate GPS) of the central location of the building cluster. On each observation day, they recorded the number of disposers coming to the truck from each cluster but naturally could not observe households that did not dispose of their waste into the truck on a given observation day. The number of non-disposing households can be inferred from the census. In longer interviews, households reported that they go to close-by locations to dispose of their waste into the truck. If they miss the truck in their usual location, they go to the next halt of the truck and so on, with all typically going within a 450 metres radius of their residence. The census has the road segment or by-lane of every building, and so we know the number of households within 450 metres of the GPS of the building cluster (the 97.7 percent of households in the census covered by waste truck routes). A single household can fall within more than one building cluster for its waste disposals, and we take the inverse of the distance of the household to each building cluster to be proportional to the probability of disposing of its waste in that cluster. This weighting accounts for the fact that households can go to the nearest or other nearby truck stops for disposal, while at the same time, it ensures that the number of households across all clusters sum to the actual number of households recorded in the census. The household weight of a building cluster, denoted by N_c for cluster c, is higher if more households are close by, and later we also discuss alternative weighting schemes. Statistics reported from the enumerator observation data are weighted by this inverse distance-weighted number of census households for each building cluster and so correctly aggregate disposer/non-disposer level observations to the aggregate number of census households.[26]

Descriptive Statistics

The waste observation data comprise 657 disposing building clusters with 10,196 census families residing in areas located on or near a waste truck route. Overall, the data has observations over 23 weeks on 51 different days. This covers 49 bi-weekly data collections running from 2 December 2021 to 31 May 2022. There are 5 pre-treatment data collections, 33 that took place while the staggered rollout of citizen training took place, 11 once all treatments had been administered, plus 2 days in the August 2022 follow-

[25] One route has a slum area that the truck cannot access, where there are community bins for citizens to dispose of waste. Citizen training was undertaken there, but enumerated observations do not cover these alternative forms of waste disposal. Later, enumerated observation results are shown excluding clusters where the slum is located.

[26] Enumerators collecting observational data were different individuals from the intervention team doing the training. These activities had different hours of operation because data collection occurs in the morning, while training of citizens in households takes place in the afternoons when waste managers, typically female members, of the household have time free from domestic commitments that are concentrated in mornings and evenings.

up. This gives a total of 33,507 (= 657 × 51) unique building cluster-day observations covering 519,996 (= 10,196 × 51) household-days.

The upper panel A of Table 1 reports aggregate summary statistics for all observation days of data collection, from the pre-intervention period, the post-intervention period ending once all households had received training and through to the end recording of observation data following the full rollout. It finishes with the follow up that took place four months after the full rollout. Column (1) shows over the entire period that the share disposing of their waste segregated into dry and wet waste in the truck is 11.33 percent of all disposers. The waste volumes measured as the share of segregated waste in the total waste volume is broadly similar – at 10.87 percent of all disposed waste (=154 grams of segregated waste/1417 grams of total waste per household-day).

The full set of observation days are split into pre-, post-, full rollout and follow-up periods, respectively in columns (2), (3), (4) and (5) of the upper panel of Table 1. Aggregate rates of segregation climb significantly over the duration of the experiment. Initially quite low levels of waste segregation are seen for disposers prior to training, with pre-intervention waste segregation rates of about one in ten disposers (9.48 percent). This rises substantially by 5.67 percentage points, climbing to an average 14.57 percent across the post-intervention period. Once the training rollout is complete, segregation rates continue to increase to 29.14 percent. By the end, in the follow-up in August 2022, around a third of all disposers are segregating their waste. This is over 200 percent higher than the pre-intervention average. Similarly large pre- to post-intervention increases occur also for the weight-based volume measures.

The aggregate numbers show big increases in waste segregation. Of course, grouping the four time periods in panel A of Table 1 means that raw summary statistics contain composition effects from grouping time differences in treatment together (i.e. as households randomised into receiving citizen training later are pooled with those starting the training earlier). It is important with this structure that an appropriate experimental design and estimation sample is formulated to obtain a causal impact not containing composition bias from the staggered timing of treatment. The next section makes clear the experimental design used to elicit a causal impact of citizen training on household waste segregation in this setting.

4. Experimental Results

Estimation Sample

The spatial staggered over time research design firmly fits into the recent econometrics literature on difference-in-differences estimators with staggered treatment (see these surveys: Baker et al. forthcoming, de Chaisemartin and d'Haultfoeuille 2023, Wing et al 2024). The staggered design makes use of an orthodox two-way fixed effect model inappropriate, except in the improbable case of identical experimental estimates across all the staggered treatments with differing durations of pre- and post-treatment periods. To permit heterogeneous estimates across staggers, the Callaway and Sant'Anna (2021) estimator, appropriately weighted by population and corrected for composition bias following Dube et al. (forthcoming) and Wing et al. (2024), is used. This compares waste outcomes of households before and after they have received the training with waste outcomes of those that have not yet received the training because they were randomised to receive it at a later date. Because the durations differ and are sometimes unbalanced (for the pre-treatment

sample on earlier treatment groups, and the post-treatment sample on later treatment groups) – see the treatment order structure of the experiment in Figure 1 - estimation samples need to be adjusted accordingly.

Summary statistics for the main estimation sample are in the lower panel B of Table 1. There are 23,652 building cluster-day observations covering 367,056 household-days over the 36 different days of the pre- and post-intervention timeline. Observation days are included until 13 April 2022, stopping that day because all clusters receive citizen training by the following week. The estimation sample consists of 38 building groups, of which 35 start citizen training in the sample period before 13 April. The remaining three groups are pure control households as they start citizen training after 13 April (respectively on 14, 16, and 18 April). The difference between the full observation data in the top panel and the estimation sample in the lower panel of Table 1 arises due to the additional pre-treatment weeks of the three control groups and the longer post-treatment period for the full observation data in Panel A. For the salient items and sub-periods contained in both panels, the descriptive statistics are highly reassuring in their similarity.

Difference-in-Differences Staggered Research Design

Due to the staggered design, composition of treatment and control groups varies over time. Thus the estimation method places each pair of treatment-control groups on a given stagger date of treatment into treatment-control stacks. The first stack 1 has treatment clusters treated on the first treatment date that start the citizen training on 16 December 2021, using all not-yet-treated clusters that start treatment from the 2nd to the 35th treatment dates as controls until their training start dates. The last three groups to start treatment (dates 36th to 38th) are pure controls throughout, because their households receive training after the end date. Following best practice from the staggered difference-in-differences literature (Cengiz et al 2019, Callaway and Sant'Anna 2021), only "clean" controls are included in the estimation sample, i.e. pre-treatment observations of clusters in treated group 1 are not included in stack 2, and so on for other stacks.

A stack set s is a group of treated building clusters c' starting treatment on calendar date $t_{c'} = \tilde{t}$, with corresponding control clusters c^o that have not yet started their own training and up to the time when training begins at calendar date t_{c^o}. Formally, $s(\tilde{t}, r) = \{c', c^o \mid t_{c'} = \tilde{t},\ t_{c^o} > \tilde{t}, \tilde{t} + r\}$ for each relative time $r \equiv t - \tilde{t}$ that recentres calendar time period t to be relative to the start date of training $\tilde{t}$ of the stack under study, with $r = 0$ denoting the start of citizen training for the treated clusters c' in the stack and $r = 0,1,2, \dots, T$ denoting the set of relative times since the start of training. Appending all stacks together gives the full dataset of 35 stacks of treated groups of building clusters and their control clusters.

Baseline experimental estimates for waste outcome W_{dcrs} of disposer d residing in building cluster c at relative time r in stack s (of the treated and corresponding control group) are from the specification:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r=0}^{T} \beta_{rs} D_{dcrs} + \varepsilon_{dcrs} \qquad (1)$$

where α_{cs} are cluster-stack fixed effects, α_{rs} are relative time-stack fixed effects and ε_{dcrs} is an error term. D_{dcrs} is an indicator that switches on to one for households in the treated group in each stack after the start of their citizen training and zero otherwise.

In equation (1), β_{rs} is the DiD ATET (difference-in-differences average treatment effect on the treated) at each relative time r for stack s. Because a number of group-time ATET coefficients are estimated,

they are weighted to produce an overall staggered DiD average treatment effect (SDiD ATET), $\beta \equiv \sum_s \sum_{r \geq 0} \beta_{rs} \omega_{rs}$, by averaging across the β_{rs} for $r \geq 0$ over time and across all stacks, where the weight ω_{rs} is the share of households covered at each relative time by stack. The weight is $\omega_{rs} \equiv N_{rs} / \sum_{s'} N_{rs'}$ for the number of households covered by the clusters at each relative time in the stack: $N_{rs} \equiv \sum_{c \in s(\tilde{t},r)} N_c$. In the special situation of constancy of estimates across groups and time, the SDiD ATET estimate is the orthodox two-way fixed effect ATET estimate, which will generally be biased in the presence of heterogeneity.

The SDiD ATET compares households that have and have not started citizen training. A pair of white and black squares that face the same set of waste conditions (as they are in geographically matched locations), but that have and have not received citizen training differ in their productivity to manage waste. Households in white squares that have begun citizen training would be more likely to manage their waste than households in black squares that have not because training acts as a positive productivity shifter for household waste management activities.

Event study SDiD estimates come from generalising equation (1) to incorporate time varying estimates across relative time (in both pre- and post-treatment periods) as:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r=-\tau,\ r \neq -1}^{\mathrm{T}} \beta_{rs} D_{dcrs} + \varepsilon_{dcrs} \qquad (2)$$

where the DiD ATET estimate is normalised to zero just before the start of training at $r = -1$, the reference relative time period for the event studies. The event study SDiD ATET estimates are obtained as weighted averages $\beta_r \equiv \sum_s \beta_{rs} \omega_{rs}$ for each relative week $r = -\tau, -\tau + 1, \ldots, -2, 0, 1, 2, \ldots, T$ where the weights are again the stack sample shares across all stacks.

The SDiD ATET estimates contain compositional differences based on who has and has not received the intervention at a given relative time. These have been shown to lead to erroneous inferences for pre-trends and event studies (Wing et al. 2024). Balanced SDiD ATET estimates overcome these problems by focusing on relative times and clusters that are fully balanced on a specified set of relative times. They are similar to the balanced event time aggregate of Callaway and Sant'Anna (2021) implemented through weighted stacked DiD with compositional balance in pre-treatment and post-treatment periods, and show the dynamic treatment effects at each point in time since treatment. The results discussion to follow starts with standard SDiD ATET estimates because they retain more information and cover more stacks (Dube et al. forthcoming) and then moves on to show partly and fully balanced estimates.

Results

Table 2 contains the first set of experimental SDiD estimates. The specification in column (1) shows the SDiD treatment effect for the full estimation sample with the staggered design comparing treatment at a given time to those not-yet-treated and the never treated. There is a 4.50 percentage point increase in the probability that a household disposes of waste that is segregated into dry waste and wet waste into the truck. This is large, corresponding to about a fifty percent increase relative to the aggregate pre-treatment segregation rate for all disposers of 9.31 percent.[27]

[27] The standard two-way cluster and relative time fixed effects DiD ATET is 4.86 (1.19).

Columns (2) to (7) of Table 2 report estimates from refined specifications that vary the estimation weights, control groups and relative time periods of the estimation sample. Column (2) fixes the weights ω_{rs} to the share of the stack at relative week $r = -1$ just before the start of citizen training to reduce compositional changes over time, while Column (3) fixes the weights to the average across all treatments $r \geq 0$. The SDiD ATET estimates increase to 5.55 and 4.54, respectively. Column (4) only includes control households in the three pure "never treated" control groups to reduce compositional changes from different control groups across treatments and time, and this takes the SDiD ATET somewhat higher to 6.10.[28]

Estimates reported in columns (5) to (7) of the Table are from specifications that balance the estimation sample on relative time. Column (5) includes treated and control groups that have at least four relative weeks of observations before and after the start of citizen training in each stack (i.e. have relative weeks $r = -4, -3, -2, -1, 0, 1, 2, 3$ for every treated and control group included in the sample). Column (6) does the same for six weeks before and after the start of citizen training. Finally, column (7) is a more stringent version of column (5) that also balances on each building cluster in the sample in relative weeks $r = -4, -3, -2, -1, 0, 1, 2, 3$. The SDiD estimates for these more balanced panels range from 4.46 to 4.94. Baseline results therefore take a range of 4.46 to 6.10 depending on when composition is adjusted through the structure of balancing, weightings to compute the SDiD, definition of control groups, and relative weeks since treatment.

Figure 3 shows event study estimates. The upper Panel (a) corresponds to column (7) of Table 2, the specification fully balanced on building clusters and that have at least two relative weeks before and four or more relative weeks after the start of citizen training. The lower Panel (b) shows estimates from a longer duration time window, for six weeks before and five weeks after. Both show a strong tick up in segregation that follows a week from the start of citizen training and that persists at a higher level.[29] They also clearly confirm the pre-treatment parallel trends assumption required for a causal interpretation of the DiD estimates is fully satisfied.[30]

Common pre-trends of treated and control groups imply households are likely to be balanced on observable and unobservable characteristics, including the randomised order of the intervention. Another way to confirm this is to compare pre-intervention segregation rates and household characteristics for phase 1 and phase 2 treatments. The means of the segregation rates for those treated in phase 1 and phase 2 are similar for the full data collection (at 8.9 and 9.8 percent) and for the experimental sample (at 8.9 and 9.6 percent), as shown in Appendix Table A2. Phase 1 and 2 pre-treatment means of observable household characteristics collected in interviews are highly similar for an array of observable demographic, waste and building characteristics (see the phase 1/phase 2 pre-intervention balancing tests in Appendix Table A3A).

[28] Excluding clusters in slum parts of the truck route slightly lowers the DiD ATET in column (1) of Table 2 to 4.41 (0.87) when excluded from treatment and 4.06 (0.90) when also excluded from controls. Adding in enumerator fixed effects increases the estimates slightly, with a range of 5.31 (1.00) to 6.81 (1.08) for columns (1) to (4) of Table 2.

[29] A close look at the event studies reveals that the treatment week of training does not see a tick up in segregation rates, as they jump up sharply from the week after and stay higher. Depending on their timing of disposal, households received training in the treatment week before and after going to the waste truck as training spanned a few days.

[30] Event studies for the unbalanced sample and for a less restrictive balance (on group and time) than Figure 3 are similar and shown in Figure A6 in the Appendix.

5. Spillovers and City Geography

Spatial Spillovers

The experimental estimates show sizable increases relative to the initial baseline that, in the absence of local spillovers or externalities, can be viewed as direct, causal effects. However, to varying extents in different building clusters and localities, although there is some physical distance between treated and control clusters, citizens may communicate with those in control clusters about the programme activities, giving scope for spillovers to arise in clusters that have not yet started their own citizen training.

Spillovers are explicitly included in the research design through the city geography. A first, direct approach restricts the analysis to situations where spillovers are not able to occur because of the presence of spatial discontinuities (for examples of spatial discontinuity studies, see Gibbons et al. 2013, Turner et al. 2014, Michaels et al. 2021). Features of city geography generate natural and built environment spatial discontinuities that reduce or prevent crossings, and hence rule out communications with not yet treated households. A second method, in line with recent developments in spatial economics, explicitly models multilateral proximity spillovers in the full sample. This is done in gravity and spatial decay research designs. Considering each in turn:

1). Spatial discontinuities

Restricting the sample to set elements where treated cluster c' and control cluster c^o are on either side of a spatial discontinuity that is not crossed, denoted by Φ_{ij} for side i of discontinuity j, acts to rule out spillovers. It results in a very strict form of matching of treated clusters to control clusters, where not all black squares are pooled together as controls and instead the white squares are only matched to black squares adjacent to them on the other side of a spatial discontinuity that is not connected to other white squares. Treated clusters c' are matched to their control clusters c^o on the other side of a spatial discontinuity ($c' \in \Phi_{i'j}, c^o \in \Phi_{i^o j}$ for $i' \neq i^o$). Matched control clusters remain in the stack until training starts for them or for the building clusters c^m with which they are not separated by a spatial discontinuity, denoted by $\mathcal{B}_{c^o}$. This produces a staggered difference in spatial discontinuity differences, or SDiSD ATET, estimator defined as β earlier from equation (1) for stack sets re-defined as $s(\tilde{t}, r) = \{c' \in \Phi_{i'j}, c^o \in \Phi_{i^o j}\ \forall j \in J\ |i' \neq i^o,\ t_{c'} = \tilde{t},\ t_{c^o} > \tilde{t}, \tilde{t} + r,\ t_{c^m} > \tilde{t}, \tilde{t} + r\ \forall c^m \in \mathcal{B}_{c^o}\}$ across all spatial discontinuities in J with appropriately rescaled weights for the discontinuity sub-sample. Because the order of treatment is randomised, at least one group on one side of a discontinuity gets randomised into treatment before its corresponding matched group on the other side of the discontinuity.

2). Proximity spillovers

Rather than ruling them out through discontinuity sub-samples, the proximity spillover model-based approach recognises that nearby control clusters are more likely to feature information flows from spatially proximate treated clusters. For example, control group citizens who are closer to, or share a truck route or border the truck route of treatment citizens, would be more likely to observe or to communicate about the training or their waste behaviour with treatment citizens. Consider a disposer d in control cluster c^o with potential spillovers from already treated clusters c^m. A spillover is more likely if the disposer is located closer to already treated clusters. Let M_{dcrs} denote the sum of the disposer's proximity to all the treated

clusters at any relative time r of stack s. Equation (1) can be generalised to permit multilateral proximity spillovers through inclusion of M_{dcrs} as follows:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r=0}^{\mathrm{T}} \beta_{rs} D_{dcrs} + \gamma(1 - D_{dcrs}) M_{dcrs} + \varepsilon_{dcrs} \quad (3)$$

In (3), β_{rs} is the own DiD ATET estimate over time and stacks, and its SDiD ATET estimate β is obtained by averaging across the different DiD ATET estimates, as before. The new key outcome of interest in equation (3) is γ, the average effect on the "control" households (that have not yet been treated on their own) from training starting in clusters that are proximate to them. This spillover effect is evaluated at the mean of proximity over the entire sample (including treated clusters) during the post period as $\gamma\bar{M} \equiv \sum_s \sum_c \sum_d \sum_{r=0}^{T} \gamma M_{dcrs}(1 - D_{dcrs})\omega_{rs}$.[31]

Multilateral proximity spillovers are incorporated in two ways conducive with empirical models from related literatures on gravity and spatial decay. For gravity models, there are a number of ways to measure proximity and functional forms to be included in empirical specifications (Head and Mayer 2014). Two measures of multilateral proximity are used. The first is based on geographic distance defined as the sum of the inverse distance (in kilometres) of the control group to all treated groups, so that $M_{dcrs} = \sum_{c^m \neq c', c^o} (1/Distance_{om})$ for the other already treated clusters that have $t_{c^m} < \tilde{t} + r$ at relative time r of the stack $s(\tilde{t}, r) = \{c', c^o \mid t_{c'} = \tilde{t},\ t_{c^o} > \tilde{t}, \tilde{t} + r\}$. The second is the number of treated groups with which the control cluster shares a waste truck route or a waste truck route border, $M_{dcrs} = \sum_{c^m \neq c', c^o} Border_{om}$ where $Border_{om}$ is an indicator for control clusters with treatment date t_{c^o} that share a waste truck route or border with already treated clusters that started treatment at t_{c^m}. In each case, the multilateral proximity measure M_{dcrs} rises with bilateral proximity (inverse distance or shared border with the treated clusters in each stack) and with the number of treatments that are proximate to the control cluster.

The second way of considering the role of proximity spillovers is in a model of spatial decay. Decay models have been increasingly used in a number of areas (for examples, see Miguel and Kremer 2004 in a randomised trial, Rossi-Hansberg et al. 2010 in the context of housing externalities, Davis et al. 2025 on race segregation, and Redding 2023 for quantitative urban models). In the experimental setting, spatial decay is incorporated from combining the presence of spatial discontinuities with gravity measures. This is defined as the inverse distance-weighted number of treated groups with which the control cluster shares a waste truck route or a waste truck route border without a spatial discontinuity, so that $M_{dcrs} = \sum_{c^m \neq c', c^o} (1/Distance_{om}) \times Border_{om} \times \mathbb{1}(c^m \in \mathcal{B}_{c^o})$.

Spatial Discontinuities - Results

The city geography is characterised by natural barriers and those from the built environment that can limit information flows across space. Spatial discontinuities arise from geographical barriers that make it hard, or even not possible, to cross from treated to control clusters, but that maintain similarity across treated and control clusters. Two clear examples in Patna are shown in Figure 4. The first is a spatial

[31]Spillovers from proximate treated clusters after the start of own treatment are subsumed in the time-varying β_{rs} estimates for treated households. Extending the multilateral proximity specification in equation (3) to include $D_{dcrs}M_{dcrs}$ would separate the pure own treatment effect from these proximate spillovers.

discontinuity from a city canal that flows into the River Ganges to the north of the city (also shown in map form in Panels C and D of Figure A2), the second is from a north-south major road in the city centre that divides the city area through its built environment. The canal does have two narrow bridges, but they are far apart and so the canal prevents crossing across building clusters on either side of the canal that are further from the bridges. The second spatial discontinuity is Buddh Marg road that has a long metal barrier at the median to prevent people from crossing this busy road with heavy traffic. The traffic is speedy in parts of the road, particularly where it merges with large crossroads and highways. Buildings on either side of the road are similar to each other, but separated by a hard-to-cross barrier, showing greater likelihood of balance across household characteristics in the treatment and control groups and lower likelihood of spatial spillovers due to the built environment.

City features such as other major roads, a park, an open area, a shopping mall and government buildings that bifurcate parts of the city from each other are also exploited as spatial discontinuities in the DiD analysis. There are 508 treated and control building clusters in the discontinuity sample, of which 192 are treated building clusters that start citizen training before the control clusters on the other side of the spatial discontinuity. Sample sizes are smaller for the discontinuity sample since the focus is placed on groups on either side of a discontinuity. Appendix Table A3B shows that groups on one side of a spatial discontinuity that receive the training earlier are similar and balanced in terms of household characteristics to those residing on the other side of the discontinuity that receive the training later. This is particularly important as boundary discontinuities may also create sorting-induced differences across neighbourhoods, but in our setting the residents are highly balanced on a wide range of observable measures.

Table 3 shows pre-post descriptives for the discontinuity subsample of 11,821 unique cluster-day observations covering 189,425 household-days (or over half of the full estimation sample). Compared to the full sample, shown in Table 1, segregation rates are marginally lower in the discontinuity sample to start with, and they rise by a similar amount in the aggregate across treated and control clusters, as shown in Table 3 in the post-period rise of about 4 percentage points (from 8.3 to 12.1 percent).

When the difference-in-differences estimator that deals with the composition issues in the staggered research design is implemented for the discontinuity sample, much bigger rises in waste segregation occur. Table 4 shows results structured in the same way as Table 2, but for the restricted sample. Columns (1) to (4) show big increases, between 13.37 and 16.72 percentage points. Bigger magnitudes of increase are confirmed when the sample is balanced on relative days since the start of citizen training and on building clusters, as shown in columns (5) to (7). Event study estimates for the discontinuity sample are in Figure 5. While, as for the full sample, treated and control groups have similar segregation rates before the start of citizen training in the treated clusters, and in the training week, a sharp jump in segregation follows one week afterwards and further tick ups occur in subsequent weeks.[32]

Table 5 shows results for particular, more and less stringently defined, spatial discontinuities. The most stringent in column (1) just uses the treated and control clusters for the strong canal/road discontinuities shown in Figure 4, namely those on either side of the city canal flowing into the Ganges to the north of the

[32] Event studies for equivalent unbalanced sample and for a less restrictive balance (on group and time) than Figure 5 are shown in Appendix Figure A7.

city or on either side of the main Buddh Marg road (including with metal/concrete barriers at the median). Column (2) expands the discontinuities to include clusters on different sides of the main city mall that separates the centre along all four directions and three major roads that bifurcate the space around them. Column (3) has the least stringent measure, from expanding the definition of spatial discontinuities to include three other main roads not included in the definitions of Tables 3 and 4. The results in Table 5 vary from a SDiSD ATET of about 12 to 18 percentage points, which monotonically decrease with less stringency, as the higher estimated effect is for the more stringent definition.

The sharper rise in segregation rates among treated clusters in the spatial discontinuity sample suggests that the effects of the citizen training may have been larger than those estimated in the baseline experimental own treatment results of Table 2. If treated households have more interactions with control clusters that are not separated from them by spatial discontinuities, then the baseline treatment effects for the full estimation sample underestimate the effects of the citizen training in the presence of positive spillovers from treated clusters to control clusters. Positive spillovers would dampen the *relative* effect of the training because segregation would rise in both treated and control clusters, and the opposite would have occurred under any negative spillovers.

Multilateral Proximity Models - Results

Table 6 shows model-based estimates incorporating spillovers, with column (1) reproducing the baseline own treatment estimate from column (1) of Table 2, columns (2) to (4) presenting the gravity based estimates and columns (5) and (6) the spatial decay estimates. The lower panel of the Table displays pre-post differences in means of control clusters, allowed to vary with the multilateral proximity measures.

When inverse distance to already treated clusters is computed for each control cluster to obtain a gravity measure of multilateral proximity, shown in column (2), the staggered DiD ATET rises to 7.91 and the estimated spillover onto control households, evaluated at the mean of M_{dcrs} for control clusters in the post period, is 3.18. The total effect goes to a higher 11.09 percentage points (=7.91+3.18). Column (3) replaces distance with borders, measured as the sum of the number of already treated clusters where a control cluster shares a truck route or a common truck route border at each point in time. The own treatment effect rises to 9.23, with a mean spillover effect on controls of 4.35 that is more precisely estimated than for inverse distance, showing substantial spillovers to own and adjacent truck routes. Border and distance are combined in column (4), generating an ATET of 8.20 and proximate treatment ATET of 3.46.

Next consider the spatial decay models. Columns (5) and (6) show results that add in the spatial proximity measure of the number of treated groups with which the control cluster shares a waste truck route or a waste truck route border without a spatial discontinuity. The SDiD ATET for treated households from their own citizen training now rises from 4.50 to 13.58 percentage points when an indicator for connected treatments $M_{dcrs} = \mathbb{1}\left(\sum_{c^m \neq c', c^o} Border_{om} \times \mathbb{1}(c^m \in \mathcal{B}_{c^o})\right)$ is included to account for spillovers. Households in control clusters that are spatially connected to treated clusters receiving the citizen training become more likely to start segregating their waste as more and more clusters connected to them begin to get trained. The positive spillover is substantial – the proximate treatment effect is 4.69. Almost all of the rise in segregation rates of 5.20 percentage points in the *control* clusters can therefore be explained by the proximate treatments creating positive spillovers on to control clusters. And the SDiD ATET estimate of

own treatment accordingly increases to 8.89. The sum of the own treatment effect and the proximate treatment effect is 13.58 (=8.89+4.69). Column (6) further considers a value measure of spatially connected treatments, $M_{dcrs} = \sum_{c^m \neq c', c^o} (1/Distance_{om}) \times Border_{om} \times \mathbb{1}(c^m \in \mathcal{B}_{c^o})$, rather than an indicator measure. The proximity effect is 2.98 and the total is 10.20.

Each specification for spillovers conducts different experiments, such as intentionally reducing communication channels to approximate direct effects in the spatial discontinuity specification and varying distance metrics in multilateral proximity models. While these provide different decompositions of the own and proximate effects, the total of own and proximate treatment effects ranges from 10.20 to 13.58 percentage points – a full set of summary results are shown in Appendix Table A5. Overall, the spillover from proximate treatments is about half the size of the own treatment effect in row III of the Table, suggesting that awareness of segregation had a smaller effect than direct citizen training. The magnitude is consistent with Miguel and Kremer (2004) and Aker and Jack (2025) that find spillover effects of about three-quarters and half of the direct own treatment effect in their studies.[33]

Panel B of Table 6 confirms positive spillovers for not-yet-treated clusters that are indirectly exposed to citizen training through their proximity to clusters that have started the training. Of the 5.20 pre-post difference in segregation rates of not-yet-treated control clusters, about 3 percentage points is explained by the spatial proximity measures across different specifications in columns (2) to (6). Table A4 in the Appendix adds in interactions of household characteristics with relative time indicators as independent variables and finds that the estimated effects lie in the middle of the range of estimates from several additional specifications.[34]

Figure 6 offers a visual representation of how estimated treatment effects vary with proximity to connected treatments by plotting the sum of own and proximate treatment effects for the value measure from the spatial decay specification ($\beta + \gamma M_{dcrs}$) in column (6) against the distance to proximate treatments ($1/M_{dcrs}$). Over 11 percent of households in the control clusters have zero proximate treatments and hence zero spillover. The rest are control households that have proximate treatments, ranging from 0.01 to 0.29 kilometres, with a mean distance of 0.11. Plotted coefficients show spillovers from proximate treatments decay with distance and the estimated proximate treatment effect falls below 1 percentage point at about 100 metres or more.

6. Survey Comparison and Economic Valuation

Comparison With Survey

To compare with magnitudes of the experimental estimates, and to gain additional insight into the channels through which households are affected by citizen training, qualitative survey responses were examined. Table 7 shows summary statistics from the experimental data for clusters (in unstacked form) in

[33] See Bhattacharya et al. (2024) for positive spillovers of environmental education from children to parents.

[34] Considering equal weights for all disposers (rather than weighting by numbers of households), the main results remain highly stable at 12.03pps (with a standard error of 2.18) and showing very similar contributions from own and proximate treatments to Table 6. This is unsurprising because the clusters were designed to have similar numbers of households, and therefore alternative weighting schemes do not alter the results substantially. Adding pairs of enumerator fixed effects gives a highly similar overall treatment effect of 11.96 pps.

Panel A, and survey responses in Panels B and C, respectively for all survey respondents in B and only for households where the same member of the household responded in each survey wave in C so as to reduce the possibility of the knowledge answer changing due to compositional changes in the members answering the surveys over time.

The same waste segregation measure used so far in the experimental data can be computed in the survey data from self-reported responses to three survey questions - dispose of their waste in the waste vehicle, report segregating their waste (verified where possible by surveyors checking if the bins/bags are segregated) and know how to segregate (measured as answering correctly that an empty milk packet is recyclable dry waste, as opposed to non-recyclable dry waste, wet waste, biomedical waste, e-waste or do not know). The survey segregation rate is the product of the percentage of households answering positively to all three of these questions.[35]

In Table 7, experimental and survey responses align closely for both pre- and post-period differences in segregation rates. Segregation rates in the (unstacked) observation data rise from just over 10 percent of households to nearly 30 percent, almost triple, going up by 18.3 percentage points. The survey measure of segregation rate rises by 16.5 (all respondents) and 17.5 (same respondent). The same high level of similarity emerges in the estimation sample, shown in the row of Intervention Periods (that correspond to the time window of the estimation sample). The experimental segregation rate rises by 19.2 percentage points, and the survey responses for all and the same respondent respectively by 16.5 and 17.7.

The survey permits further investigation into the components of the waste segregation measure. Some useful insights can be gleaned from these, as shown in Table A6 of the Appendix. One interesting feature is that the fraction of households that dispose of their waste for municipal collection is very high in both periods, and if anything, there is a small tick up, suggesting reduced waste dumping by some of these households that were previously not disposing of waste for municipal collection. More strikingly, the fraction of households who report already segregating or being willing to segregate their waste doubles between the pre- and post-periods. That the citizen training programme increased knowledge is also confirmed in the survey responses.

The survey asked households for reasons why they do and do not segregate their waste. Three categories were considered – time or ease of segregating, care for the community or local area and concern for the environment. Table 8 shows these qualitative responses, for all respondents in Panel A, and broken down by whether the household segregates their waste or not in Panels B and C. The training bundled several potentially relevant mechanisms: information on the social and environmental costs of mixed waste, procedural knowledge about what belongs in dry and wet waste, and practical skill acquisition through demonstrations and household-level practice.

The experimental design identifies the effect of this bundled training package. Though these channels are not experimentally decomposed, the survey evidence helps interpret the mechanisms. Among all respondents, time or ease of segregating and care for the community or local area emerge as the most important reasons for segregation choice. All three measures increase between the pre- and post-periods of

[35] Summary statistics for the three survey questions are given in Appendix Table A6.

the experiment, with care for the community or local area rising the most (almost doubling). These patterns, suggests that citizen training operated through both private and social channels. On the private side, training improved households' ability to segregate waste correctly, reducing the ongoing effort and time costs of compliance, thereby enhancing productivity of managing waste. On the social side, it increased awareness of the community and environmental benefits of segregation, raising the perceived collective value of participating in waste management. By simultaneously lowering the private costs and increasing the perceived social benefits, training generated sustained improvements in waste-management behaviour.

The lower two Panels show, both pre- and post-levels and post-pre changes to be qualitatively similar for segregators and non-segregators. Households that do and do not segregate their waste are similar before the intervention and all see an increase in the three factors that they report to have influenced their segregation choices. But the magnitudes of post-pre change do differ, particularly with there being much bigger changes before and after the experimental intervention for care for the community or local area (up by 36 percent) and concern for the environment (up by 25 percent) among segregating households. This is also further reflected in other qualitative responses from the survey shown in Appendix Table A6. Increases in correct responses to waste-classification questions, combined with observed improvements in actual disposal behaviour, suggest that procedural knowledge and practical capability were important. At the same time, reported reasons for segregation indicate that time/ease and concern for the local area also matter, consistent with training reducing the private effort cost of segregation while increasing awareness of its social benefits. Some of the other interesting consequences following from the training are a rise in the number of bins, suggesting increased waste segregation, and more environment-friendly attitudes.

Alternative Waste Measures

Appendix Tables A7A to A7D present further SDiD ATET estimates for four waste outcomes – the share of segregated waste and the volumes of segregated, unsegregated and total waste. Consider first Table A7A for the share measure. The SDiD ATET experimental estimates for this measure are highly similar to that for the extensive margin, ranging from 4.04 (own) to 14.77 (including spillovers) across different specifications. The volume of waste is considered in Appendix Tables A7B to A7D. As shown in Tables A7B and A7C, segregated waste volume rises as a consequence of citizen training and the volume of unsegregated waste falls. On net, the rise in segregated waste disposed of accompanies a slightly larger fall in the volume of unsegregated waste, resulting in a fall of about 0 to 200 grams in total waste (Appendix Table A7D). The different specifications suggest a fall in total waste volume that would further contribute to environmental benefits, but the magnitude varies from negligible to small drops and we therefore do not include them in the valuation that follows. The waste literature in advanced economies usually finds that improved waste management productivity has a positive effect on recycling behaviour, but the effect on waste disposal is ambiguous theoretically and empirically (Kinnaman and Fullerton 2000).

The percentage of disposers per day also rises due to the intervention (Appendix Table A7E), consistent with the self-report evidence from the surveys in Table A5 in the Appendix suggesting reduced waste dumping. Increased disposals and improved segregation also imply that monitoring of waste through enumeration is unlikely to have been a central mechanism for improved waste segregation. A pure monitoring response would be more likely to discourage disposers from going to the truck on days when

they see enumerators, but this does not arise in the enumerated measures and in various survey measures, such as knowledge, frequency and method of disposal.[36] This is consistent with the fact that the intervention was not paired with penalties and waste workers and enumerators had little enforcement authority. Moreover, waste sorting occurs before households approach the truck, providing further reassurance that observed improvements in source segregation go beyond inducements from monitoring alone.

Economic and Environmental Value of Citizen Training

Next consider the economic and environmental benefits that the citizen training programme generated. To accurately do so, it is critical to include the spillovers alongside the direct experimental effects to compare with a counterfactual of no citizen training and hence no direct or indirect treatment effects in the intervention areas. The range of the rise in the share of disposers who segregate waste is between 10.20 to 13.58 percentage points across the different approaches for proximity from city geography for the full sample in the model-based estimates with spillovers in Table 6. Taking a midpoint whole number of these estimates gives a rise in segregation rate of 12 percentage points that can be used in calculations of the benefits from a reduced need for landfilling of waste.[37]

Panel A of Table 9 summarises the direct landfilling cost savings and the environmental benefits of the intervention from greenhouse gas emission savings at market and social value. A challenge in quantifying economic benefits of improved waste outcomes is the paucity of granular estimates of waste costs and pollution from waste, particularly in developing countries. Standard international sources are used to quantify the benefits, and we explain how these can be benchmarked to India. The OECD (2022) reports landfilling costs of 25 to 30 Euros per ton of waste per year. Directly applying these and converting with the market exchange rate (of 88 Indian Rupees per Euro from the IMF), reduced landfilling from increased segregation at source amounts to gross savings of Indian Rupees ₹137-164 per household per year for the average daily disposal of 1.417 kilogram of waste (reported earlier in Table 1).

This is the monetary value of the direct cost savings from waste not going to landfills. It does not yet account for environmental benefits, which can be assessed from the greenhouse gas emission savings that result when segregated waste is not landfilled and is instead diverted away towards composting and recycling. Reduced landfilling of segregated waste and material displacement from segregated recyclables yields greenhouse gas emission savings. It also provides other environmental benefits, such as reduced groundwater, soil and river pollution, that are hard to precisely evaluate due to a lack of standardised emission and monetary valuation factors.

To quantify emission savings, landfill emission factors for unsegregated waste and composting of segregated wet waste (food and vegetable waste) are from the US Environmental Protection Agency (EPA). Emission factors for recycling of dry waste (plastic, textile, paper, leather, glass and metal) are from life

[36] Enumerators asked disposers of the gap in days between when they returned to the truck. Disposers did not alter their frequency systematically with the intervention, and magnitudes of changes in frequency are tiny and statistically insignificant (available upon request). This can also be seen in the survey self-report in Tables A3A and A3B.

[37] Assuming that they were previously openly dumping their waste and it was being taken by street cleaners, there is no additional landfill saving because the waste was already being landfilled. If instead, they were previously mismanaging their waste, such as through open burning, then there are additional emission savings but these are small because only 0.21 percent of households report burning their waste.

cycle assessments in Turner et al. (2015) that specifically account for source-segregated dry waste and corresponding savings from reduced primary production due to recycling of source-segregated materials. The factors differ by waste material, and waste shares are from previous studies in Patna (Pandey 2019, Jha et al. 2020). Emissions from landfilling of unsegregated waste and from composting and recycling of segregated wet and dry waste are aggregated to arrive at the average emissions per household.

Formally, consider two types of waste that can be segregated at source into wet waste and other waste material. Let R_g denote the emission factor for composting of source-segregated wet waste that goes into the green compartment of the waste vehicle, denoted by g. Other waste material of type m, when it is segregated at source and recycled, has emission factor R_m (for dry material $m \neq g$). Landfilling emission factors are F_g for green waste and F_m for material type m. The total volume of waste per household per year is V and the composition of household waste is summarised by (θ_g, θ_m) where θ_g is the share of green waste in total waste volume and θ_m is the share of material type m in total waste volume. For disposer d that does not segregate, all of their waste ends up in the landfill after collection and the resulting emissions are accordingly $V_d(\theta_g F_g + \sum_{m \neq g} \theta_m F_m)$. For disposer d' that segregates, let $V_{gd'}$ denote the volume of wet waste that they dispose and $V_{bd'}$ denote the segregated dry waste that they dispose into the blue compartment of the waste truck. When the segregated waste is recycled, the resulting emissions for the waste disposed of are $V_{gd'}R_g + V_{bd'}(\sum_{m \neq g} \theta_m R_m) + (V_{d'} - V_{gd'} - V_{bd'})(\theta_g F_g + \sum_{m \neq g} \theta_m F_m)$.

Aggregating across households, the mean emission is $(V - \omega V_g - \omega V_b)(\theta_g F_g + \sum_{m \neq g} \theta_m F_m) + \omega V_g R_g + \omega V_b(\sum_{m \neq g} \theta_m R_m)$ for mean total waste volume per household of V, the share of segregating households ω and the mean green and dry waste volume per household of ωV_g and ωV_b.[38] A rise in the segregation rate ω generates emission savings as the composition of total waste shifts towards segregated green and blue dry waste that have lower emission factors from recycling (compared to landfilling). Substituting for Pre period waste volumes and segregation rates, the average household generated 274.2kg of CO2e per year from waste. During the experimental time window, the segregation rate ω rose by 12 percentage points so that greenhouse gas emissions fell to 201.5kg of CO2e per household per year. The Post-Pre emissions savings were 72.7kg of CO2e per household per year, shown in column (2) of Panel A.

To generate monetary values of the savings requires a price of CO2e. This is obtained from the carbon emissions trading system enabled by the Clean Development Mechanism and Joint Implementation under the Kyoto Protocol which allowed countries to offset their own emissions by reducing those of another country. Using the average carbon price of $49.8 per ton under the European Union (EU) Emissions Trading Scheme in 2021 from the World Bank's carbon pricing dashboard produces a reported carbon price of ₹3,485 per ton of CO2e. At this market value of carbon, the greenhouse gas savings per household per year amount to ₹253=72.7/1,000 tonnes CO2e × ₹3,485. Valuing at the carbon credit price does not fully reflect the social cost of CO2e that is usually recommended for impact assessments. The EPA recommends a social

[38] $V \equiv \sum_d V_d / (\sum_{d'} 1(V_d > 0))$, $\omega V_g \equiv \sum_{d'} V_{gd'} / (\sum_d 1(V_d > 0))$ and similarly $\omega V_b \equiv \sum_{d'} V_{bd'} / (\sum_d 1(V_d > 0))$, where $\omega \equiv \sum_{d'} 1(V_{gd'} + V_{bd'} > 0) / (\sum_d 1(V_d > 0))$ is the segregation rate across disposers.

cost of $193 per ton, with a range of $76 to $337 (Hahn et al. 2024),[39] which at the exchange rate adjusted ₹13,510 is under four times the market cost. Using the EPA's central estimate of social cost (row II(b) of Table 9), the savings rise from ₹253 to ₹982. This results in total savings of ₹1,118 to ₹1,146 when landfilling cost savings are added to the greenhouse gas emission savings.

The total cost for 5 months of training for all 10,434 households was ₹2,581,000.[40] The variable cost component including field staff and campaign tools was ₹1,881,000. Part of the total expenditure had a fixed cost component – the ₹700,000 spent on a senior manager and software support. The average expenditure thus comprised a one-off cost of ₹247 per household. Placing this in perspective, the total cost amounts to only about three percent of the Patna Municipal Corporation's budget for solid waste management in 2021-22.[41]

From the estimated benefits and costs, a lower bound estimate for the benefit to cost ratio over a five-year horizon - the usual term of an elected city mayor - is 2.8 to 3.3 ($=137\text{-}164 \times 5 \,/\, 247$) if only landfill cost savings from increased segregation are accounted for in the benefits. This rises to 5.1 when greenhouse gas emission savings at carbon credit prices are considered ($=253 \times 5 \,/\, 247$). Further adding direct landfilling cost savings and emission savings at market value, the benefit-to-cost ratio ranges from 7.9 ($=2.8+5.1$) to 8.4 ($=3.3+5.1$).[42] When social costs are taken instead of market prices, the benefit to cost ratio rises further to 22.7 to 23.2 for the central EPA estimate of the social cost of carbon. Because costs are incurred only once, it could rise even further over a horizon longer than five years, further confirming the policy's cost effectiveness for delivering environmental sustainability to local communities.

While directly comparable estimates for India are not as well-developed, recent work enables some benchmarking of magnitudes. Table 9 (column (1)) uses landfilling costs of ₹2,220 to 2,640 per ton of waste, that are slightly higher than engineering provisioning costs of ₹1,845 to 2,849 for Patna from the Indian Institute of Technology. The engineering costs are for active landfill disposal and are therefore expected to be smaller than OECD figures (as the full lifecycle costs of landfilling is not included).[43] In recent analysis, Jardosh and Kathuria (2025) provide a cost-benefit analysis of landfilling in Mumbai. A broader range of ₹1585 to 4952 is obtained when their costs are adjusted for land values in semi-urban

[39] Alternatively, the EU's Environmental Prices Handbook recommends a central estimate of 130 Euros and an upper value of 160 Euros per ton of CO2. Incorporating the range of estimates, the savings from reduced landfilling needs are between ₹385 to 1,266 for the US range and between ₹671 to 822 for the EU range. Notably, the average shadow price of "undesirable" unsegregated waste estimated for Chilean municipalities lies in these ranges (Sala-Garrido et al. 2023). Inferred from recyclable material embodied in unsegregated waste, the average shadow price is 297.66 Euros per ton of waste, with a wide range of 0.045 to 2536.46 per ton across municipalities.

[40] Some new households moved to the intervention areas after the census and they were covered by the training, so the number of households is in practice slightly larger than that in the original census of intervention areas.

[41] $3\% = ₹247 \text{ per household} / (5.2 \text{ residents per household} \times (₹2.57 \text{ billion total spending} / 1.7 \text{ million residents}))$.

[42] The marginal value of public funds is the ratio of benefits from reduced emissions and landfilling costs to the expenditure on citizen training. Assuming a five-year horizon for benefits with a discount rate of 2 percent, it ranges from 7.6 to 8.1 (Panel A.III of Table 9), placing it at the upper end of climate policies in Hendren and Sprung-Keyser (2020). Using social-cost valuations raises the ratio to 21.8-22.3. These estimates are likely conservative, as time costs of segregation appear minimal (see Appendix) and because existing evidence suggests limited effects of waste-site cleanups increasing property values/rents (Greenstone and Gallagher 2008).

[43] Costs for waste treatment and conveyance are taken here but not waste collection costs as these are unlikely to be affected by segregation though these costs would be reduced from lower waste volumes. The report is available at https://cganga.org/wp-content/uploads/2023/06/Vol-10.pdf.

Patna, taken from circle rates set by the Bihar government (which are likely to be lower bounds of market-based land prices). Their work also provides emission factors for greenhouse gases and other pollutants, based on IPCC's methodology. The range is 420 to 734 kg CO2e per ton of waste. Our estimates are based on EPA emission factors that are available for different waste materials and can be applied to the observed composition of waste in Patna. The average emission factor in our study turns out to be 425, and should therefore be interpreted as a conservative estimate of greenhouse gas emission intensity. An alternative emission factor can be calculated based on methane emissions from landfills divided by tonnage of waste going to landfills. This observed emission intensity is 527 kg CO2e per ton of waste, based on 2020 figures reported by the Indian government to the United Nations Framework on Climate Change in 2024.[44]

Finally, two factors could reduce the benefits shown in Table 9. First, behavioural responses may decay over time and though we do not see this happening over a six-month period (as we discuss in the next sub-section), it may occur over the five year period. While this cannot be ruled out, globally many OECD countries show a stabilisation over time in waste recycling rates. Second, we use carbon prices from the US and the EU as climate change is a global pollutant. However, China's recent carbon market prices are estimated to be much lower - between 40 to 60 RMB per ton of CO2e (Goulder et al. forthcoming) or ₹460 to 690 per kg. This would substantially reduce the monetary value of emission savings in Table 9 from 9.2 in B.II(a) to 1.2 to 1.8. The benefit to cost ratio would naturally be much lower at this lower carbon price, but the range would still be 6.5 to 8.1 in B.III.

To sum up, these large emission savings should be interpreted as lower bounds on the potential reduction in greenhouse gas emissions from improved waste outcomes and even at conservative China-based market prices for greenhouse gas emissions, the expected benefit to cost ratio is estimated to be at the upper end of climate change interventions.[45]

Follow-up Temporal Spillovers

The experimental analysis, and benefit-cost calculations, so far focus on the pre- and post-periods of the intervention before the last three clusters had started the training (13th April 2022). Once full treatment had occurred, data collection of waste observations continued on a bi-weekly basis until 31st May 2022. A second household survey was conducted at the end of all treatments to record longer interviews with households. Enumerators followed up two months after the last waste observation from 27th July to 8th August 2022 to undertake two more data collections.

Segregation rates in the observation data continued to rise after the experimental intervention was complete. Segregation rose from 10.88 percent before any training (column (1) of Table 7) to 19.45 percent by 18th April 2022 when all households had started citizen training. After that, further environmental benefits resulted as segregation rates rose to 29.14 percent over the period between 19th April and 31st May (column

[44] By contrast, when we apply the emission factors recommended by the Indian Ministry of Housing and Urban Affairs to the composition of waste in Patna, the lowest possible emission factor is 1,668.50 kg CO2e per ton of waste and the range is 1,853.89 (for unmanaged landfills) and 2,085.63 (for well-managed landfills). This could be driven by the fact that the methodology includes more potent greenhouse gases and the quality of landfills in India. It reiterates the interpretation of emission savings as a lower bound.

[45] We do not account for the benefits from reduction in other pollutants, such as PM 2.5 that feature in the Mumbai study, due to a lack of reliable emission factors for air pollution.

(2) of Table 7) when some time had elapsed since the start of training for all households. Although these results are not from an experimental DiD design, bi-weekly observations in the follow-up period between 27th July and 8th August showed that 32.31 percent of households continued to segregate waste (column (4) of Table 1). The citizen training programme thus resulted in a persistent tripling of the household segregation rate, suggesting that once households learn how to manage waste efficiently, continuing to segregate is much easier. This is important in light of studies where effectiveness of the intervention relies on behaviour change, but where effects may fade out after the intervention has ceased (Della Vigna and Linos 2022 and Brandon et al. forthcoming). No such fade out occurred, as temporal spillovers led to a higher segregation rate at the end of data collection.

The timing of the roll-out of the intervention did not disadvantage late treated clusters. Their waste segregation rates fully caught up with the early treatments four months after. Splitting clusters into early treated phase 1 clusters (starting training in the first half of the intervention schedule) and late treated phase 2 clusters (starting training in the second half) shows segregation rates of 33 percent for early first half treatments and 31 percent for late second half treatments in Appendix Table A2.[46] Including these temporal spillovers in the benefit-cost calculations cumulates up to generate even higher benefit-cost ratios from the programme, as shown in Panel B of Table 9, which on their inclusion easily move into the territory of double-digits reaching 14.4 to 15.5 at market values and rise to 40.8 to 41.8 at social cost values.

7. Conclusions

Waste management is a critical yet understudied environmental challenge, particularly within the developing world. In these contexts, rapid consumption and accelerating urbanisation impose a burgeoning waste burden that conventional, capital-intensive technologies - such as sanitary landfills and waste-to-energy plants - have not had the ability or capacity to absorb. Although source-segregation policies are increasingly formalised into legislative frameworks worldwide, empirical evidence evaluating their capacity to reduce landfill reliance and curb emissions remains scarce. This paper studies a large-scale randomised field experiment that delivered structured citizen training to over 10,000 households across a staggered timeline in Patna, India. By enhancing environmental literacy and practical skills in dealing with waste, the intervention successfully boosted household productivity in waste management, catalysing a substantial and immediate increase in source-segregation rates. When integrated with extensive spatial and temporal externalities, these behavioural shifts yielded big economic and environmental returns, reducing greenhouse gas emissions by more than 25% and generating robust, double digit benefit cost ratios.

The post-intervention source-segregation rate reached approximately one in three households, which is highly notable in a global comparative context. While cross-country comparisons must be caveated due to different municipal waste compositions across countries, average OECD recycling rates have largely plateaued around 30 percent (Fullerton and Kinnaman 2024). Strikingly, the low-cost citizen intervention in Patna elevated household source segregation to levels on par with the average advanced economy. This threshold is structurally significant; prior literature demonstrates that achieving this magnitude of separation

[46] The phase 1/phase 2 gap is small and statistically insignificant at -2.07 with an associated standard error of 5.55.

for organic-heavy waste streams can tip the ledger of municipal incineration from net positive emissions to net carbon savings (Dong et al. 2013).

Overall, the findings demonstrate that promoting citizen training and community education are effective policy instruments for alleviating the endemic municipal waste crises plaguing developing countries. By cultivating self-enforcing pro-environmental behaviour, this capacity-building approach optimises household waste management without necessitating continuous, top-down regulatory oversight. This decentralised, low-cost strategy yields fiscal and societal dividends—simultaneously shrinking the urban waste footprint and enhancing localised environmental quality. Crucially, the documented presence of substantial spatial and temporal knowledge spillovers indicates that the strategic deployment of citizen training and community education offers opportunity for scaling up municipal waste efficiencies and advancing global climate change mitigation.

To conclude, urban waste management has long been seen as an intractable problem in developing cities. The empirical evidence presented here shows that relatively simple, well-designed, and operationally transparent interventions can make a difference in managing the urban waste footprint and altering the ecological trajectory of cities. Deciphering the mechanisms underpinning spillovers, mapping their interactions with demographic characteristics, and optimising their geographic deployment represent avenues for future inquiry. Looking forward, intensive training of waste generators can be productively paired with complementary structural policies that formalise or support the informal waste collection that is prevalent in many developing economies (see Bañares-Sánchez and Wiskamp 2025). Ultimately, these findings open the door to broader, decentralized community participation in environmental governance, and moving towards zero landfill, a key sustainability aim in need of effective solution the world over.

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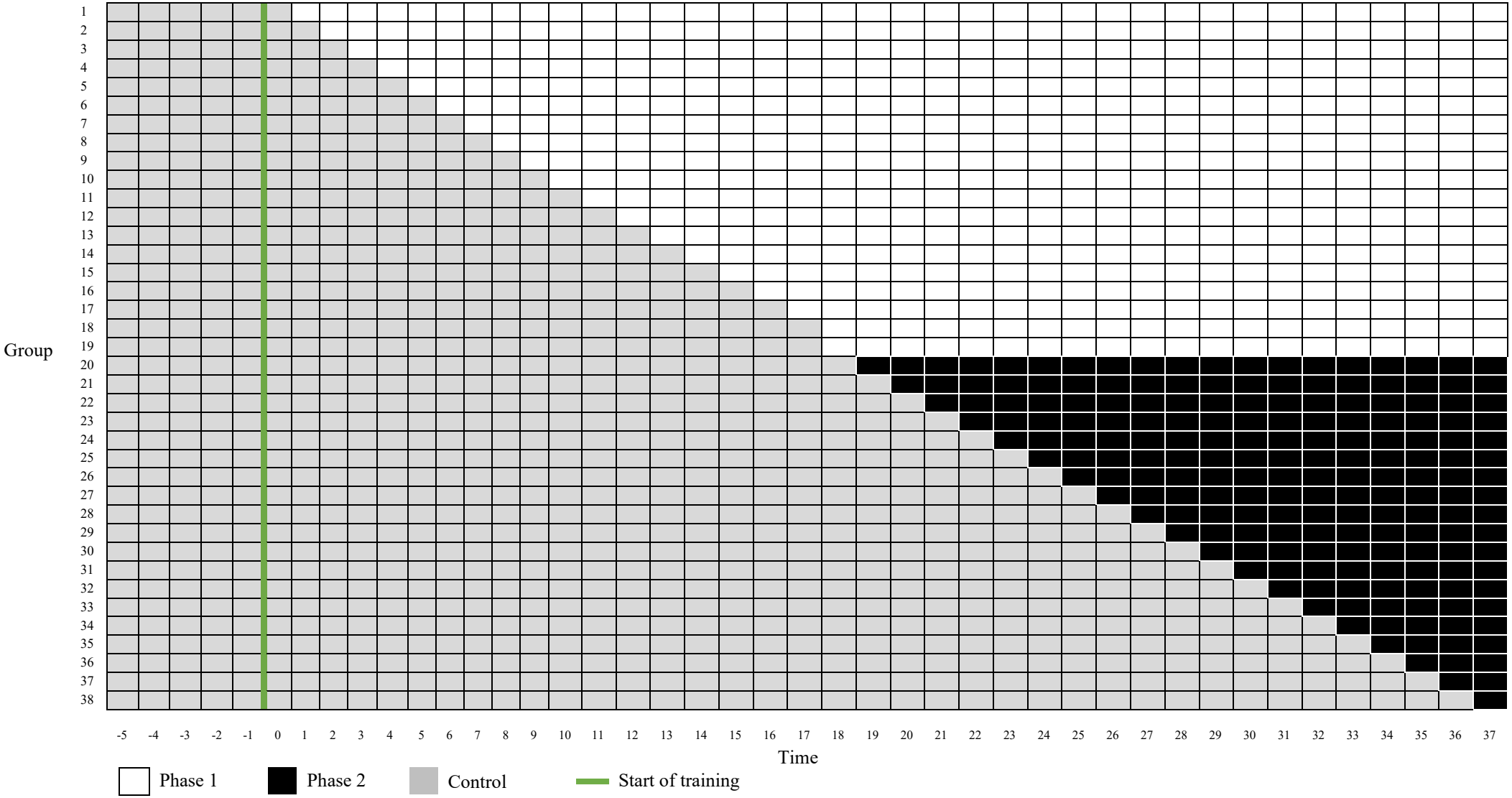
Figure 1: Treatment Order



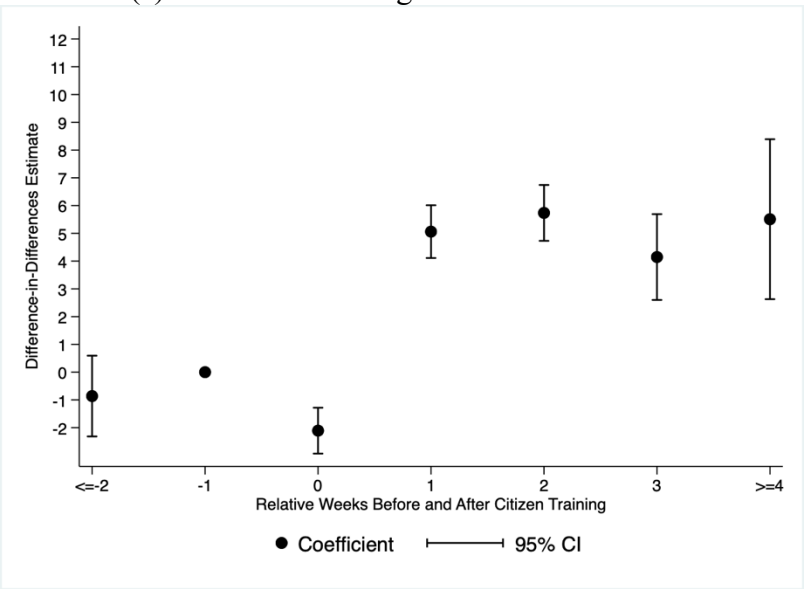
Notes: Rows show groups of building clusters ordered by time of starting training. Columns show time periods: -5 to -1 are pre-training periods, 2 to 16 December 2021; 0 to 37 are the 38 intervention periods of citizen training, 17 December 2021 to 18 April 2022. White squares refer to phase 1 of citizen training for the first half of clusters in order of treatment from 0 to 18, 17 December 2021 to 3 February 2022; black squares to phase 2 of citizen training for the second half in order of treatment from 19 to 37, 7 February 2022 to 18 April 2022. Each phase 1 treatment group has a geographically matched phase 2 treatment group.

Figure 2: Waste Training Material for Households

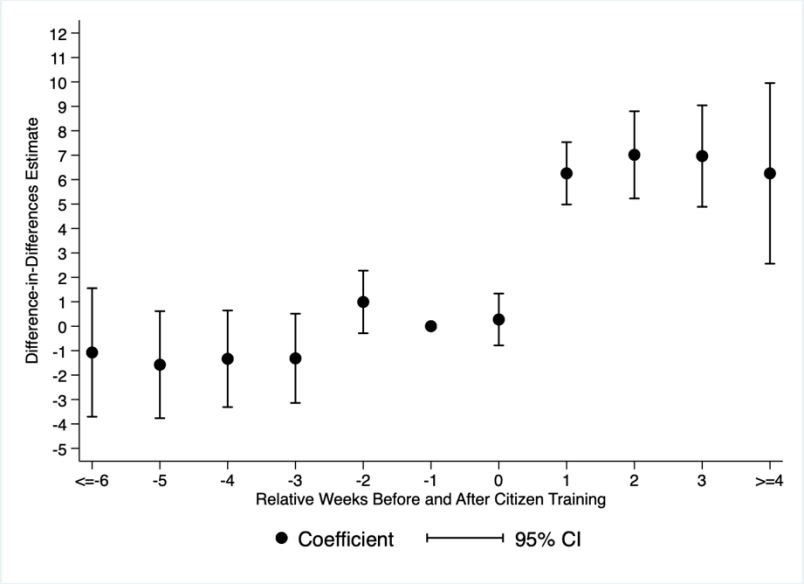
Notes: Picture to the top left shows that wet waste (marked on the bin) is generated during cooking and can be easily kept separately from dry waste. Pictures were drawn by a local artist. The bottom left picture poses a choice between landfilling, with a photo of the landfill outside Patna city and compost from wet waste. Picture to the right is an information sheet for households showing common items that are under green (wet) waste, blue (dry) waste, e-waste and hazardous (red) waste and also contains images of waste dumping (marked with a red cross) and segregated waste being disposed of in designated compartmentalised bins (with a tick).

Figure 3: Event Studies

(a) Balanced Building Clusters and Relative Time



(b) Longer Duration Event Study



Notes: The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. Panel (a) fully balances the estimation sample on building clusters with at least two weeks of disposals before and four weeks of disposals after the start of the citizen training of each stack. It covers 215,575 disposer-day observations or 13,612 cluster-day observations, ranging from relative days ≤-15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27, ≥28. The event study coefficient estimates (and associated standard errors) comparable to Table 2 column (7) are -0.86 (0.71), 0.00 (reference time, $r = -1$), -2.11 (0.40), 5.06 (0.46), 5.74 (0.49), 4.15 (0.75), 5.51 (1.40). Panel (b) shows a longer duration of relative weeks before and after the start of citizen training for ≤-36,…,0,…,≥35 relative days with 191,052 disposer-day observations or 12,317 cluster-days. The event study coefficient estimates (and associated standard errors) comparable to Table 2 column (6) are -1.08 (1.26), -1.58 (1.05), -1.33 (0.95), -1.32 (0.88), 0.99 (0.62), 0.00 (reference time, $r = -1$), 0.28 (0.51), 6.26 (0.61), 7.02 (0.86), 6.96 (1.00), 6.26 (1.78). Standard errors clustered two-way by building clusters and stacks.

Figure 4: Canal and Road Discontinuities

(a) Canal, Aerial View

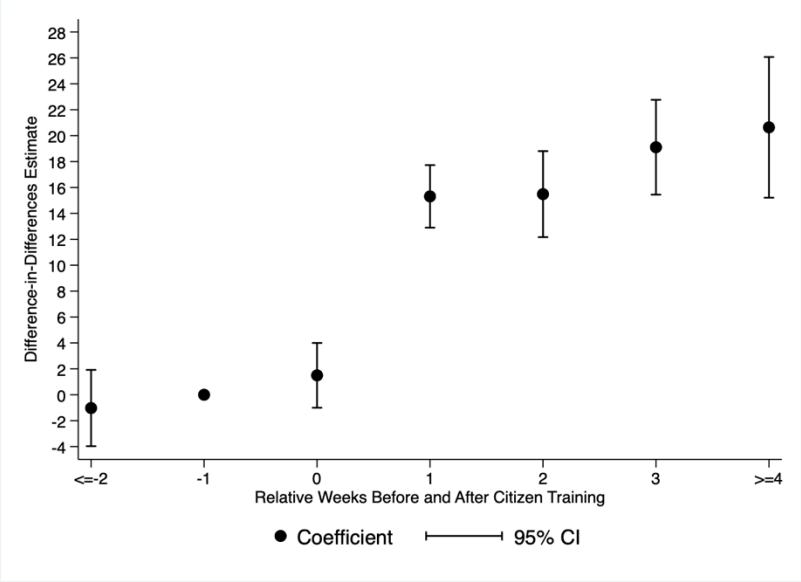
(b) Canal, Photo

(c) Road, Aerial View

(d) Road, Photo

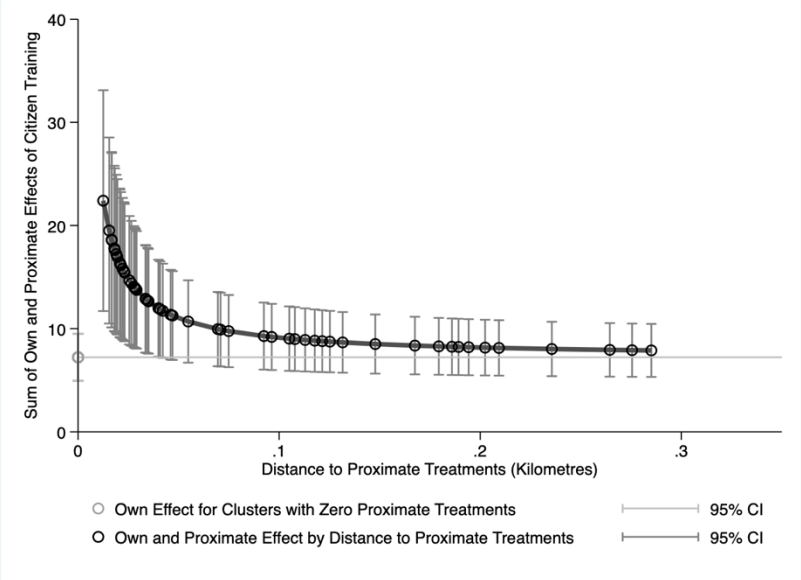
Notes: Panel (a) shows an aerial view of the city canal that runs north to south from the River Ganges through the centre of the city. Panel (b) shows buildings along the west side of the canal are in the spatial discontinuity estimation sample with buildings on the east side of the canal as their control clusters. Panel (c) shows an aerial view of the main road, called Buddh Marg, in the centre of the city. Panel (d) shows buildings along the west side of the road are in the spatial discontinuity estimation sample with buildings on the east side of the road as their control clusters. The median of the road has a metal barrier to prevent crossings due to heavy traffic. Maps and photos are from Google Maps.

Figure 5: Event Study - Spatial Discontinuity



Notes: Same as Figure 3 (a), for the spatial discontinuity estimation sample of 81,222 disposer-days or 4,865 cluster-days. The event study coefficient estimates (and associated standard errors) comparable to Table 4 column (7) are -1.02 (1.28), 0.00 (reference time, $r = -1$), 1.50 (1.08), 15.31 (1.05), 15.49 (1.44), 19.11 (1.59), 20.64 (2.35).

Figure 6: Spatial Decay and Spillovers



Notes: Coefficients and confidence intervals for the sum of own and proximate treatment effects $\beta + \gamma M_{dcrs}$ are shown against the distance to proximate treatments. Proximate treatments consist of building clusters that have started citizen training and share the same waste truck route or share a waste truck route border without a spatial discontinuity with a not-yet treated cluster. Distance to proximate treatments is defined as the inverse of the proximity measure M_{dcrs} in column (6) of Table 6, that ranges between 0.01 to 0.29 for non-zero values. Coefficients and confidence intervals are evaluated at each of the 56 distinct distance values. For reference, the horizontal line shows the (own) treatment effect β.

Table 1: Waste Outcomes

A. All periods of data collection	All Dec 2 - Aug 8	Pre Dec 2 - Apr 16	Post Dec 17 - Apr 18	Full rollout Apr 19 - May 31	Follow-up Jul 27- Aug 8
	(1)	(2)	(3)	(4)	(5)
Households that dispose of waste segregated into dry and wet waste (% of disposing households per day)	11.33	9.48	14.57	29.14	32.31
Segregated waste volume	154	141	173	378	342
Unsegregated waste volume	1263	1322	1138	1164	1026
Waste disposed of in truck (gram per household per day)	1417	1463	1311	1542	1368
Number of household-days	519,996	153,553	231,979	114,072	20,392
Number of building cluster-days	33,507	9,864	15,008	7,321	1,314

B. Periods of experiment	All Dec 2 - Apr 13	Pre Dec 2 - Apr 13	Post Dec 17 - Apr 13
	(1)	(2)	(3)
Households that dispose of waste segregated into dry and wet waste (% of disposing households per day)	10.95	9.31	14.30
Segregated waste volume	150	140	171
Unsegregated waste volume	1266	1329	1139
Waste disposed of in truck (gram per household per day)	1416	1469	1310
Number of household-days	367,056	148,101	218,955
Number of building cluster-days	23,652	9,532	14,120

Notes: 657 building clusters covering disposals of 10,196 households are observed by enumerators along the truck route twice a week consisting of 51 unique periods of three days each. Or 657×51 building-days and 10,196×51 household-days. 38 stacks with each stack consisting of a treated group of building clusters that follow a staggered same treatment schedule and their control clusters. All periods are divided into a Pre period covering observations days from 2/12/2021 to 16/4/2022 before the start of citizen training for the treated cluster in each stack, a Post period covering observation days after the start of citizen training from 17/12/2021 to 18/4/2022, a Full Rollout period after every cluster has started citizen training from 19/4/2022 to 31/5/2022 and a Follow-up period two months after the full rollout covering observation days from 27/7/2022 to 8/8/2022. Control clusters in each stack are building clusters that have not yet been treated or are never treated during the Pre and Post periods. Panel A contains the full dataset and Panel B contains the estimation sample. Panel B differs from Panel A in that the Pre and Post period ranges are 2/12 to 13/4 and 17/12 to 13/4 because all clusters have started citizen training in the week following 13/4. The unstacked unique household-days and building cluster-days underlying each column are reported.[47]

[47] There are a few missing observations for waste volumes due to malfunctioning of the weighing scale on one observation day in some clusters. There are also missing observations for waste outcomes of one group in April because of the breakdown of its waste truck. The missing observations will be accounted for in several specifications reported later because they balance the estimation clusters on relative weeks.

Table 2: Staggered DiD Estimates

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	All				Fully balanced		
	Current weights	Constant weights (time -1)	Constant weights (treatments)	Pure controls	-28 to -22, …,21 to 27	-42 to -36, …,35 to 41	Buildings and days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staggered DiD estimate	4.50	5.55	4.54	6.10	4.82	4.94	4.46
	(0.85)	(0.94)	(0.84)	(1.41)	(0.70)	(0.90)	(0.82)
Fixed effects							
Stack-building cluster	yes	yes	yes	yes	yes	yes	yes
Stack-relative week	yes	yes	yes	yes	yes	yes	yes
Sample size	261,839	261,839	261,839	261,839	163,290	161,766	121,102

Notes: Estimates of equation (1). DiD ATETs are estimated for each stack-relative week. The specification includes stack-building cluster fixed effects and stack-relative week fixed effects. Relative week of a stack refers to the week relative to the start of the citizen training for the cluster being treated in that stack, and it ranges between -19, -18,…-1, 0, 1,…, 15, 16 corresponding to a relative day range of -131,…,0,…117. Stack-specific DiD ATET estimates for each of the five weeks of relative days 0 to 6, 7 to 13, 14 to 20, 21 to 27, 28 to 34 and ≥35 are estimated in columns (1) to (4). The Staggered DiD ATET estimate is an average of the stack-relative week DiD ATET estimates, weighted by the share of the stack in the clean control estimation sample. Weights to average across stacks are the sample shares of the stack, including its treated households and clean controls. Current weights vary across stacks by relative week in column (1). Constant weights are applied in columns (2) and (3), where the weight of the stack is fixed at its weight in relative week -1 in column (2) and across all treatments in column (3). Column (4) excludes all controls except those that do not start citizen training throughout the Post period of the estimation sample and are therefore the "never treated" households in the sample. Column (5) fully balances the estimation sample of column (1) by including treated and control groups that must each have four relative weeks before and after the start of citizen training in each stack of the sample of the column, ranging from relative days -28 to -22, -21 to -15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27. Column (6) does the same for an alternative balancing of six relative weeks before and after the start of citizen training. Column (7) is fully balanced on each treated and control building cluster (rather than groups of building clusters based on their training start dates) as well as on relative days. Each treated building cluster and its control building cluster has all four relative weeks before and after the start of treatment of the stack in column (7). The unstacked unique household-days are reported in each column, and refer to the subset of households that dispose of waste from the full estimation sample of Panel B in Table 1. Standard errors in parentheses are clustered two-way by building clusters and stacks.

Table 3: Waste Outcomes - Spatial Discontinuity

Periods of experiment, discontinuity	All Dec 2 - Apr 13	Pre Dec 2 - Apr 13	Post Dec 17 - Apr 13
	(1)	(2)	(3)
Households that dispose of waste segregated into dry and wet waste (% of disposing households per day)	9.98	8.30	12.14
Segregated waste volume	141	128	158
Unsegregated waste volume	1271	1321	1207
Waste disposed of in truck (gram per household per day)	1412	1449	1365
Number of household-days	189,425	82,926	106,499
Number of building cluster-days	11,821	5,033	6,788

Notes: Same as panel B of Table 1 for the spatial discontinuity estimation sample, which is a subset of the estimation sample where a treated cluster and its control clusters are on either side of a spatial discontinuity (including the city canal, the main road, city centre or other major roads). Stacks where the treated clusters start citizen training after clusters on the other side of the discontinuity are excluded from this sample. The spatial discontinuity estimation sample consists of 508 building clusters, of which 192 are treated building clusters that start citizen training before the control clusters on the other side of a spatial discontinuity from them.

Table 4: Staggered DiD Estimates, Spatial Discontinuity

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	All				Fully balanced		
	Current weights	Constant weights (time -1)	Constant weights (treatments)	Pure controls	-28 to -22, …,21 to 27	-42 to -36, …,35 to 41	Buildings and days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staggered DiD estimate	13.37	13.84	13.53	16.72	19.61	12.94	22.68
	(0.92)	(0.89)	(0.89)	(1.57)	(1.38)	(1.28)	(1.66)
Fixed effects							
Stack-building cluster	yes	yes	yes	yes	yes	yes	yes
Stack-relative week	yes	yes	yes	yes	yes	yes	yes
Sample size	134,334	134,334	134,334	92,157	34,158	45,582	23,475

Notes: Same as Table 2, for the spatial discontinuity estimation sample.

Table 5: Staggered DiD Estimates, Different Spatial Discontinuities

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	Treated and control clusters only on either side of the city canal and the city main road	Treated and control clusters only on either side of the city canal, city main road, city centre mall, and major city roads	Treated and control clusters on either side of the city canal, city main road, city centre mall and all major city roads
	(1)	(2)	(3)
Staggered DiD estimate	18.46	15.66	12.02
	(1.23)	(0.99)	(0.86)
Fixed effects			
Stack-cluster	yes	yes	yes
Stack-relative week	yes	yes	yes
Sample size	83,466	122,471	141,967

Notes: Same specification as column (1) of Table 4. Columns (1) to (3) start with the strictest spatial discontinuities and then add in less strict ones. Column (1) restricts the spatial discontinuity estimation sample to treated and control clusters that are only on either side of the city canal flowing into the River Ganges to the north of the city or on either side of the main road (including with metal/concrete barriers at the median). For example, if buildings to the west of the city canal get treated first, their observations are included in column (1) as treated clusters. Buildings to the east side of the canal are their control clusters, and buildings to the west that get treated afterwards are not included in column (1) as treated or control clusters. Column (2) expands the discontinuity of column (1) to the city centre mall that divides the centre in all four directions along with three other major roads and non-residential buildings that are hard to cross physically due to heavy traffic or physical barriers. Column (3) expands the spatial discontinuity estimation sample of Table 3 to three more major roads/non-crossing buildings and does not exclude control clusters connected by bridges to treated clusters on the other side of the canal.

Table 6: Spillover Estimates, Gravity and Spatial Decay

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	Baseline	Gravity			Decay	
	Own	1/Distance	Borders	(2)×(3)	Indicator	Value
	(1)	(2)	(3)	(4)	(5)	(6)
A. Multilateral proximity						
I. Staggered DiD estimate (β)	4.50	7.91	9.23	8.20	8.89	7.22
	(0.85)	(3.06)	(1.49)	(1.23)	(1.34)	(1.12)
II. Proximity DiD estimate (γ)						
Post×Control×Proximity		0.09	1.54	0.17	5.61	0.19
		(0.08)	(0.39)	(0.05)	(1.19)	(0.06)
III. Proximity effect at mean ($\gamma\bar{M}$)		3.18	4.35	3.46	4.69	2.98
		(2.89)	(1.11)	(0.93)	(1.00)	(0.87)
IV. Own β + Proximity $\gamma\bar{M}$ (I+III)		11.09	13.58	11.66	13.58	10.20
		(5.89)	(2.49)	(2.02)	(2.21)	(1.84)
Fixed effects						
Stack-building cluster	yes	yes	yes	yes	yes	yes
Stack-relative week	yes	yes	yes	yes	yes	yes
Sample size	261,839	261,839	261,839	261,839	261,839	261,839
B. Post-Pre of controls						
Post	5.20	-1.62	2.70	3.42	2.23	3.21
	(1.05)	(1.75)	(1.45)	(1.33)	(0.98)	(1.27)
Post×Proximity		0.17	0.78	0.08	2.91	1.90
		(0.05)	(0.36)	(0.04)	(1.04)	(0.93)

Notes: Same as column (1) of Table 3 (reproduced in column (1) of Panel A here). Columns (2) to (6) of Panel A report estimates of equation (3). The Staggered DiD ATET estimate is reported in row I of Panel A and the estimated effect from multilateral proximity of control clusters to treated clusters is reported under row II of Panel A. The Control cluster indicator is interacted with five different multilateral proximity variables M_{dcrs}. Proximity is defined as the sum of the inverse distance (in kilometres) to treated groups on each relative day in column (2), the sum of the borders shared with treated groups on each relative day in column (3), and the sum of border multiplied by the inverse distance to each treated group in column (4). Column (5) has an indicator for control clusters that have spatially proximate treatments, defined as sharing the same waste truck route or sharing a waste truck route border without a spatial discontinuity to clusters that have started citizen training at each relative time, and column (6) has the value of the sum of the inverse distance to these spatially proximate treated clusters. The Proximity DiD estimate is evaluated at the mean of Post×Control×Proximity, where the mean is over the entire sample (including treated clusters) during the Post period. Panel B shows the Post-Pre of controls (difference in means of the dependent variable between the Post and Pre periods within stack-building control clusters, with standard errors in parentheses) in column (1) and includes Post×Proximity corresponding to each column in (2) to (6). Standard errors in parentheses are clustered two-way by building clusters and stacks.

Table 7: Comparison With Survey

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	Pre intervention	Post intervention	(2) – (1)	Sample size
	(1)	(2)	(3)	(4)
A. Experiment				
All periods	10.88	29.14	18.26 (1.06)	232,499
Intervention periods	11.03	30.22	19.19 (1.14)	192,088
B. Survey, all respondents				
All periods	12.70	29.17	16.47 (1.69)	8,813
Intervention periods	12.78	29.25	16.47 (1.72)	8,677
C. Survey, same respondent				
All periods	12.01	29.49	17.48 (1.96)	2,930
Intervention periods	12.02	29.67	17.65 (1.97)	2,912

Notes: Comparisons of waste segregation pre and post the full citizen training intervention (pre before 17/12 and post after 19/4 running to 31/5 to match the survey data). Panel A reports segregation from observations undertaken for all disposers in All periods and Intervention periods (excluding pure control households that start citizen training on the last three dates in the intervention schedule). Panels B and C report segregation from the surveys, defined as the product of whether the household reports disposing of their waste into the vehicle, reports segregating their waste and answers correctly on a knowledge question to identify the waste stream of an empty milk packet. Panel B has all households, while Panel C only has households where the same respondent answers the survey across both waves. Standard errors in parentheses clustered by building clusters in A and two-way by households and building groups in B and C.

Table 8: Survey, Reasons for Segregation Choice

Household chooses as reason for segregation choice (% of surveyed households)

	Pre intervention	Post intervention	(2) – (1)	Sample size
	(1)	(2)	(3)	(4)
A. Survey, all respondents				
Time and ease of segregating	50.40	60.52	10.12 (3.59)	8,206
Care for community or local area	25.66	46.45	20.79 (4.11)	8,206
Concern for the environment	10.26	24.98	14.72 (2.52)	8,206
B. Survey, household does segregate waste				
Time and ease of segregating	48.12	60.57	12.45 (4.55)	2,394
Care for community or local area	24.23	59.82	35.59 (4.55)	2,394
Concern for the environment	9.19	40.95	25.15 (3.87)	2,394
C. Survey, household does not segregate waste				
Time and ease of segregating	51.34	60.50	9.16 (3.66)	5,812
Care for community or local area	26.26	40.95	14.69 (4.19)	5,812
Concern for the environment	10.70	21.13	10.43 (2.36)	5,812

Notes: Segregation defined in the same way as for Panels B and C of Table 7. Shares of households who choose time or ease of segregation, community (including options saying care about my community/others do it/is or is not my job to do it) and environment (including care about the environment or have children who care about the environment) as factors in their decision to segregate/not segregate are reported in columns (1) and (2).

Table 9: Valuation of Citizen Training

Benefit type	Rate (Rupees)	Units per household per year	Benefit per household per year (Rupees)	Benefit to cost ratio for 5 years
	(1)	(2)	(3)=(1)×(2)	(4)
A. Benefits in Post				
I. Landfilling cost savings	2,220 to 2,640 per ton of waste	62.0 kg of waste	137 to 164	2.8 to 3.3
II. Greenhouse gas emission savings				
(a) Carbon market prices	3,485 per ton of CO2e	72.7 kg of CO2e	253	5.1
(b) Social cost values	13,510 per ton of CO2e	72.7 kg of CO2e	981	19.9
III. Total in Post at market value = I + II(a)			390 to 417	7.9 to 8.4
IV. Total in Post at social value = I + II(b)			1,118 to 1,145	22.7 to 23.2
B. Benefits in Follow-up				
I. Landfilling cost savings	2,220 to 2,640 per ton of waste	118.0 kg of waste	260 to 312	5.3 to 6.3
II. Greenhouse gas emission savings				
(a) Carbon market prices	3,485 per ton of CO2e	129.8 kg of CO2e	452	9.2
(b) Social cost values	13,510 per ton of CO2e	129.8 kg of CO2e	1,753	35.5
III. Total in Follow-up at market value = I + II(a)			712 to 764	14.5 to 15.5
IV. Total in Follow-up at social value = I + II(b)			2,013 to 2,065	40.8 to 41.8

Notes: Panel A shows the benefits and costs for the experimental time window and Panel B for the Follow-up period. Panel A is based on the central SDiD ATET estimate of a 12% rise in waste segregation and Panel B on the 32.31% segregation rate in the Follow-up period (from column (5) of Panel A in Table 1). Column (1) reports the landfilling costs per ton of waste per year in row I, the carbon price per ton of CO2e in row II(a) and the social cost of carbon in row II(b). Column (2) shows the volume of waste that does not need to be landfilled in row I and the volume of greenhouse gas emissions saved in rows II(a),(b) of each panel. Waste that does not need to be landfilled is the product of the rise in segregation and the average volume of waste per year (from 1.417 kilogram per household per day in column (1) of Table 1 multiplied by 365 days to arrive at an annual figure). Greenhouse gas emissions saved in column (2) is the drop in greenhouse gas emissions from increased segregation rates since the Pre period, holding waste volumes at Pre period levels. Column (3) is the value per household per year, obtained as the product of columns (1) and (2). Column (4) gives the benefit to cost ratio over a five year period for the incurred one-off cost of training of 247 Indian Rupees per household, computed as five times of column (3) divided by 247.

Supplemental Appendix

1. Theoretical Framework

Consider an economy of n households with a strictly concave utility function u, defined over consumption c and with $\partial u/\partial c > 0$. Consumption c produces waste material $m = c/\alpha$ where $1/\alpha < 1$ is the proportion of consumption that forms waste. Waste material must either be disposed of as waste for collection, g, or recycled r, such that $m = g + r$. The utility function $u = u(c(g,r), G)$ is increasing in c but decreasing in the stock of waste G (which is defined as $G = (1-\gamma)ng$ for $\gamma \geq 0$ that is the natural rate of degradation of waste in Smith 1972 and $\gamma = 0$ in Kinnaman and Fullerton 2000). Because $m = c/\alpha$ and $m = g + r$, consumption can be written as $c(g,r) = \alpha(g + r)$.

Households take prices in factor and output markets as given. Each household is endowed with $\bar{l}$ units of labour that earns a wage rate w. It chooses g and r to maximise u subject to $y = w\bar{l} = p_c c(g,r) + p_g g - p_r r + \delta w r^2/2$ where p_i denotes the price of activity i (p_g is paid for garbage fees and p_r is received for recyclables if they have some market value). The last term $\delta w r^2/2$ is the opportunity cost of recycling where δ is the rate at which the marginal cost rises with recycling r. A decrease in the parameter δ implies less household effort is required for recycling. In the application of this paper, citizen training reduces δ and more generally, the literature considers various policies such as kerbside recycling facilities, which increase the ease of recycling.

Solving for households' optimal recycling and disposal choices gives $r = (p_g + p_r)/\delta w$ and $g = w\bar{l}/(p_c\alpha + p_g) - (p_c\alpha + p_g/2 - p_r/2)(p_g + p_r)/\delta w(p_c\alpha + p_g)$. Comparative statics show that households recycle more when the ease of recycling increases, $\partial r/\partial\delta = -r/\delta < 0$. For a pair of households ($h \neq h'$) that face the same set of prices (because they are in the same narrowly defined geographic area), $\Delta r_h - \Delta r_{h'} = (1/\delta - 1/\delta')(p_r + p_g)/w > 0$ for $\delta < \delta'$. Because citizen training improves households' recycling technology, they would choose to recycle relatively more after training. The effect of reduced δ on waste disposal is ambiguous, $\partial g/\partial\delta = (w\bar{l} - (p_c\alpha + p_g)g)/\delta(p_c\alpha + p_g)$ and depends on relative prices and other initial conditions.

In general equilibrium analysis, production of aggregate consumption C is specified to require labour and material inputs, $C = f(L_c, M_c)$ where $M_c = M(V_c, R_c)$ consists of virgin resources V_c used in production and recyclables R_c that can substitute for some of the virgin resources. Firms choose their inputs to maximise profits $\pi_c = p_c f(L_c, M(V_c, R_c)) - wL_c - p_v V_c - p_r R_c$. Garbage disposal and processing of recycled material can also require virgin resources and labour. The context of the waste collection and the type of recycling under consideration would be important in specifying how prices for waste disposal and recyclables are determined. Finally, resource clearing ensures $n\bar{l} = \sum_{i=c,g,r} L_i + n\delta r^2/2$ and $V = \sum_{i=c,g,r} V_i$. Further, recyclables must also clear to preserve the law of conservation of mass, $C/\alpha - G = R_c$ (see Smith 1972).

The literature examines the set of Pigouvian taxes and subsidies that can address externalities from waste generation/management, like: policies targeting households - consumption taxes or advance disposal fees, garbage disposal fees, recycling subsidies, t_{hc}, t_g, s_{hr} (that change the constraint to $y = (p_c + t_{hc})c(g,r) + (p_g + t_g)g - (p_r + s_{hr})r + \delta w r^2/2$); and policies targeting firms - production taxes, virgin resource taxes and firm recyclable input subsidies t_{fc}, t_v, s_{fr} (that change the profit problem to $\pi_c = (p_c - t_{fc})f(L_c, M(V_c, R_c)) - wL_c - (p_v + t_v)V_c - (p_r - s_{fr})R_c$). In contrast, the focus in this paper is on directly reducing effort costs of recycling δ through citizen training. This is equivalent to increasing the productivity of households in recycling that results in a direct rise in recycling and a fall in total waste disposal as long as greater ease of recycling dominates freeing up of resources for consumption.

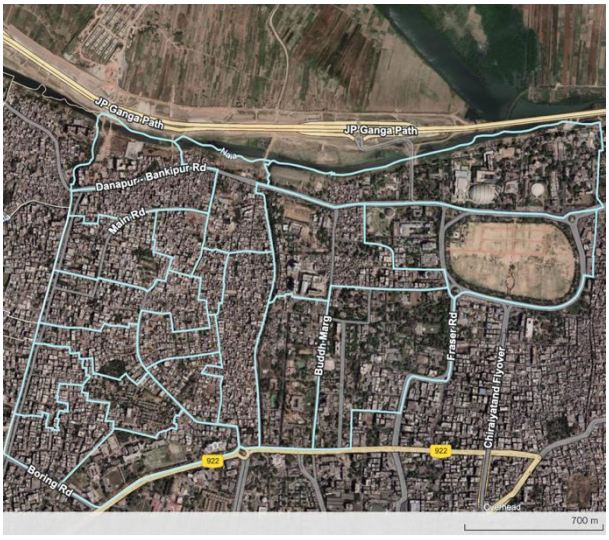
2. Additional Figures

Figure A1: Segregated Waste Collection by Waste Trucks and their Truck Routes in Patna

A. Photo of Waste Disposal

B. Landfill Outside the City

C. Waste Truck Routes in the City Centre

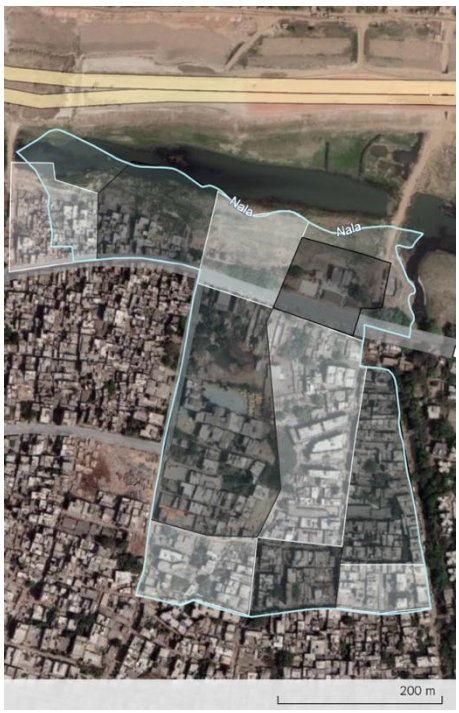


Notes: The photo in Panel A is from instagram.com/cityofpatna and in Panel B is from Democratic Charkha's news report on the landfill outside Patna city. The map in Panel C shows the city centre of Patna that lies to the south of the River Ganges, north of National Highway 922, east of Fraser Road and west of Boring Road. Blue boundaries mark the area covered by a unique waste truck route. Map drawn in Google Earth with coordinates provided by the City of Patna.

Figure A2: Order of Treatment

A. Example of a Waste Truck Route in Chessboard Design

B. Buildings in Squares of A



C. Example of a Spatial Discontinuity in Chessboard Design

D. Buildings in Squares of C

Notes: Map in A reproduces Panel C of Figure A1 to illustrate the chessboard design for one waste truck route in the city centre. Map in B zooms in on this waste truck route to show the buildings in the squares. Households residing in buildings in white squares start citizen training in the first phase of the schedule of Figure 1 and the geographically matched black squares start their citizen training in the second phase. Map in C illustrates georaphically matched spatial discontinuity squares outlined in green on either side of the city canal, with the waste truck route of B shown as reference. Map in D zooms in on the white and black canal squares of C to show the underlying buildings.

Figure A3: Citizen Training Material for Waste Management

Picture explaining that composting wet waste reduces the burden on the city's landfill (pictured at the bottom) and provides free and convenient compost for plants at home.

Picture explaining that disposing of waste in the truck is easy and takes away the shame of being caught dumping waste.

Picture explaining that segregation of waste into wet (green) and dry (blue) is easy because wet waste is generated just 2-3 times a day during cooking.

Picture explaining that segregating wet waste could reduce the burden of frequent trips to the waste truck to dispose of waste.

Figure A4: Citizen Training Material for Segregation and Recycling

Photo of information leaflets for citizens. Consent taken for posting photo.

Picture explaining which items are wet waste (green) that can be composted and which items are dry waste (blue) that can be recycled.

Picture to the left explains how different items are recycled, such as compost from wet kitchen waste and paper from old newspapers.
Picture to the right explains how waste affects soil, air and water pollution and has consequences for public health, city budgets, climate change and biodiversity.

Figure A5: Examples of Enumerator and Training Activities

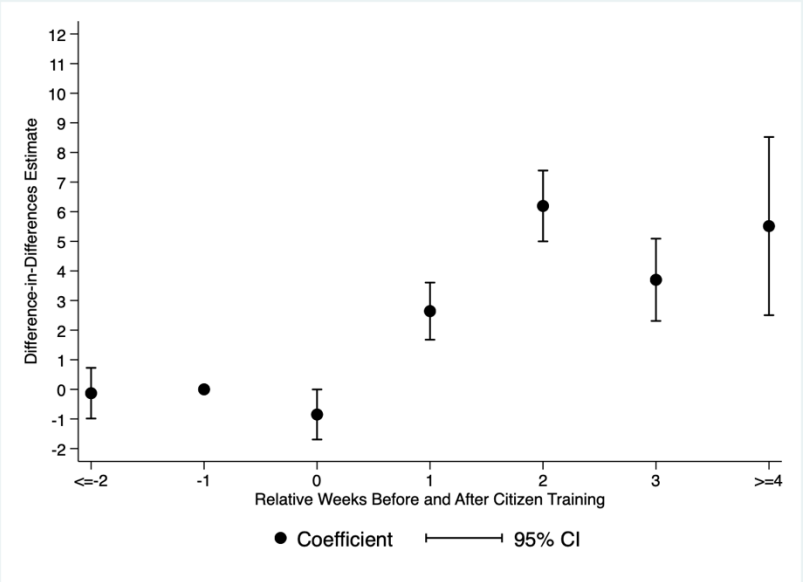
Photo of enumerator weighing waste disposed of in the truck. Consent taken for posting photo.

Photo of information material and demonstration tools of the intervention team.

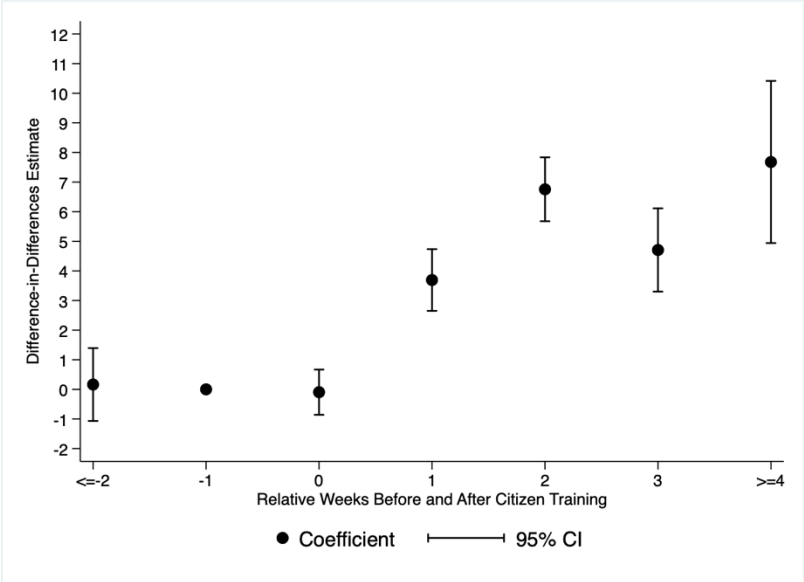
Photos of intervention teams conducting citizen training across different households. Consent taken for posting photos from individuals.

Figure A6: Event Study, Unbalanced and Balanced

(a) All Groups and Relative Time



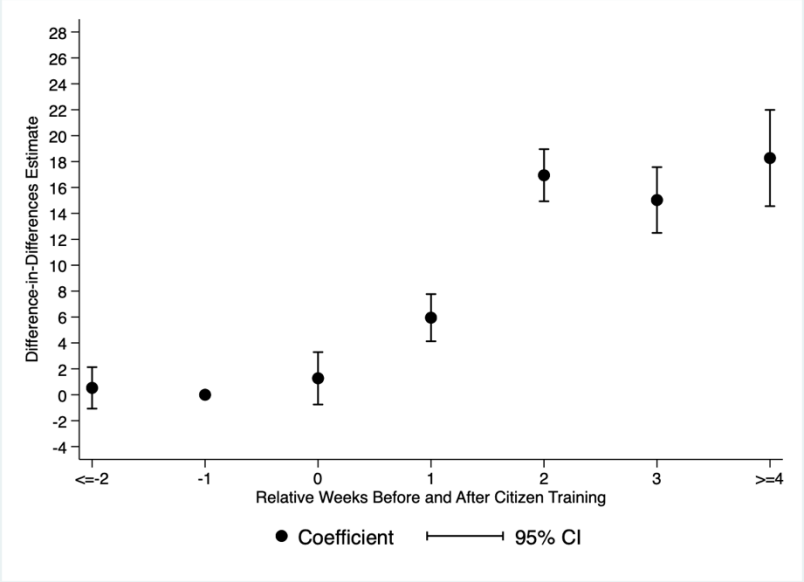
(b) Balanced Groups and Relative Time



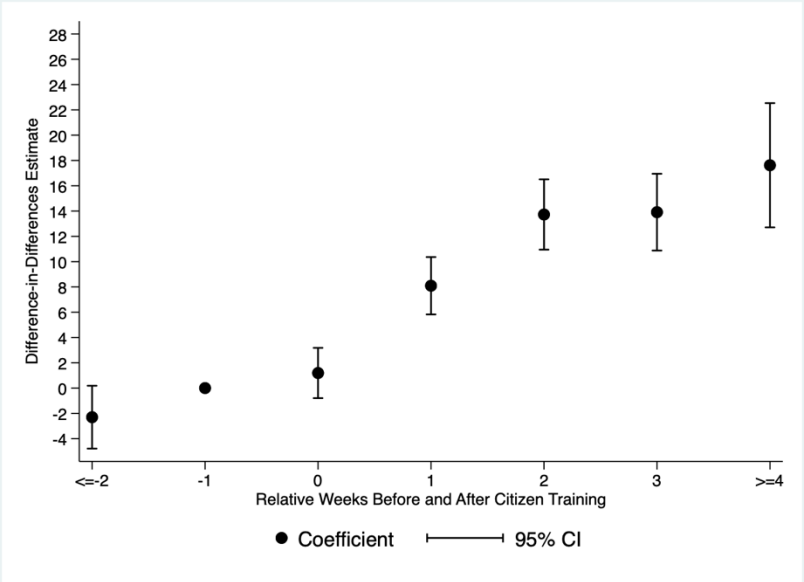
Notes: Comparable to event study, balanced, in Figure 3 (a). The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. The observations range from ≤-15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27, ≥28 relative days. Full estimation sample of 261,839 disposer-day observations or 16,714 cluster-days in (a) and estimation sample balanced on groups of building clusters with at least two weeks of disposals before and four weeks of disposals after the start of the citizen training in (b) covering 257,060 disposer-day observations or 16,339 cluster-day observations. The event study coefficient estimates (and associated standard errors) comparable to Table 2 column (3) are -0.13 (0.42), 0.00 (reference time, $r = -1$), -0.85 (0.42), 2.64 (0.47), 6.19 (0.59), 3.70 (0.68), 5.51 (1.48) in (a) and 0.16 (0.60), 0.00 (reference time, $r = -1$), -0.09 (0.37), 3.69 (0.51), 6.76 (0.53), 4.71 (0.69), 7.68 (1.33) in (b).

Figure A7: Event Study - Spatial Discontinuity, Unbalanced and Balanced

(a) All Groups and Relative Time



(b) Balanced Groups and Relative Time



Notes: Comparable to event study, balanced, in Figure 5. The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. The observations range from ≤-15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27, ≥28 relative days. Spatial discontinuity estimation sample of 134,334 disposer-days or 8,306 cluster-days in (a) and estimation sample balanced on groups of building clusters with at least two weeks of disposals before and four weeks of disposals after the start of the citizen training in (b) covering 105,570 disposer-days or 6,476 cluster-days. The event study coefficient estimates (and associated standard errors) comparable to Table 4 column (3) are 0.53 (0.74), 0.00 (reference time, $r = -1$), 1.27 (0.94), 5.95 (0.84), 16.94 (0.93), 15.03 (1.17), 18.27 (1.72) in (a) and -2.30 (1.10), 0.00 (reference time, $r = -1$), 1.19 (0.88), 8.09 (1.00), 13.73 (1.23), 13.91 (1.34), 17.62 (2.17) in (b).

3. Additional Tables

Table A1: Research Design Timeline

Dates	Description of activity	Conducted by
June 11 2021	Permissions and allocation of intervention areas	City government
July 21 2021	Maps of waste truck routes and property tax record numbers	City government
July 21 2021	Project ethics approval	Authors at LSE
September 8 2021	Project registry	Authors at LSE
September 23 2021	Maps and census of buildings and households	Enumeration team
November 23 2021	Start of first survey of longer household interviews	Enumeration team
December 2 2021	Start recording bi-weekly observations of waste disposal	Enumeration team
December 2 2021	Randomise order of citizen training across clusters	Authors at LSE
December 2 2021	Grouping of buildings for training	Authors at LSE
December 17 2021 - February 3 2022	Citizen training for phase 1 treatments	Intervention team
February 7 2022 - 18 April 2022	Citizen training for phase 2 treatments	Intervention team
April 16 2022	Start of second survey of longer household interviews	Enumeration team
May 31 2022	End recording bi-weekly observations of waste disposal	Enumeration team
July 27 2022 – August 8 2022	Two observations of waste disposal in follow-up period	Enumeration team

Table A2: Waste Segregation By Treatment Phase

Households that dispose of waste segregated into dry and wet waste (% of disposing households per day)

A. All periods of data collection	All Dec 2 - Aug 8	Pre Dec 2 - Apr 16	Post Dec 17 – Apr 18	Full Rollout Apr 19 - May 31	Follow-up Jul 27- Aug 8
	(1)	(2)	(3)	(4)	(5)
Phase 1	11.40	8.90	13.38	32.74	33.46
Number of household-days	278,180	56,885	164,295	48,382	8,618
Number of building cluster-days	17,726	3,676	10,405	3,091	554
Phase 2	11.26	9.82	19.54	26.41	31.39
Number of household-days	241,816	96,668	67,684	65,690	11,774
Number of building cluster-days	15,781	6,188	4,603	4,230	760

B. Periods of experiment	All Dec 2 - Apr 13	Pre Dec 2 - Apr 13	Post Dec 17 - Apr 13
	(1)	(2)	(3)
Phase 1	11.00	8.90	13.18
Number of household-days	222,062	61,760	160,302
Number of building cluster-days	14,118	3,992	10,126
Phase 2	10.89	9.59	19.22
Number of household-days	144,994	86,341	58,653
Number of building cluster-days	9,534	5,541	3,993

Notes: Same structure as Table 1. Phase 1 contains the first half of treated households from Figure 1 that started citizen training in the first 19 treatment groups and their control households. Phase 1 therefore refers to stacks 1 to 19 that cover the first two months of the start of citizen training from 16/12/2021 to 3/2/2022. Phase 2 contains the second half of treatment households that start citizen training in the next two months from 7/2/2022 to 18/4/2022 and their controls, which make up stacks 20 to 38.

Table A3A: Pre-Intervention Self-reported Characteristics of Households by Phase of Intervention

Characteristic	Phase 1	Phase 2	Phase 1 – Phase 2
	(1)	(2)	(3)
Household characteristics of cluster			
Mean household size	5.21	5.22	-0.01 (0.11)
Hindu %	91.68	94.48	-2.80 (2.53)
Muslim %	7.62	5.02	2.60 (2.50)
General caste %	32.68	37.49	4.82 (5.85)
Scheduled caste %	26.27	21.16	5.11 (6.83)
At least one member with class 10 education %	73.02	75.92	-2.90 (4.34)
At least one member with college %	67.61	65.42	2.19 (3.40)
Waste manager is female %	58.52	61.02	-2.50 (3.26)
Household ownership of assets in cluster			
Owns a refrigerator %	51.06	48.34	2.72 (4.49)
Owns an air cooling unit %	87.33	81.46	5.87 (4.78)
Owns a washing machine %	24.33	20.57	3.76 (4.03)
Owns a motorcycle/scooter %	46.43	45.24	0.12 (4.32)
Owns a car %	11.55	6.51	5.04 (2.58)
Owns residence %	61.93	58.09	3.84 (5.32)
Waste management characteristics of households in cluster			
Waste disposed of in vehicle %	92.97	91.42	1.55 (2.54)
Already segregates or willing to segregate waste %	26.20	24.28	1.92 (3.33)
Knows how to segregate waste %	50.75	47.35	3.40 (4.67)
Waste disposed of segregated in vehicle % (product of the 3 above)	13.74	12.59	1.15 (2.13)
Number of bins	0.99	0.93	0.06 (0.06)
Waste last disposed of less than a day ago %	96.06	95.08	0.98 (1.27)
Time spent on waste management (minutes per week)	24.00	23.92	0.08 (1.99)
Waste not disposed of in vehicle or designated pick-up %	6.82	8.42	-1.60 (2.46)
Willing to pay 30 or more per month for segregated waste disposal %	17.36	13.84	3.52 (2.99)
Distance to waste truck stop (scale of 1-4)			
1=in front of the house,.., 4 = >4 buildings away	1.79	1.88	-0.09 (0.11)
Mosquitoes/flies problem at home %	16.35	19.53	-3.19 (4.85)
Mean of household attitudes (scale of 1 to 5)			
5=strongly agree,.. 3=neutral,.. 1=strongly disagree)			
The effects of the so-called environmental crisis are exaggerated[48]	3.20	3.16	0.04 (0.18)
I find it hard to change my habits to be more environmentally-friendly[49]	2.60	2.69	-0.09 (0.25)
Waste workers should be paid more and be provided better working conditions	4.56	4.65	-0.09 (0.11)
Waste workers are discriminated against in our society	2.42	2.29	0.13 (0.25)
Covid-19 has made us value essential workers, such as waste workers, more	4.54	4.64	-0.10 (0.10)

Notes: Survey responses of household interviews before the start of any citizen training. 2,139 households in phase 1 and 2,571 in phase 2. Standard errors clustered by building group. Fraction of households that were willing to pay a randomised amount between Rupees 30 to 180 to get segregated waste collection in exchange for free compost. Waste disposed of in vehicle includes collected by government or private providers, but not disposed of within the house/yard, open area/water body, burned and do not know.

[48] Adapted from Public Opinion and the Environment: The Nine Types of Americans, 2014.
[49] Adapted from Huebner et al. (2015).

Table A3B: Pre-Intervention Self-reported Characteristics of Households on Either Side of Spatial Discontinuity by Phase of Intervention

Characteristic	Phase 1	Phase 2	Phase 1 – Phase 2
	(1)	(2)	(3)
Household characteristics of cluster			
Mean household size	5.16	5.18	0.02 (0.12)
Hindu %	92.60	94.18	-1.58 (2.58)
Muslim %	6.66	5.26	1.40 (2.54)
General caste %	32.43	37.65	-5.22 (6.44)
Scheduled caste %	24.87	19.75	5.12 (7.43)
At least one member with class 10 education %	74.76	76.33	-1.57 (4.58)
At least one member with college %	70.09	65.93	4.15 (3.36)
Waste manager is female %	59.51	60.56	-1.05 (3.12)
Household ownership of assets in cluster			
Owns a refrigerator %	47.92	46.48	1.44 (4.43)
Owns an air cooling unit %	84.76	81.37	3.39 (5.68)
Owns a washing machine %	21.97	19.45	2.52 (3.80)
Owns a motorcycle/scooter %	44.18	44.54	-0.36 (4.07)
Owns a car %	10.43	6.03	4.40 (2.36)
Owns residence %	61.99	57.92	4.08 (4.85)
Waste management characteristics of households in cluster			
Waste disposed of in vehicle %	89.62	90.74	-1.12 (3.31)
Already segregates or willing to segregate waste %	25.06	24.93	1.27 (3.17)
Knows how to segregate waste %	49.60	46.71	2.89 (4.26)
Waste disposed of segregated in vehicle % (product of the 3 above)	12.58	12.80	0.22 (1.99)
Number of bins	0.96	0.93	0.03 (0.05)
Waste last disposed of less than a day ago %	96.21	95.41	0.80 (1.19)
Time spent on waste management (minutes per week)	24.61	23.94	0.67 (1.87)
Waste not disposed of in vehicle or designated pick-up %	8.42	9.11	-0.69 (2.46)
Willing to pay 30 or more per month for segregated waste disposal %	16.41	13.38	3.03 (2.79)
Distance to waste truck stop (scale of 1-4)			
1=in front of the house,.., 4 = >4 buildings away	1.89	1.94	0.05 (0.13)
Mosquitoes/flies problem at home %	15.99	17.89	-1.90 (4.66)
Mean of household attitudes (scale of 1 to 5)			
5=strongly agree,.. 3=neutral,.. 1=strongly disagree)			
The effects of the so-called environmental crisis are exaggerated	3.14	3.11	0.03 (0.17)
I find it hard to change my habits to be more environmentally-friendly	2.56	2.61	-0.05 (0.23)
Waste workers should be paid more and be provided better working conditions	4.55	4.65	-0.10 (0.10)
Waste workers are discriminated against in our society	2.43	2.24	0.19 (0.23)
Covid-19 has made us value essential workers, such as waste workers, more	4.52	4.64	-0.12 (0.09)

Notes: Same as for Table A2A but for households that are in groups of buildings on either side of the spatial discontinuities in Table 4. 1,878 households in phase 1 of the intervention and 2,319 in phase 2.

Table A4: Staggered DiD ATET Estimates, Spatial Decay with Household Controls

Household disposes of waste segregated into dry and wet waste (% of disposing households)

	(1)	(2)	(3)
A. Multilateral proximity			
I. Staggered DiD estimate (β)	7.27	8.65	8.04
	(1.75)	(1.61)	(1.33)
II. Proximity DiD estimate (γ)			
Post×Control×Proximity	5.84	5.42	6.16
	(1.31)	(1.30)	(1.26)
III. Proximity effect at mean ($\gamma\bar{M}$)	4.88	4.53	5.15
	(1.09)	(1.09)	(1.05)
IV. Own β + Proximity $\gamma\bar{M}$ (I+III)	12.15	13.18	13.19
	(2.41)	(2.46)	(2.18)
Household characteristic × Relative time	Religion	Social group	Owns a car
Fixed effects			
Stack-cluster	yes	yes	yes
Stack-relative week	yes	yes	yes
Sample size	261,839	261,839	261,839

Notes: Same as column (5) of Table 6 but with household characteristics interacted with indicators for the stack-relative time. Column (1) adds the share of Hindu families and the share of Muslim families in the group interacted with the relative time indicators as independent variables to equation (3). Column (2) has the share of General Caste families and the share of Scheduled Caste families, and column (3) has the share that own a car. Additional specifications, with education and gender of the waste manager, are almost identical to the estimates in Table 6 (available upon request).

Table A5: Summary of Findings

Household disposes of waste segregated into dry and wet waste (% of disposing households)		
Specification	Range of SDiD Estimates	
	Minimum	Maximum
Baseline Current/constant weights and pure controls (Table 2, 1-4)	4.50 (0.85)	6.10 (1.41)
Fully balanced -28,..,27/-42,..,41/-28,..,27 and building clusters (Table 2, 5-7)	4.46 (0.82)	4.94 (0.90)
City geography:		
Spatial discontinuities (Table 4, 1-4)	13.37 (0.92)	16.72 (1.57)
Gravity (Table 6, 2-4 IV)	11.09 (5.89)	13.58 (2.49)
Spatial decay (Table 6, 5-6 IV)	10.20 (1.84)	13.58 (2.21)

Notes: Summary of estimates from Tables 2, 4 and 6.

Table A6: Other Survey Responses

Waste Management Characteristic	Pre	Post	Post-Pre
	(1)	(2)	(3)
Waste disposed of in vehicle %	90.23	91.54	1.31 (1.52)
Already segregates or willing to segregate waste %	24.99	48.26	23.27 (1.85)
Knows how to segregate waste %	48.03	55.98	7.96 (2.33)
Waste disposed of segregated in vehicle % (product of the 3 above)	12.70	29.17	16.48 (1.69)
Number of bins	0.95	1.02	0.07 (0.04)
Waste last disposed of less than a day ago %	95.77	98.78	3.01 (0.61)
Time spent on waste management (minutes per week)	24.24	24.78	0.54 (0.90)
Waste not disposed of in vehicle or designated pick-up %	8.80	8.46	-0.34 (1.29)
Willing to pay 30 or more per month for segregated waste disposal	14.76	13.82	-0.94 (0.17)
Mean of household attitudes (scale of 1 to 5) *5=strongly agree,.. 3=neutral,.. 1=strongly disagree)*			
The effects of the so-called environmental crisis are exaggerated	3.12	2.86	-0.26 (0.11)
I find it hard to change my habits to be more environmentally-friendly	2.59	2.38	-0.21 (0.13)
Waste workers should be paid more and be provided better working conditions	4.60	4.74	0.14 (0.05)
Waste workers are discriminated against in our society	2.33	2.16	-0.17 (0.13)
Covid-19 has made us value essential workers, such as waste workers, more	4.58	4.79	0.20 (0.06)

Notes: As for Table A3A, 8,813 randomly sampled households before and after the citizen training intervention.

Table A7A: Summary of Findings, Segregated Waste Share

Waste disposed of segregated into dry and wet waste (% of waste volume)		
Specification	Range of SDiD estimates	
	Minimum	Maximum
Baseline Current/constant weights and pure controls	4.04 (0.86)	5.55 (1.35)
Fully balanced -28,..,27/-42,..,41/-28,..,27 and building clusters	3.65 (0.85)	4.95 (0.93)
City geography:		
Spatial discontinuities	11.52 (0.89)	14.77 (1.47)
Gravity	10.42 (5.77)	13.34 (2.57)
Spatial decay	9.82 (1.69)	13.52 (2.12)

Notes: Same as for Table A5 covering 260,177 unique disposer-day observations.

Table A7B: Summary of Findings, Segregated Waste Volume

Segregated waste volume (gram per disposer per day)		
Specification	Range of SDiD estimates	
	Minimum	Maximum
Baseline Current/constant weights and pure controls	39 (15)	65 (17)
Fully balanced -28,..,27/-42,..,41/-28,..,27 and building clusters	43 (15)	69 (13)
City geography:		
Spatial discontinuities	126 (15)	143 (26)
Gravity	43 (111)	185 (46)
Spatial decay	83 (29)	172 (47)

Notes: Same as for Table A5 covering 260,177 unique disposer-day observations.

Table A7C: Summary of Findings, Unsegregated Waste Volume

Unsegregated waste volume (gram per disposer per day)		
Specification	Range of SDiD estimates	
	Minimum	Maximum
Baseline	-160	-189
Current/constant weights and pure controls	(20)	(41)
Fully balanced	-83	-187
-28,..,27/-42,..,41/-28,..,27 and building clusters	(16)	(22)
City geography:		
Spatial discontinuities	-216	-346
	(23)	(42)
Gravity	-158	-228
	(137)	(50)
Spatial decay	-101	-126
	(41)	(73)

Notes: Same as for Table A5 covering 260,177 unique disposer-day observations.

Table A7D: Summary of Findings, Waste Volume

Waste volume (gram per disposer per day)		
Specification	Range of SDiD estimates	
	Minimum	Maximum
Baseline	-106	-122
Current/constant weights and pure controls	(25)	(24)
Fully balanced	-14	-119
-28,..,27/-42,..,41/-28,..,27 and building clusters	(18)	(25)
City geography:		
Spatial discontinuities	-90	-202
	(23)	(37)
Gravity	-12	-115
	(65)	(162)
Spatial decay	-19	45
	(41)	(76)

Notes: Same as for Table A5 covering 260,177 unique disposer-day observations.

Table A7E: Summary of Findings, Disposers

Disposers (number per building per day)		
Specification	Range of SDiD estimates	
	Minimum	Maximum
Baseline Current/Constant weights and pure controls	0.16 (0.03)	0.51 (0.08)
Fully balanced -28,..,27/-42,..,41/-28,..,27 and building clusters	0.37 (0.05)	0.56 (0.07)
City geography:		
Spatial discontinuities	0.26 (0.06)	0.82 (0.11)
Gravity	0.24 (0.08)	0.91 (0.20)
Spatial decay	0.19 (0.09)	0.30 (0.07)

Notes: Same as for Table A5 covering 367,056 unique household-day observations (that includes zeros filled in for non-disposers).

Online Appendix

Registration

The census and intervention were registered at ISRCTN, a primary clinical trial registry recognised by the World Health Organisation. The census, survey and trial registries are available at Springer Nature registries here:

https://www.isrctn.com/ISRCTN14047604,

https://www.isrctn.com/ISRCTN16964926 and

https://www.isrctn.com/ISRCTN25429617.

Additional Information

Protocols for the census, surveys and training are provided here. All documents have been translated from Hindi to English.

Listing Protocol

Introduction for Listing

Hello. My name is ..... I am from XX. The Patna Municipal Corporation is making efforts to ensure that we all separate wet waste, dry waste, and hazardous waste. If possible, compost should be made from wet waste and used in gardening. In this context, a survey is being conducted.

Listing will only be done in PMC allocated areas.

The listing work will include all houses, apartments, families, vacant land, unused or half-constructed houses, businesses, booths/stalls (shops, temples, mosques, schools, colleges, offices, etc.) in that ward.

Listing will be done in two steps – buildings and occupants:

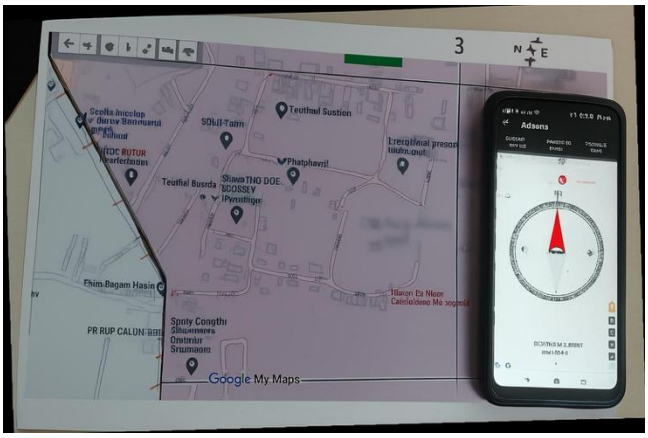
- Step 1 – Apartments, houses, vacant land, unused or half-constructed houses, booths/stalls.
- Step 2 – Families, businesses, shops.

For a single house, the following forms need to be filled:

- House listing form
- Family listing forms (for each family living in the house, including the house owner's family)
- Business/shop listing form (if a business or shop is present)

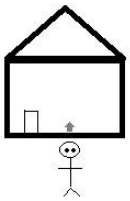
Instructions for recording details:

- When writing the road number, always use the internal road number provided on the map.
- If a new road is found that is not marked on the map, label it as A1, A2, A3 etc., and record the same road number in the house/apartment/business/shop survey forms.
- If a house faces two roads, write down both road numbers (e.g., 8, 10).
- Within your pocket area, follow the right-hand rule while listing, so that no house is missed.
- Use the compass on your mobile phone to identify road orientation (picture below).
- If individuals in the house cook separately, they should be listed as separate families.



Notes: Original text on the map has been blurred with ChatGPT.

GPS Instructions:



- GPS coordinates must be taken for every house/apartment/shop/office.
- Do not take GPS near the gate; instead, take it from the centre of the house/building (picture to the right).

Survey Protocol

Consent Form

My name is ....., I am from XX, Patna.
This survey is being conducted on the topic of community service in the solid waste service sector for research by Dr. Swati Dhingra of the London School of Economics. We request you to give about 20 minutes of your time to participate in this survey.

Participation is voluntary. You may refuse to answer any question at any time. Your information will be kept completely confidential and will not be shared with anyone. It will only be used for analysis in research work.

If you have any questions after the survey, you can contact our office at xxxxxxxxxx between 10 AM and 5 PM.

Verbal Consent

- My name cannot be directly used in any written documents or presentations.
- The information I provide may be combined with the responses of other participants and used by the London School of Economics solely for internal and external research purposes.

Survey Design

- The survey will be conducted with a total of about 10,000 households.

Survey Area Categories:

- *Category M*: PMC allocated areas will be called the M survey area. If a house across Road XX falls just outside the allocated areas, it will be included in the M survey area.
- *Category L*: Survey will be conducted in wards adjoining Category M. These will be called the L survey area.
- Surveys will be conducted simultaneously in both M and L areas, with equal numbers of surveyors.

Selection of Survey Areas

Survey Situation 1

- *Category M*: Houses located on the boundary of PMC allocated areas, including those across Road XX.
- *Category L*: Houses just beyond the boundary of PMC allocated areas.

Survey Situation 2

- *Category M*: Pockets within the ward boundary covered by PMC garbage collection truck rounds. Houses on the boundary already surveyed in Situation 1 will not be repeated.
- *Category L*: Similarly, pockets adjoining the ward boundary, surveyed in coordination with Category M.
- If garbage trucks visit an area 2–3 times a day, surveys will be conducted alternately in Category M and in coordination in Category L.

Survey Situation 3

- *Category M*: PMC allocated areas that are not directly on the boundary (e.g., at a distance X meters from the boundary).
- *Category L*: Similarly, houses in adjoining wards at the same distance (0–X meters).

Selection of Buildings and Families for Survey

The number of families in each building will determine how many households are surveyed:

Number of families in a building	Number of families to survey	Comments
1 family	0.5	Survey alternate buildings
2 families	0.5	Survey alternate buildings
3 families	0.5	Survey alternate buildings
4–9 families	1	Survey every building
10–17 families	2	Survey every building
18–24 families	3	Survey every building
25+ families	4	Survey every building

Selection of Respondents

- Any adult member of the family.
- Preferably an adult responsible for waste disposal.
- Do not survey outsiders who come only for work purposes (e.g., domestic staff, commercial workers, office staff).

Participant Information Sheet and Consent Form

Participant Information Sheet
Version 1
1/9/2021

You are being invited by the London School of Economics to take part in a research study. The responses to this survey will be used for research purposes to produce academic and policy literature on the experience of workers and the waste management services in urban areas. Therefore please think about the responses to all the questions carefully. All information collected for this study is confidential and all personal data will be anonymised. Please contact s.dhingra@lse.ac.uk or +91 xxxxx xxxxx for any further questions or suggestions. Thank you for your cooperation.

Training Protocol and Timeline

1. Greeting, introduction and state objectives
   I, …… welcome you all to this meeting. We work with the Patna Municipal Corporation. Our main objective is to ensure that our neighbourhoods and surroundings are clean and litter-free. All of this is possible when wet, dry and medical waste is all separated and if possible the wet waste is composted and the compost is used in gardening and waste is not strewn outside. We have all gathered here for this aim.

2. Distribute pamphlets
   Give the pamphlet related to zero-waste to all the members gathered in the meeting. Make sure you inform everyone what the different types of wet and dry waste are as well as inform them about the composting process and how to explain or communicate this subject

3. Question – answer process
   - Open the box full of questions
   - Ask someone in the audience to pick up a chit from the box and ask them to read out the question on it
   - Everyone can answer the question in turn
   - Ask others to pick up different chits after each question is answered completely

Examples
Is it easy to separate wet and dry waste?
Where in the house is wet waste likely to be generated?
How is the separated wet and dry waste useful?
How long does it take to ensure the garbage is given to the garbage collector on a typical day?
What do you do every morning when you listen to this song on the road, “The garbage collector is here, remove the waste from the home?”

4. Detailed demonstration of composting and segregation of waste with own and household bins/waste.

5. Give everyone a box of home-made compost
   - Open the box of compost
   - Encourage everyone to take a little compost on their hand and feel it

6. Conclusion and thank everyone
   Thanks everyone for taking out the time to come and attend this talk.

7. Share number and information for next meeting

8. A selfie with the group

Same-day meeting: if the main person is agreeing to a meeting then tell them to gather all their family members and give them the zero-waste pamphlets and request them to participate in the discussion.

Refusal of meeting: Ask for availability on a future date