Citizen Training and the Urban Waste Footprint

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Abstract

Diverting waste away from and zero waste to landfills are key sustainability policy aims of local and national governments around the world, particularly in countries with large waste footprints from rapid consumption growth and urbanisation. Segregation at the source of waste generation can offer a low-cost solution to urban waste footprints, yet segregation rates are low in many places, especially in the cities of developing economies. This paper studies a staggered randomised intervention offering training and education to citizens about waste segregation. Citizens in the city of Patna in India were given training on waste segregation at source, recycling and its environmental benefits in a large experimental intervention undertaken in collaboration with the city administration. Segregation-at-source increased substantially among households that received the intervention, and additional boosts to segregation arose from spatial spillovers, as the programme delivered at least a double-digit benefit-cost ratio. Citizen training, when effectively designed and implemented, does deliver a low-cost solution for the cities of developing countries to both reduce their waste footprint and enhance local environmental sustainability.

Keywords: waste; citizen training; experimental intervention; spatial spillovers.
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1. Introduction

Managing the waste footprint created by rapid urbanisation is a key part of the United Nations' Sustainable Development Goals of making cities and human settlements sustainable and ensuring responsible consumption and production. Inadequate waste management impacts climate change[1], groundwater and soil pollution[2], riverine and marine pollution, biodiversity[3] and public health.[4] It is hard to overstate the scale of the problems from waste and, more than this, globalisation and technological change further exacerbate the environmental consequences.

The shifting international geography of waste, amid increased volumes, is magnifying environmental and health problems. In the past century, waste production has risen tenfold, and by 2050, it is anticipated to be another 70 percent higher (Hoornweg et al. 2013). Yet less than a third of waste is managed in an environmentally responsible way (Kaza et al. 2018). This is likely to increase because waste generation is growing the fastest in developing economies where waste mismanagement is much higher (Kaza et al. 2018, Lebreton and Andrady 2019).[5] Waste generation rises with income levels and urbanisation, with scarce evidence of it following an environmental Kuznets curve (Kinnaman 2009,

[1] Waste directly makes up a fifth of global methane emissions and, while estimates for the overall impact remain uncertain, it is generally agreed that postconsumer waste, through its production and management, contributes to climate change and that displacement of materials and energy through waste reuse offers big opportunities for greenhouse gas abatement (see Vergara and Tchobanoglous 2012, for a survey).

[2] When waste is dumped in landfills, it creates landfill leachate, one of the main anthropogenic sources of groundwater pollution (Parvin and Tareq 2021).

[3] Uncontrolled disposal of waste generates heavy metals contamination in groundwater and soil, and waste flowing into rivers and water bodies creates marine litter that affects biodiversity, such as from ocean plastics (e.g. Jambeck et al. 2015, Borelle et al. 2020, Lau et al. 2020, Ferronato and Toretta 2019, Hoornweg eta al. 2013, see UNEP 2021a for compilation of key findings).

[4] Public health concerns over inadequate waste management have been a recurring theme through the history of waste and landfill legislation (example, Abelson 1985). Improper waste disposal and exposure to waste has been shown to be significantly associated with toxic contamination, respiratory problems, adverse pregnancy outcomes and childhood cancers, and increased infant mortality (Brender et al. 2011, Currie et al. 2011, 2015, Tanaka et al. 2022, see also Shaddick et al. 2018, Tomita et al. 2020).

[5] For example, a fifth of global methane emissions are from poorly managed landfills and a “disturbing” trend is an exponential increase in methane emissions from non-OECD landfills (UNEP 2021b).

Mazanti and Zoboli 2008, UNEP 2010, Velis et al 2023). At the same time, technology changes featuring the rise of plastics and electronic consumer products, put together with a lower ability to recycle biodegradable waste outside of rural areas, has made waste streams and their management more complex and expensive.[6]

Waste management is economically important for policy at the national and local levels. Waste expenditures are estimated to make up 0.5 percent of global GDP and between 0.5 percent to 2.6 percent of GDP in low- and middle-income countries (Matheson 2019). Management is typically the responsibility of local governments, and it often makes up their single largest municipal budget item, accounting for an average 20 percent in low income countries, and more than 10 percent in middle income countries, and 4 percent in high-income countries (Kaza et al 2018).

Most city governments however lack the budgets needed to construct proper waste disposal facilities, such as landfills and incineration plants, and these are often financed at a higher level of government. Landfills continue to be the most prevalent way of disposing of waste across the world (Kaza et al. 2018). But landfilling requires significant outlays, whilst posing growing health hazards and environmental concerns. Thus, diverting waste away from and zero waste to landfills have become common policy aims of local and national governments the world over.[7]

[6] Plastic is now ubiquitous in historically plastic-free waste streams, and it persists and accumulates in the environment and in organisms over long periods of time (Atalar et al. 2025, Mathis et al. 2024, Worm et al. 2017). Despite being often recyclable, plastic has much lower recycling rates than paper or metal because of the complexity and diversity of compositions and the presence of chemical additives (Singh and Walker 2024, Landrigan et al. 2025). Record volumes of electronic waste intensify the problems because they contain hazardous substances that can get released into the environment (The Global E-Waste Monitor 2024, https://www.itu.int/hub/publication/d-gen-e_waste-01-2024/). These factors also reduce the quality of compost that can be obtained from green waste in modern waste streams (Okori et al. 2024, Zhang et al. 2023).

[7] For example, the United States 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 and the Global Methane Initiative identifies zero landfilling of degradable wastes as a priority project.

Policies to promote the separation of waste and recycling are viewed as best practice methods to help achieve these aims.[8] The high recycling rates in many advanced economies are primarily a result of high shares of source-separation leading to cleaner fractions of waste streams for recycling (UNEP 2015). Separation of waste at the source of waste generation – in households and factories or other waste creating institutions - enables more waste to be diverted away from landfills. It improves the efficiency of waste management systems by reducing the upstream sorting costs and providing cleaner feedstocks to downstream recyclers, enabling greater value to be captured from post-consumer material.[9]

Landfilling poses particularly difficult problems in developing countries, which often lack the resources and large land area needed to build sanitary landfills near urban agglomerations.[10] Landfills also come with concerns over poor management, as witnessed in various serious episodes of collapses and fires (for example, in Bandung, Shenzhen, Java and Delhi).[11] Many developing economies – such as, India, Brazil, China, Philippines - with large waste footprints arising from rapid consumption growth and urbanisation, have introduced laws to divert waste away from landfills, focusing particularly on segregation-at-source policies. But, and despite segregation-at-source being a low-cost solution to manage waste footprints (UNEP 2015), take-up remains low in many places.

This significant environmental question is very understudied, and as a consequence credible evidence on how to increase waste segregation remains scarce. The focus of this paper is on the scope for citizen training to reduce the waste footprint through a large-scale

[8] 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

[9] Also see UN Habitat 2022 at https://www.urbanagendaplatform.org/best-practice/source-segregation.

[10] To benchmark landfilling outlays, the top two companies that own or operate landfills in the United States had a revenue of 21.57 billion USD in 2011. They made up 39 percent of the revenue of the industry, implying landfill companies had an annual revenue of 55 billion USD (EPA 2014).

[11] 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

experimental intervention in the city of Patna in India in 2021/22. A randomised research design was implemented to train citizens in segregation-at-source and in circular economy principles of reduction, reuse and recycling of waste. A staggered timing research design offered citizen training across clusters of buildings along waste collection routes. The experiment was run in collaboration with the city administration and used to elicit a causal impact of training on waste segregation.

Intervention areas (the clusters of buildings) were partitioned in a geographical chessboard design, where white squares of the chessboard received the training intervention first and black squares later. The order of the training across different white and black squares was randomised and every square in the area was eventually covered. This was a deliberate feature of the intervention to ensure fairness and equity in that every household received the training.

A doorstepping intervention offered training to residents in waste management principles. The training included an education information component about the public health and environmental impacts of poor waste management and was followed by multiple sessions on waste management principles and methods to practically train households in reduction, segregation, recycling and composting. The content provided the basic knowledge that would be needed to correctly undertake waste management at source. The focus was geared to principles of basic knowledge and training because they are a precondition for any waste management intervention that leverages public participation to reduce costs.

Observations to record waste outcomes were undertaken twice a week by enumerators who walked along with the waste trucks that were doing their usual rounds of the city. Segregation-at-source increased substantially among households that received the intervention. About 10 percent of households segregated their waste into biodegradable and non-degradable waste before training receipt. In the four months after the start of the first intervention to a cluster, the rate of segregation rose by over 5 percentage points more among households that received the training relative to those that had not yet been trained. After all households had received the training, the segregation rate reached a much higher 29 percent. And, importantly, it persisted at this considerably higher level as corroborated in a subsequent follow up. In other words, through the entire study period, the aggregate segregation rate went up by over 200 percent, from about 10 percent at the outset to 32 percent in a follow-up eight months later.

The intervention was evaluated through a staggered difference-in-differences research design explicitly structured to enable causal inference. The experimental estimates identify a significant impact of citizen training generating an improvement in waste segregation. Building clusters that had started the citizen training experienced a rise in segregation rates a week after the start of the training programme, and this created a gap of about 4.5 to 6.1 percentage points in their segregation rates (relative to an initial baseline of 10 percent) when compared to clusters that had not yet started citizen training.

The baseline experimental estimates were then generalised to permit study of a highly relevant issue in practical terms that can arise in this kind of intervention, namely spatial spillovers from the citizen training programme. This is important to consider because of the scope for knowledge spillovers, that are key drivers of interactions between locations in the study of systems of cities and regions (Redding 2023). Spillovers are estimated by drawing on spatial variation in treatment households induced by randomization. The research design generalisation was operationalised through both spatial discontinuity designs and in econometric gravity and spatial decay models that leverage geographical features of the city.

The first, direct means of appraising scope for spillovers, restricts the analysis to situations where spillovers are not able to occur. Features of city geography generate natural and built environment spatial discontinuities that reduce crossings, and hence communications with not-yet-treated households. These boundary discontinuities were used in a discontinuity-matched staggered difference-in-differences estimator that compared outcomes of building clusters that started the citizen training on one side of a spatial discontinuity relative to their counterparts on the other side of the discontinuity that had not yet started the training.

The second and third approaches return to the full sample, and adopt methods from the spatial econometrics literature –specifically, gravity and spatial decay models – which are combined with the experimental variation of the intervention to decompose its effect into a direct training effect and a spillover effect on not-yet-trained proximate buildings. Incorporating these features into the empirical analysis reveals positive, sizable, spatial spillovers from the intervention, and the overall impact, including sizable positive spatial spillovers, rises to a 13.5 percentage point increase in waste segregation in the time window of the experiment.

The last part of the paper undertakes a cost-benefit analysis. The citizen training programme is highly beneficial and cost effective. Reduced need for landfilling of segregated waste breaks even the costs of the intervention in less than a year and a half. Measuring benefits only as landfill cost savings, produces a benefit to cost ratio between 3.3 to 4. Incorporating environmental savings of methane emissions from the intervention at carbon credit prices raises this to just over 10. This offers strong testament to the citizen training programme on delivering environmental sustainability to local communities from waste segregation.

The rest of the paper is organised as follows. Section 2 places the citizen training intervention into the context of waste management more broadly. It makes connections to related literature that has largely focused on developed economies and discusses waste both in India and more specifically for the context of the experimental intervention in the city of

Patna. Section 3 describes the experimental research design and offers an initial descriptive analysis. Section 4 provides baseline experimental findings for the randomised intervention. Section 5 moves on to the estimates that permit spatial spillovers, by producing estimates leveraged from aspects of the natural and built environment geography of the city of Patna and from statistical gravity and spatial decay models. Section 6 discusses implications of the findings by reconciling magnitudes from the array of empirical estimates, together with offering a valuation of the intervention in terms of economic costs and environmental benefits. Section 7 concludes.

2. Waste Management, Related Literature and Study Context

Waste Management

Many advanced economies have explicit policies in place for diverting waste away from landfills. Separation of waste at source to achieve greater recycling potential is an essential first step in achieving this objective. Methods to incentivise or enforce households and firms to segregate their waste into recyclable or compostable components are widely prevalent, even when there are costs of time, storage, transportation, infrastructure, and management systems in doing so (see Kinnaman 2009, Briguglio 2016, Fullerton 2024 for comprehensive surveys).

Results evaluating waste segregation do show substantial savings and benefits relative to other waste management solutions. For example, the net greenhouse gas emissions for a given material are generally lowest for source reduction and recycling and highest for landfilling (e.g. Smith et al 2001; Eunomia 2002; Dehoust et al 2005; EPA 2006).[12] While much of the research has focused on developed country settings, emerging

[12] For example, Wünsch and Simon (2017) finds separate waste collection and individual treatment in Germany leads to an average of -0.129 Mg of CO_2e/Mg of GHG emission (savings) as opposed to 0.239 from collection

economies are quickly adopting segregation-at-source policies, though evidence remains sparse. Among what does exist on actual effects, for example recent work on China shows substantial emissions reductions and greater waste-to-energy potential from mandatory segregation-at-source laws in Shanghai.[13]

Over half of the waste in low- and middle-income countries is food and green waste that does not need to be sent to landfills (UNESCAP 2015, Meys et al. 2021). Moreover, organic material contains a high moisture content and has low calorific value, making it unsuitable for incineration without considerable pre-treatment (Lacoste and Chalmin 2006; UNEP 2009; Vishvanathan and Glawe 2006; see UNEP 2010). Even Shanghai which has the most 'internationally standard' waste stream (with a higher fraction of plastics and papers and less moisture) has a waste composition that can barely burn on its own. Supplemental fuel is needed in most cities in developing countries to incinerate their waste, implying no net energy generation to offset the high costs of incineration (World Bank 2005, ADB 2011, Kaza et al. 2018).

Segregation of waste, for example into "dry waste" that can be reused or recycled such as paper, plastic bottles, and "wet waste" such as food waste that is biodegradable, reduces the amount that needs to be landfilled and increases the potential for thermal recovery and other treatment options (Kumar et al. 2017, Ahluwalia and Patel 2018). But it

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of mixed municipal waste that is disposed of in landfills, or -0.015 from collection of mixed waste and treatment in Mechanical and Biological Treatment plants and -0.039 from collection of mixed waste that is treated in waste incineration plants.

[13] For example, Zhang et al. (2023) find that after Shanghai forced segregation of waste into dry and wet waste at source, the composition and physiochemical properties of municipal waste changed substantially. Organic matter content in dry waste fell from 77 percent to 48 percent, leading to a fall in the water content of dry waste from 57 percent to 36 percent and a rise in the low heating value from 6600 kJ/kg to over 12,580 to 13,525 kJ/kg (which could lower GHG emissions by 0.41 tCO_2e per ton MSW on average). This made waste incineration more viable, and the share of landfilling fell from 41-45 percent before 2019 to 6.8 percent in 2021. The proportion of organic matter in wet waste became almost 100 percent and diversion of organic waste from landfills lowered the GHG emissions from 0.13 tCO_2e to 0.08 tCO_2e. Also see Pimenteira et al 2004, Chintan 2009 and Xin et al. (2020) for projections and Krause (2024) for a related application.

requires citizen participation to increase the efficiency of waste management systems and for achieving safe management at scale in a cost-effective way (Briguglio 2016). A large literature has studied the value of waste clean-ups and the incentives for public participation in waste and recycling policies in advanced economies (e.g. Smith 1972, Levinson 1999, Greenstone and Gallagher 2008, Kinnaman 2006, Viscusi et al. 2011, Gamper-Rabindran and Timmins 2011).[14] These include property values, state-contingent valuations and various incentive and penalty policies, such as kerbside bag fees, tariffs, trade taxes or plastic return deposits, which find mixed evidence for recycling behaviour and willingness to pay for waste management. In contrast, this paper examines a developing country setting and builds on the recent literature on enviro-spatial economics to gain insights from more closely combining the spatial and environmental approaches to understand how policy design and implementation can leverage spatial settings in environmental applications (see Balboni and Shapiro forthcoming for a survey).

Take-up of segregation and recycling tends to be low in developing countries. The nature of the waste management problem is also different because most studies in advanced economies focus on non-biodegradable waste while preventing biodegradable waste from landfills is a key challenge in lower-income settings (Briguglio 2016). Monitoring of waste practices is difficult and the few studies that exist in developing economies find little impact of recycling campaigns (Chong et al. 2015, Nepal et al. 2023) or focus on highly educated sub-populations (Wadehra and Mishra 2018). Measurement often relies on 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

[14] Also see, Fullerton and Kinnaman (1996), Bueno and Valente (2019), Akbulut-Yuksel and Boulatoff (2022) in developed country contexts.

and willingness to pay need not translate into actual improvements in waste management (Basistha et al. 2024 and Fuhrmann-Riebel et al. 2024, see also Kayamo 2022).

Some aspects of the environmental behaviour literature focusses on achieving environmental education goals, and this is of relevance to the citizen training intervention design used here. The potential for investments in community education for waste management in particular and public goods and services more generally has been proposed in early work in the economics of behaviour and psychology (e.g. Moore and Lowenstein 2004). Recent work has highlighted a role for education and community connectedness to influence pro-environmental attitudes and outcomes (e.g. Bernstad et al. 2013, see Ballard et al. (2024) for a survey of related literature and Bhattacharya et al. 2024 for a developing country application).[15] There is a strong reliance on self-report data and the studies are usually relatively small scale and often focused on economies with advanced waste management systems. The intervention research design of this paper is a citizen training programme embedded in a large scale field experiment conducted in collaboration with the city of Patna in the low-income state of Bihar in India.

Waste in India

Most of the growth in waste is expected to take place in the developing world, especially in South Asia, where 85 percent of waste is mismanaged, compared to less than half on average across all countries. Waste generation per capita in India is similar to that in many low and lower middle-income countries, at about 0.5 kilograms a day per person (Kaza et al. 2018). Population growth, and economic development in the country have been associated with greater volumes of municipal solid waste and methane emissions from their inadequate disposal (Singh et al. 2018). Globally, India is the third largest emitter of

[15] Also see Briguglio (2016) and Carlsson et al. (2021) for discussion and exhaustive sets of papers surveyed.

methane, making up a quarter of methane emissions from landfills (see, inter alia, Kumar and Sharma 2014, Siddiqui et al. 2011).[16] And this problem is expected to increase over the next two decades as the proper disposal of growing urban waste is 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.[17] Consequently, waste has 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, and 27 percent is processed (Centre for Science and Environment 2021). Various waste processing methods have been tried, but have not been successful due to low calorific value of the waste, 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 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). The bulk of waste generated in urban areas however is disposed of as unsegregated waste containing a mixture of biodegradable, non-degradable, inert and hazardous waste, which ends up untreated in landfills or other waste dumps. While waste pickers recover some material in landfills and dumps, the value and recyclability of items is compromised, and the efficiency of the waste management process is reduced due to disposal of unsegregated waste.

Community awareness and participation in segregation is considered an essential first step in improving the efficiency of waste management systems (Singh 2020). The 2016 Solid

[16] https://www.bloomberg.com/features/2022-methane-landfills-south-asia-climate-health-hazard/
[17] https://mohua.gov.in/upload/uploadfiles/files/Part2.pdf; Hanrahan et al. (2006)

Waste Management Rules mandate door–to-door collection of segregated waste. Waste generators must segregate their waste into wet, dry and hazardous waste. A fee is charged to generators for door-to-door collection of segregated waste by their municipalities and fines can be levied if generators are found to be in violation. Nonetheless, segregation rates are low and community awareness has not kept pace with the changing composition of waste.

Waste in the City of Patna

The intervention was conducted in Patna, in collaboration with the city government of the Patna Municipal Corporation. Patna is the capital of Bihar, one of the lowest-income states in India, with a per capita GDP of approximately $975 (Government of India). Patna district had a population of 5.8 million in the 2011 census, with over 40 percent residing in urban areas and 1.68 million in the City of Patna. It is the fifth fastest growing city in India and had a decadal growth rate of 23 percent in the census.

Patna was named the dirtiest city out of 47 cities in the 2020 survey of Indian cities.[18] The City budgeted revenue and capital expenditures amounting to USD 1.83 billion (0.89 + 0.94) in 2021-22.[19] Of this, USD 0.31 billion or 17 percent was spending on solid waste management, making it the largest budget item. There were additional sizable expenditures on composting facilities and plastic processing plants that are reported separately under air pollution control expenses. To benchmark this amount, 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 a little over 17 percent and it includes staff costs for waste management (the figures are not broken down by job characteristics).

[18] https://ss2023.sbmurban.org/assets/pdf/ss2020_report.pdf

[19] Patna Municipal Corporation Budget 2021-22 available at https://www.pmc.bihar.gov.in/budget.aspx.

As in many urban parts of India, door-to-door waste collection is provided to urban resident households in Patna (at a mandatory monthly user fee of less than USD 4.50 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 designated 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 biodegradable waste and blue for non-biodegradable waste. It also has a separate smaller compartment or container for domestic hazardous waste (small yellow bin attached to the back of the vehicle). The driver and helper are instructed by the government to not handle the waste and residents must empty out their bins or dispose of their bags on their own into the truck compartments.

The vehicle takes the same route every morning and then deposits the 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). The vehicle route was designed by the city government at least as far back as 2019 to optimise on the amount of fuel consumed during its transit. The vehicle routes remained fixed throughout the intervention. An example of the central part of the city and the distinct waste truck route boundaries in it is shown in Figure A1 (Panel B) in the Appendix.[20]

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

3. Experimental Design and Descriptive Statistics

This section explains the programme and its experimental design. It then presents an initial descriptive analysis of the array of primary data collected in the citizen training programme intervention.

Citizen Training Programme

A full timeline of the citizen training programme, the research protocol and its experimental design is given in Table 1. The timeline starts from permissions agreed about allocation of intervention areas with the city government in June 2021, followed a month later by giving access to maps of waste truck routes and property tax records on city residents. Also in July, the project received ethics approval and the initial project registration occurred in early September.[21] Later that month the mapping and census of buildings and households were undertaken and the first household baseline surveys began. The experiment implementation and data collection ran from December 2021 to April 2022 in two phases, described fully below. A second household survey began in April 2022 once full treatment coverage had occurred. Data collection continued to the end of May and in a final follow up in early August 2022.

The experimental intervention was enabled by the full enumeration census and household survey that was undertaken prior to the experiment being undertaken. It covered 10,434 households in 4,202 residences of 57,743 urban citizens. Figure 1 provides a visual summary, together with associated sample sizes, of the four key observation features of the census - coverage, location, disposal and segregation. Of the 4,202 residences covered in the census, 4,135 residences of 10,196 households (or 97.7%) were located on or near a waste

[21] 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 protocols are summarised in the Appendix.

truck route, defined as within 450 metres of a waste truck collection point.[22] The training covers all households and the experimental design focuses on households that are located on or near the waste truck routes.

Experimental delivery of citizen training was designed to have a staggered timing across clusters of buildings with service collection on waste truck routes running from mid-December 2021 to mid-April 2022. The experimental design was set up to be randomised across building clusters so that half of the buildings on each waste collection route were covered in the first two months of the trial and the remaining half on each route in the subsequent two months. The ordering of the intervention start date was randomised across the waste truck routes of building clusters. Within these two phases the treatment start dates were deliberately staggered.

The randomised staggered cluster design was adopted for a number of reasons. First, for reasons of fairness and equity, we (and the Patna government) wanted to guarantee that all households in building clusters received the citizen training intervention. Second, the staggered design enables causal inference based on appropriately specified difference-in-differences and event study analyses. In particular, it enables a dynamic treatment-control design where clusters that have not yet received the intervention serve as a control group for treatment clusters that have. Third, the splitting into two halves in a chessboard style configuration (with whites getting the intervention first and blacks afterwards) ensures that comparisons are being made across treatment and control clusters that are similar in characteristics to each other due to geographical sorting of households. Fourth, the cluster

[22] In a baseline survey, over half of the households reported that 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 into the truck. At a usual walking speed of 3 miles per hour, the average walking distance is 450 metres. It is worth noting that several urban studies find that 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 2023).

approach enables spillovers and scaling up among households within a cluster while maintaining balancing of household characteristics across treated and control clusters. This is important in a setting where spillovers may arise from citizen interactions with one another, something we explicitly incorporate into the research design to test for below and find to be important. Fifth, and also related to the spillovers question, the design can be combined with geographical features of the city, such as boundary discontinuities based on the natural and built city environment that reduce citizen communication and hence may result in spillovers to control groups.

Household Census and Building Structures

As the Table 1 timeline shows, in July 2021 the experiment involved an intensive exercise from the enumeration team using detailed maps and buildings 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 in practice. Maps of the waste truck routes in these designated areas were provided by the city, together with a roster of all buildings from property tax records. 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 be vital, not least because the city has grown very significantly since the last official population census was conducted in 2011.

Even more important was that the enumerator census determined that the number of households actually living in a building differed from the administrative records due to renting out of buildings by property owners. Another 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. 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 if it had been disposed of in the open or by the doorstep or thrown elsewhere outside the building. Of the 97.7 percent of all households on the waste truck route, the vast majority (9,948 households, or 97.6 percent) stored their waste in bins/bags that were disposed of in the waste truck. Of these, 12.7 percent were observed to have segregated their waste or reported doing so.[23]

From the enumeration team information for each truck route, 38 groups of an average size of just over 100 contiguous buildings were created. Contiguous buildings were clustered together for treatment at the same time as households residing close by would likely either see or be aware of training activity or hear about it from their neighbours. The areas to be included were selected by the city government based on a requirement of covering the main city centre and the location of the composting facility of the city. A memorandum of understanding was signed with the London School of Economics that mandated provision of citizen training to every household in the intervention area over the four-month time period.

Experimental Design

Groups of building clusters were numbered from east to west and north to south on a map, with the grouping designed to ensure geographical spread. Because of the 50/50 splitting of contiguous areas into the two phases, odd-numbered groups can be thought of as synonymous with white squares on a chessboard and even-numbered ones with black

[23] Among the 2.3 percent of all households that were neither on nor near a waste truck collection point, disposals of waste took place mostly in designated areas. Further, the mean segregation rate of 12.7 percent is similar to the mean of about 14 percent from a later, smaller scale, intervention covering just over 1,000 households in Patna in a seven-day time window that tried to boost waste segregation through religious messaging (Basistha et al. 2024).

squares. A bi-weekly staggered timing of treatment was randomised to set up the first phase delivery of treatments to white squares and, once completed, the matched black square units then received the intervention in a second phase in an analogous staggered design.[24]

In practice, the first data collection for all clusters was on 2 December 2021. Five pre-treatment data collections occurred until the first citizen training intervention of the staggered design was delivered by the intervention team on 16 December 2021 (after the waste observations across clusters for the day). And then the data collection occurred bi-weekly, with treatments sequentially administered across odd numbered, and then even numbered groups, until the last, 38th, group received training on 18 April 2021. 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, which we will study in more detail later. Some overlap did occur on the start date of groups across waste truck routes, and so in practice the experiment contains 31 unique treatment dates.[25] Overall, in the intervention period, there were 38 days of data collection across all clusters, giving a 38×38 square group by time structure, finishing when the last group of building clusters received treatment.

Figure 2 shows the randomised start dates for all 38 groups and the phasing in over the two halves from 16 December 2021 to 2 February 2022 (Phase 1 for white squares) and between 3 February to 18 April 2022 (Phase 2 for black squares). Figure A2 in the Appendix provides a visual summary through a map that zooms in on the city centre to show the order of the start of citizen training for different clusters of buildings represented as circles. The grey boundaries denote the area covered by a unique waste truck route that remains fixed

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[24] 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.

[25] There were periodic breaks in the training schedule for New Year's holiday, the festival of Holi, and the festival of Ram Navami.

throughout the programme. Lighter circles are clusters that get randomised into starting the training before the darker clusters. Only building clusters located on major roads are shown for clarity.

Once full treatment was complete, data collection through waste observations continued again on a bi-weekly basis until 31 May 2021. A second household survey was also conducted at the end of all treatments to record longer interviews with households. Enumerators followed up two months after the last waste observation to undertake two more data collections from 27 July to 8 August 2022.

Citizen Training

The intervention administered a detailed and extensive citizen training programme to every household within a group on its randomised start date and subsequent days. Door-to-door visits were undertaken by two members of the intervention team to train citizens in the group (see the Appendix for the research protocols of the intervention). 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 across multiple visits. They visited the group of households repeatedly until every household had been covered and received training.

Training pairs first showed a letter of introduction from the Patna Municipal Corporation. They then asked about the primary waste manager in the household (or group of households if they were in close vicinity) and proceeded with the citizen training. The training supplied: information on the landfill outside Patna and its operation mode and functioning; information on the health and environmental impacts on the community of inadequate waste management and open dumping; practical training on reducing, segregating, reusing and recycling waste; and demonstrations and practice sessions for segregation and home composting.

The information supplied to residents consisted of drawings by a local artist articulating the benefits of waste management, pictures of examples of different types of waste and photographs of the Patna landfill site. The team members trained citizens through practical demonstrations and practice sessions of segregating waste using the waste bins/bags present in the household. This was followed by a demonstration of setting up bins for segregation and composting using the intervention equipment of the training providers and the bin facilities of the households. Citizens were left with documents on different types of waste for reference, information on the landfill outside Patna and 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 for segregation or their own home composting kits. An example of some of the sample material used in this detailed training and education activity is depicted in Figure 3, and additional examples are in Figures A3 and A4 of the Appendix.[26]

Intervention Outcomes and Measurement

A big challenge for waste studies in developing country settings is the lack of reliable or representative data on waste practices. Existing studies are mostly small scale and low public awareness can make self-reported waste outcome information inaccurate and unreliable as shown in Wadehra and Mishra's (2018) pioneering study of waste management. Additionally, in an interview we undertook before beginning the intervention with Shivani Wadehra about her work very much reinforced this issue. Even in a highly educated neighbourhood of Delhi, many residents were unaware that wet waste and dry

[26] Drivers and helpers (sitting in the trucks) were not involved in citizen training, but they were informed of the programme before the start of any enumeration or intervention. While it may be argued that training of drivers and helpers may have been helpful in advancing better waste management, it is worth noting that waste work in India is typically done by those from some of the most socioeconomically disadvantaged backgrounds. On the ground, these waste workers have little authority in enforcing waste management rules.

waste referred to the properties of the waste as opposed to that of the material from which the waste was generated.[27] A quote from that interview stated: “Many residents thought they were segregating-at-source because they were selling a few valuable metal items to informal sector recyclers 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 features of the intervention were designed to ensure a large scale representative data collection and one that counters possible mismeasurement or difficulty of collection of the waste outcome measures. First, the data collection and the intervention are, to our knowledge, much larger in scale and sample than the small body of environmental work that studies waste segregation. 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 of waste practices. Enumerators collected distinct measures of waste segregation. As a first measure, they 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 be carrying at least two bags/bins and the enumerators would also be able to see the content of the waste when the disposer tipped it into the waste truck compartments. This first measure is the primary outcome of interest in this study and is the main focus of most of the empirical analysis below.

This main waste segregation metric is also triangulated and cross-validated with other measures of waste segregation. The share of waste volume that is segregated was measured

[27] Wet and dry waste are common terms in waste management in China and India, used to refer broadly to biodegradable and non-biodegradable waste.

as enumerators had a weighing scale with a hook to record the volume of dry, wet and unsegregated waste disposed of in the waste truck (this is one of the photos, the one on the far left, of enumerator activities shown in Figure A5).[28] The 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.[29] Households can generate all three types of waste – dry, wet and unsegregated and the volumes of all three types of waste are considered later as alternative measures of waste segregation.

Longer interviews on waste practices were conducted separately through surveys undertaken before and after the full intervention for all households to cover all areas. The measures included indicators for 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 data and are discussed in the final section of the paper and in the Appendix.

For the main measures based on waste observations, enumerators walked with the waste truck to record their waste observations at the level of a disposer. A disposer can be assigned to a residential building cluster, because clusters of buildings (as opposed to an individual building) can be visually identified when viewed by enumerators during disposal into the waste truck. On average, a building cluster in the waste observations is about five to six buildings on average, and these can be visually identified as separate from the next cluster

[28] 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).
[29] On one observation day for some clusters weights were not recorded due to problems with the weighing scale.

of buildings. The visual identification ensures 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. Additionally, 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 that they were from multiple households). Enumerators were trained for three weeks before the data collection started to enable them to record data at speed.[30]

Enumerators recorded the GPS (or the approximate GPS) of the central location of the building cluster of disposers. 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 primary location, they go the to the next halt of the truck and so on, with everyone typically going within 450 metres radius of their residence. The census has the road segment or by-lane of every building, and we therefore get the number of households that are within 450 metres of the GPS of the building cluster. 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 as the probability of disposing of its waste in that cluster. This ensures that the number of households across all clusters sum to the actual number of households recorded in the census, and the household weight of a building cluster, denoted

[30] In one cluster there is a slum area that the truck cannot access and so there is handcart coverage of waste collection and community bins for citizens to dispose of waste. Citizen training was undertaken there, but our enumerated observations do not cover these alternative forms of waste disposal. Later we report results that exclude clusters lying in the coverage area of the truck route to which the slum belongs.

by N_c for cluster c, is higher if there are more households close to it. The statistics reported from the enumerator observation data are weighted by this inverse distance-weighted number of census households and therefore correctly aggregates disposer/non-disposer level observations to the aggregate number of census households.

The enumeration team collecting observational data were different individuals from the intervention team providing 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 tend to be concentrated in the mornings and evenings.

Descriptive Statistics

The waste observation data comprise 657 disposing building clusters with 10,196 census families that reside 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-up. This amounts to 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 2 reports aggregate summary statistics for all observation days of data collection, running from the pre-intervention period, to the post-intervention period ending once all households had received training and, after that, through to the end recording of observation data and finishing with follow up that took place four months after the full rollout of the programme. 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 show that the share of segregated waste in the total waste volume of a cluster is broadly similar – at 10.87 percent of all disposed waste (= 154 grams of segregated waste / 1417 grams of total waste per household per day).

When the full set of observation days are split into pre-, post- and follow-up periods, respectively in columns (2), (3) and (4) of Table 2, it is evident that aggregate rates of segregation climb significantly over the duration of the experiment. Initially quite low levels of waste segregation are seen for disposers before the intervention, when pre-intervention waste segregation rates feature just about one in ten disposers (9.48 percent). This rises substantially by 5.67 percentage points, climbing to an average 15.15 percent across the post-intervention period. Once the intervention period is complete, segregation rates continue to increase. 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 (and for other survey measures discussed in the penultimate section later).

The aggregate numbers show a big increase in waste segregation. Of course, the grouping into the four time phases shown in panel A of Table 2 means the summary statistics and their evolution over time contain compositional effects from grouping time differences in treatment together, because households randomised into receiving the intervention later are being pooled with those that started the citizen training earlier. It is extremely important with this structure that an appropriate experimental design and estimation sample is formulated to obtain a causal impact that does not contain a bias from the composition changes that arise from differential timing of treatment. The next section describes and reports baseline results from the experimental design used to elicit a causal impact of citizen training on household waste segregation that accounts for the staggered nature of the intervention.

4. Experimental Results

Estimation Sample

The intervention was deliberately structured to have a staggered over time design to ensure the fairness criteria that all households received citizen training by the end. From a methodological perspective, setting up and implementing a research design that produces a causal impact of citizen training on waste segregation therefore firmly fits into the recent econometrics literature on difference-in-differences estimators with staggered treatment (see these surveys of this literature: 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. (2025) and Wing et al. (2024), is used. It compares waste outcomes of households before and after they have received the intervention with waste outcomes of those that have not yet received the intervention 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 2 - estimation samples need to be adjusted accordingly.

Summary statistics for the main estimation sample are in the lower panel B of Table 2. 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 serve as pure control households as they start citizen training after 13 April (respectively on 14, 16, and 18 April). Estimates from samples that are more or less stringent on balancing the estimation sample by requiring a minimum number of pre- and post-observations are also reported and discussed below.

The difference between the full observation data in the top panel of Table 2 and the estimation sample in the lower panel of Table 2 therefore arises due to the additional pre-treatment week of the three control groups and the longer post-treatment period for the full observation data in Panel A. For the salient items contained in both panels, the descriptive statistics are highly reassuring in their similarity across the two Panels of the Table.

Difference-in-Differences Staggered Research Design

In the staggered design the composition of treatment and control groups varies over time. Because of this, 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 features treatment clusters treated on the first treatment date that start the intervention on 16 December 2021, and uses all other 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 on the last three treatment dates (36th to 38th) are pure controls throughout the estimation period because their households receive training after the end date. Stack 2 contains clusters that start citizen training on the second treatment date as treated group 2 and groups 3 to 38 as controls until their own start dates. 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 group 1 are not included in stack 2, and so on for other stacks.

More formally, a stack set is $s = \{c, c'\}$ with treatment date for the group of building clusters c that start treatment on calendar date t_c occurring before that for clusters c' and the set contains all control clusters c' up to the time when they start their own training. The stack set can be written as consisting of subsets $s(c, r) = \{c, c' \mid t_{c'} > t_c, t_c + r\}$ for each relative time r for a given treatment cluster c. The time periods in the stacked data are recentred to be relative to the start date of training to citizens in the treated clusters of each stack, so that treatment effects are estimated for each relative time period r before and after the start of citizen training, with $r = 0$ denoting the start of citizen training for the treated clusters in each stack. Appending all stacks together gives the full dataset comprising 35 stacks of treated groups of building clusters and their control clusters.

The first set of 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 group and its corresponding control group) are from the specification:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r \geq 0} \beta_{rs} D_{dcrs} + \varepsilon_{dcrs} \tag{1}$$

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 (i.e. when $r \geq 0$) 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 different ATET coefficients are estimated, they need to be 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 the 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: $N_{rs} \equiv \sum_{c''\in s(r)} N_{c''}$. In the special situation of constancy of estimates across groups and over time, the stack-relative time-specific SDiD ATET estimate β_{rs} collapses to the orthodox time-varying two-way fixed effect ATET estimate, which will generally be biased in the presence of heterogeneity.

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:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r\neq -1} \beta_{rs} D_{dcrs} + \varepsilon_{dcrs} \tag{2}$$

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 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. The results discussion to follow starts with standard SDiD ATET estimates because they retain more information and cover more stacks (Dube et al. 2025) and then moves on to show partly and fully balanced estimates.

Baseline Results

Table 3 contains the first set of baseline experimental SDiD estimates of equation (1). 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 an almost fifty percent increase relative to the aggregate pre-treatment segregation rate for all disposers of 9.31 percent. Moreover, as will be shown over the rest of the analysis, for several reasons, this sizable estimate lies mostly at the lower bound of the estimated causal effects of the citizen training on waste segregation.[31,]

Columns (2) to (7) of Table 3 report estimates from specifications that vary the control 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.[32]

The estimates reported in columns (5) to (7) of the Table come from specifications that balance the estimation sample on relative time. SDiD ATET estimates for each stack and relative week are estimated on a balanced panel of clusters that contain the relative

[31] The standard two-way cluster and relative time fixed effects DiD ATET is 4.86 (1.19).
[32] Excluding clusters in the slum parts of the truck route slightly lowers the baseline DiD ATET of column (1) in Table 3 to 4.41 (0.87) when these clusters are excluded from treatments and to 4.06 (0.90) when they are also excluded from the 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 1.

weeks specified in each column. 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.

Event Studies

Figure 4 plots time-varying event study estimates averaged across all stacks from equation (2) for the estimation sample. The upper Panel (a) balances on groups with at least two relative weeks before the start of citizen training and four relative weeks after. Because the panel is balanced, the weights are also held fixed over relative time and do not feature composition changes across stacks. The treated and control households show similar trends before the start of the training. It takes a week after the start of citizen training, and then the treated households show a larger rise in the segregation rates compared to their control households. The lower panel (b) is fully balanced on building clusters that have at least two relative weeks before and four or more relative weeks after the start of citizen training in each stack to adjust for composition changes. For reference, the equivalent unbalanced full estimation sample event study is shown to be very similar in Appendix Figure A6.

Moreover, and validating the causal interpretation of the DiD estimates, pre-trends in segregation-at-source are highly similar across treated and control households in the event studies shown in both Figures 4 and 5. The differences in segregation rates are usually small and statistically insignificant until relative week 0 when the intervention starts among the treated clusters of households. Then the gap between the treated and control households widens, as shown in the SDiD ATET estimates for relative week 1 onwards.

A longer duration event study with a fuller set of pre-intervention SDiD ATET estimates for six weeks before and five weeks after is shown in Figure 5 so as to hone in even more on the pre-treatment parallel trends assumption required for a causal interpretation of the DiD estimates. The assumption is fully satisfied and the Figure reconfirms the large uptick in segregation that follows a week from the start of citizen training.

A lack of systematic differences across treated and control groups in the period before the intervention shows households to be balanced on observable and unobservable characteristics in the research design, including the randomised order of the intervention. One way of showing this further is to compare pre-intervention segregation rates and household characteristics for phase 1 and phase 2 treatments, which correspond respectively to the white and black chessboard squares scenario referred to above. 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 Table A1 of the Appendix. Phase 1 and 2 pre-treatment means of observable household characteristics collected in longer interviews also very much show treated and control groups to be balanced pre-intervention for an array of observable demographic, waste and building characteristics (see the phase 1/phase 2 pre-intervention balancing tests in Appendix Table A2A).

5. Spillovers and City Geography

The experimental estimates of the previous section identify a significant impact of citizen training generating an improvement in waste segregation in a range of average effects of 4.5 to 6.1 percentage points. These are sizable increases in household waste segregation relative to the initial baseline. In the absence of local spillovers or externalities, they can be viewed as direct, causal effects of the intervention. However, to varying extents in different building clusters and localities, although there is some physical distance between treated and control clusters, citizens may well communicate with those in control clusters about the programme activities. In the staggered design, and given local proximity of treated and yet to be treated units, this could lead to spillovers to clusters that have not yet started their own citizen training.

Evaluating the existence and extent of possible spillovers is done in three main ways. The city geography enables design of different experiments to examine spatial spillovers, either by ruling them out or by modelling them in conjunction with the intervention. The first, direct means of appraising scope for spillovers, restricts the analysis to situations where spillovers are not able to occur. Features of city geography generate natural and built environment spatial discontinuities that reduce crossings, and hence communications with not-yet-treated households, and the empirical analysis can be modelled for the sub-sample where this is the case. The second and third methods incorporate spillovers into the empirical research design. Both return to the full sample by setting up and implementing designs that incorporate and estimate spillovers in either a gravity model or a model of spatial decay that contains features of both the spatial discontinuity approach and the gravity framework.

Control groups are less likely to receive spillovers if they are spatially distant from treated clusters. If treated and control clusters are however too distant from each other, they would also be expected to differ on household characteristics because households tend to sort into residential neighbourhoods (Adukia et al. 2023, Bharathi et al. 2022). These differences in characteristics might also imply different paths of waste behaviour that are unrelated to the intervention. In other words, the treatment and control groups are more likely to be unbalanced on observable and unobservable characteristics if they are too spatially diverse. Consequently, a trade-off between spillovers and balancing on characteristics can come into play, as in many settings of randomised trials.

This section shows results drawing on a number of spatial features to vary relevant factors in this trade-off, such as the distance to the truck stop among residents in treated and control clusters, border discontinuities from truck routes, and spatial discontinuities from geographical barriers that make it harder to cross from treated to control clusters, but that maintain similarity across treated and control clusters.

Spatial Estimation Models

These spatial estimation models either modify the sample used to elicit causal effects or generalise the estimating equations from the earlier baseline specifications based on the staggered identification from the stack set $s = \{c, c'\}$.

They cover the following approaches:

1). Spatial discontinuities

This approach exploits the particular cases of the matched staggered difference-in-difference estimator set restricting the sample to set elements where c and $c'$are on either side of a spatial discontinuity. To fix ideas about the need for matching, in terms of difference-in-differences studies like the pathbreaking Card and Krueger (1994) minimum wage study, and the many more that followed, the treated unit (New Jersey, the state whose minimum wage was increased) is compared with the matched control unit (Pennsylvania, the adjacent state whose minimum wage was unchanged and not to other more distant states).

It generalises the comparison of New Jersey and Pennsylvania in minimum wage studies of Card and Krueger (1994) to a staggered setting with spatial discontinuities. Treated clusters c are matched to their control clusters c' that are on the other side of a spatial discontinuity. Matched control clusters remain in the stack until training starts for their households or for the households in building clusters from which they are not physically separated by a discontinuity. This implements a matched SDiD ATET for the discontinuity sample with appropriately rescaled weights. Because standard SDiD ATET estimators are not flexible to allow for matching, the estimator is implemented by stacking the data with matched treated and control clusters to first obtain the DiD ATET estimates and then averaged to arrive at the matched SDiD ATET estimator, as before.

2). Gravity model

In the full sample, distance and waste truck borders can be incorporated into a standard gravity framework (for example. as in Head and Mayer 2013), whereby bilateral information flows across two clusters c and c' rise with their geographical proximity. This setup recognises that control group citizens who are more distant from or do not share a truck route or common border of their truck route with treatment citizens would be less likely to observe or to communicate about the training or their waste behaviour with treatment citizens.

Consider a disposer d in control cluster c of stack s. If the disposer is located close to any cluster that has started treatment at a given point in time, then it is expected to be more likely to receive a spillover from that treated cluster. Let G_{dcrs} denote the sum of the disposer's proximity to all treated clusters at any relative time r of stack s. When proximity is defined as the inverse of the geographic distance between a control cluster and a treated cluster, the sum of the inverse distance to all treated clusters G_{dcrs} is a measure of multilateral proximity. It increases as more clusters start citizen training over time, and particularly if these starting clusters are geographically close to the control cluster under consideration. Another measure of multilateral proximity is the number of treated groups with which the control cluster shares a waste truck route or a waste truck route border. These two measures can also be combined, following the gravity literature, to the sum of shared borders where the importance weight is the inverse of the distance between the control cluster and the treated cluster with which it shares a border.

Equation (1) can be respecified by augmenting with the G_{dcrs} variable in the following way:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r\geq 0} \beta_{rs} D_{dcrs} + \gamma(1 - D_{dcrs}) G_{dcrs} + \varepsilon_{dcrs} \tag{3}$$

where α_{cs}, α_{rs} as earlier are cluster-stack and relative week-stack fixed effects of the stack and ε_{dcrs} is an error term and standard errors are clustered. As before, D_{dcrs} is an indicator that switches on to one for the treated cluster in a stack after the start of the intervention of that cluster and is zero otherwise. 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. A new key outcome of interest in equation (3) is γ because it is 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, measured by G_{dcrs}.

3) Spatial decay model

The most general model puts together the approaches in 1) and 2). Experiments exploiting geography to reduce spillovers show much larger DiD estimates in treated clusters that were geographically distinct. These experiments reduce the potential for spillovers, but the opposite can also be implemented by estimating the spillovers where they are most likely to arise. The spillovers, if any, can be directly estimated as in the literature (for example, 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 setting of this paper, the geography experiments suggest spillovers are likely larger for control clusters that are less separated from treated clusters.

For disposer d in control cluster c of stack s, let I_{dcrs} denote the sum of the number of treated groups with which it shares a waste truck route or with which it shares a border without being separated through a spatial discontinuity. Households in control clusters that are proximate to more treatments (through sharing a waste truck route or having fewer spatial discontinuities) have larger values of I_{dcrs} and this rises over relative time r because more and more clusters start citizen training over the calendar period. For example, I_{dcrs} would take a minimum value of zero for households that are separated from all 35 treated groups in the estimation sample. For control households in stack 1 that border the first treated cluster and have no spatial discontinuity with it, the value of I_{dcrs} would be 1 at relative time $r = 0$. But then as more and more clusters start their own training, the value of I_{dcrs} for the remaining control clusters would rise as more clusters that are connected to the control clusters start citizen training. From the gravity literature, spillovers from connected treatments would be expected to be larger if they are geographically closer, and the inverse of distance is taken as the weight when summing across proximate treatments.

The estimating equation in (1) is now re-estimated with I_{dcrs} as follows:

$$W_{dcrs} = \alpha_{cs} + \alpha_{rs} + \sum_{r\geq 0} \beta_{rs} D_{dcrs} + \gamma(1 - D_{dcrs}) I_{dcrs} + \varepsilon_{dcrs} \tag{4}$$

where, following the spatial discontinuity method of 1), the geography variable explicitly accounts for controls that are not separated by a spatial discontinuity and are geographically closer as being more likely to receive spillovers from adjacent treated groups. Finally, the specification can also combine the gravity method of 2) by adding different gravity variables, such as other borders and distance, to the specification in equation (4) to examine differences in information transmission along these spatial characteristics.

Spatial Discontinuities - Results

The city geography is characterised by natural barriers and those from the built environment that can limit information flows across space. The aerial view and photo in Figure 6 show how a spatial discontinuity arises from the canal flowing into the River Ganges to the north of the city. While the canal has two bridges, these are far apart and we exclude clusters that are connected to each other on either side of the bridge.

A second spatial discontinuity is shown in Figure 7, which arises from an east-west major road in the city centre that also divides the city area through its built environment. The road has a long metal barrier at the median to prevent people from crossing this busy road with heavy traffic, shown in the photo. The traffic is speedy in parts of the road because it merges with a flyover. Buildings on either side of the road appear similar to each other but are separated by a hard-to-cross barrier, suggesting a greater likelihood of balance across household characteristics in the treatment and control groups and lower likelihood of spatial spillovers across them due to the built environment.

There are more 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, and that are exploited as spatial discontinuities in the DiD analysis. Sample sizes are smaller for the spatial discontinuity sample on account of the focus being placed on groups on either side of a discontinuity. Table A2B shows that groups on one side of a spatial discontinuity that receive the intervention 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.

The spatial discontinuity estimation sample consists of those clusters that have a discontinuity between them and other clusters, such as the canal or a major road that spatially bifurcates them from each other. Because the order of treatment is randomised, there is at least one group on one side of a discontinuity that gets randomised into treatment before its corresponding group on the other side of that discontinuity. This is referred to as the first treated group and its stack can be created with its respective set of discontinuous controls groups.

The stack for the first treated group consists of itself (as the treated group) along with the corresponding control group on the other side of the discontinuity from it. If there is more than one control group on the other side of the discontinuity, then the clusters in that control group are also included in the stack of the discontinuity sample. But if there is more than one group on the same side of a discontinuity as the treated group, then it will be included only if it has a different discontinuity that separates it from the first treated group and so on for subsequent treatments. On the other side of the discontinuity, the control group for the first treated group goes into its own treatment on a subsequent date (to the first treated group). It features in the discontinuity sample as its own treated stack if there are other control groups with which it has a different spatial discontinuity and that also have a discontinuity with all other treated groups.

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. Table 4 shows the 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). The segregation rates are slightly lower in the discontinuity sample to start with, but the waste outcomes look broadly similar to that for the full estimation sample in the earlier Table 2. The segregation rates in the post-period rise by about 4 percentage points (from 8.3 to 12.1 percent) for the treated and control households in the discontinuity sample.

The difference-in-differences estimates for treated households that deal with the composition issues from the staggered research design show there to be a big rise, going up to 13.37 to 16.72 percentage points in the baseline results of columns (1) to (4) in Table 5. This is also confirmed when the sample is balanced on relative days since the start of citizen training and on building clusters in columns (5) to (7) of Table 5. Figure 8 shows event study estimates for the discontinuity sample. While treated and control groups have similar segregation rates before the start of citizen training in the treated clusters, there is a sharp pickup in segregation one week afterwards and a slight further pickup in the following weeks too.[33]

Table 6 shows results for different definitions of spatial discontinuities, with the most stringent in column (1) to the least stringent in column (3). Column (1) focuses on treated and control clusters that are on either side of the city canal flowing into the Ganges to the north of the city or on either side of the main road (including with metal/concrete barriers at the median). These are the two key spatial discontinuities in the full set of discontinuities considered in Tables 4 and 5, and only households on either side of these two discontinuities are included in the column (1) sample. For example, if the first cluster to start the citizen training is on the west side of the canal and also on the west side of the main road running parallel to the canal, then the controls in its stack are the clusters on the east side of the canal or the east side of the main road (that have not yet started the intervention). Stacks of

[33] The equivalent unbalanced spatial discontinuity sample event study is shown in Appendix Figure A7.

subsequently treated clusters that are also on the west side of the canal and the main road are excluded because they are on the same side of the first treated cluster and could have received a spillover before their own treatment. 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. Finally, column (3) expands the definition of spatial discontinuities further to include three other main roads that are not in the baseline definition of Tables 4 and 5. The results in Table 6 vary from a SDiD ATET of about 12 to 18 percentage points, with higher estimated effects for the more stringent definitions where spillovers are ruled out from the discontinuities.

The presence of a spatial discontinuity reduces the avenues for treated households to influence the control households because it is harder to cross the discontinuity, such as the city canal or the main city road with a metal barrier to prevent crossings. 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 results of Table 3. 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 in Table 3 would be underestimating 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. We next turn to estimating spillovers by incorporating them into econometric specifications that build in distance and spatial decay.

Distance and Borders Gravity Model - Results

Table 7 shows the results for the gravity model specifications. At each treatment date, the sum of the inverse of distance to already treated clusters is computed for each control cluster to obtain a first measure of its multilateral proximity to treatments. For reference, column (1) reproduces the baseline estimate from column (1) of Table 3. It also adds in the rise in segregation rates of 5.20pps for the control clusters from the pre- to the post-periods in the penultimate row in column (1) of Panel B, that suggests positive spillovers in segregation to control clusters. Column (2) shows the baseline staggered DiD ATET that goes up in column (2) to 7.91 and the estimated spillover effect on control households, evaluated at the mean of γG_{dcrs} for control clusters in the Post period, is 3.17, taking the estimated effects up to 11.09pps (= 7.91+3.17). Column (3) replaces distance with borders by taking the sum of the number of already treated clusters with which 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, along with a mean spillover effect on controls of 4.35 that is more precisely estimated than for inverse distance, suggesting substantial spillovers to own and adjacent truck routes. Border and distance are combined in column (4) that shows an ATET of 8.20 and proximate treatment ATET of 3.46. In each case, Panel B shows that the pre-post difference in control clusters falls when the gravity measures are accounted for. Finally, all three measures result in own and proximate effects ranging between 11.09 and 13.58, and this changes slightly to 10.22 to 14.79 when two or more of the three measures are added together.[34]

Spatial Decay Model - Results

Table 8 reports the results for the own SDiD ATET and the spillover from proximate treatments in equation (4). Column (2) shows results for equation (4) that explicitly adds in the spatial proximity variable I_{dcrs} to the baseline specification allowing the spillover estimates to vary for the discontinuity sample and across the (discrete) values of the spillover

[34] Available upon request. For completeness, Table A3 in the Appendix shows results for bilateral proximity.

term. The average spillover effects from proximate treatments are reported by summing across the estimated effect of each spillover value with their shares in the estimation sample as weights.

The SDiD ATET for treated households from their own citizen training now rises from 4.50 to 13.57pps when an indicator for connected treatments $I_{dcrs} > 0$ 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 5.20pps 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 8.89pps. The sum of the own treatment effect and the proximate treatment effect is 13.57pps = 8.89 + 4.69. In line with the findings of the spatial discontinuity analysis in 1), the spatial discontinuity sample barely has any spillover effects and most of the spillovers arise in the non-discontinuity sample (available upon request). Overall, the spillover from proximate treatments is about half the size of the own treatment effect, 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.[35]

Column (3) adds in a value measure - the inverse distance-weighted connected treatments – rather than an indicator measure and column (4) considers both the indicator and the value measure because the value is only defined when the indicator switches on to

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[35] Bhattacharya et al. (2024) find positive spillovers of environmental education from children to parents.

one. The proximity treatment effect is 2.98 and 4.98 respectively evaluated at the mean of the measures, showing a very slight uptick in the estimated effect with the inclusion of the value measure.

Panel B of Table 8 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. Inclusion of the spatial proximity measures accounts for about half of the pre-post rise in segregation rates among control clusters. Of the 5.20 pre-post difference in segregation rates of not-yet-treated control clusters, 1.90 to 2.91 percentage points is explained by the spatial proximity measures across different specifications in columns (2) to (4).

To sum up, the sum of the own and proximate treatments effects ranges from 10.20 to 14.57 percentage points across the specifications. Table A4 in the Appendix adds in interactions of household characteristics with relative time indicators as independent variables and finds that the estimated effect in Table 8 is in the middle of the range of estimates from several additional specifications.[36]

Figure 9 offers a visual representation of how the estimated treatment effects vary with proximity to connected treatments by plotting the sum of own and proximate treatment effects ($\beta + \gamma I_{dcrs}$) against the distance to proximate treatments ($1/I_{dcrs}$). 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 that spillovers

[36] Considering equal weights for all disposers (rather than weighting by household shares), the main results remain highly stable at 12.03pps (with an associated standard error of 2.18) and showing highly similar contributions from own and proximate treatments to Table 8. This is unsurprising because the clusters were designed to have similar numbers of households, and therefore alternative weighting schemes, that do not alter the results substantially. Additionally, when gravity variables are included in the specification of equation (4), the own and proximate effects remain very similar, ranging from 11.03pps to 15.05pps. Adding pairs of enumerator fixed effects gives a similar overall treatment effect of 11.96pps.

from proximate treatments decay with distance and the estimated proximate treatment effect falls below 1pp at about 100 metres or more (that make up over half the control clusters with positive values for the spatial proximity measure).

6. Discussion and Economic Valuation

Results Summary

Table 9 summarises the range of estimates of the citizen training impact on the segregation rates of waste disposers. The experimental estimates of the direct impact of the citizen training programme shown in section 4 become larger when spatial discontinuities prevent spillovers to control groups and when the estimation builds in spillovers to the estimation methodology as described in section 5. The estimates from exploiting the city geography strongly suggest that the effects are larger than those estimated in the baseline alone, due to the existence of spatial spillovers. It is critical and essential to include the spillovers alongside the direct experimental effects when assessing and evaluating the total economic and environmental benefits that the citizen training programme generated.

Comparison With Survey

To compare with the magnitudes of the experimental estimates, and to gain insight and an understanding into the channels through which households are affected by the citizen training programme, qualitative responses from the survey were examined. Table 10 shows summary statistics from the experimental data for clusters (in the unstacked data) in column (1) and the survey responses in columns (2) and (3), respectively for all survey respondents in (2) and in (3), only for households where the same member of the household responds to the survey in each wave so as to reduce the possibility of the knowledge answer changing due to compositional changes in the members answering the surveys over time.

For the experimental data, the waste segregation measure is the one used in the empirical analysis so far. This segregation measure can be computed in the survey data from self-reported responses to three survey questions. These take the product of the percentage of households that report disposing 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).[37]

Panel A of Table 10 shows pre- and post-period differences in segregation rates. The experimental and survey responses align closely. Segregation rates in the (unstacked) observation data rise from just over 10 percent of households to nearly 30 percent, almost triple going up by 18.3pps. The survey data measure rises by 16.5 (all respondents) and 17.5pps (same respondent). The same high level of similarity emerges in the estimation sample, shown in Panel B. The experimental segregation rate rises by 19.2 percent, 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 about what underpins the estimates can be gleaned from these, as shown in Table A5 of the Appendix. One interesting feature is that the fraction of households that dispose of their waste in the vehicle is high in both periods, at over 90 percent, and if anything, there is a small tick up, suggesting reduced waste dumping. 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.

[37] Summary statistics for the three survey questions used to compute the survey-based waste segregation measure are given in Appendix Table A5.

The survey also asked households for the reasons that 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 11 shows the responses, for all respondents in Panel A, and broken down by whether the household segregates their waste or not in Panels B and C. Among all respondents, time and ease of segregating and care for the community and local area are more important reasons for segregation choice of households. All three measures increase between the pre- and post-periods of the experimental intervention, with care for community or local area rising the most (almost doubling). But the fact that all three increase shows a clear impact of the citizen training programme on both abilities to segregate and on community environmental awareness about waste segregation.

As the lower two Panels show, both the pre- and post-levels and the post-pre changes are qualitatively similar for segregators and non-segregators. Households that segregate and do not segregate their waste are similar before the intervention and they 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 somewhat, 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 provided in the Appendix in Table A5, together with a brief discussion around them. Some of the other interesting consequences following from the intervention are a rise in the number of bins, suggesting increased waste segregation, and more environment-friendly attitudes.

Overall, the survey segregation responses and the qualitative reasons for willingness to segregate are consistent with households learning significantly from the intervention both about whether segregation is easy or difficult and hence worth the effort and time to do it, and about community or local and environmental awareness.

Alternative Waste Measures

In Tables structured the same way as the Table 9 summary estimates for segregation at source, Appendix Tables A6A to A6D present SDiD ATET estimates for four alternative waste outcomes – respectively, the share of segregated waste and the volumes of segregated, unsegregated and total waste. Consider first Table A6A for the share measure. The SDiD ATET experimental estimates for this measure of waste segregation are highly similar to that for the extensive margin, ranging from 4.04 to 14.77 across different specifications.

The volume of waste is considered in Appendix Tables A6B to A6D. As shown in Tables A6B and A6C, segregated waste volume rises as a consequence of the citizen training programme 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 A6D). The different specifications suggest a fall in total waste volume that would contribute to environmental benefits from the training, but the magnitude varies from negligible to small drops and we therefore do not include them in the environmental benefit valuation that follows next.

Economic and Environmental Value of the Intervention

Having estimated the effects of the intervention, we can proceed to an examination of the economic and environmental benefits. The range of the rise in the share of disposers who segregate waste is between 10.20 to 16.72 percentage points across the different approaches for proximity from city geography in Table 9. Because the spatial decay model encompasses both the spatial discontinuity and the gravity approaches, benefits are evaluated for the central estimate of 13.57 percentage points in the spatial decay model of column (2) of Table 8. This rise in segregation rate implies a reduced need for landfilling of waste, which has the potential to generate substantial economic and environmental benefits.[38]

A key challenge in quantifying the economic benefits of improved waste outcomes from the intervention is the paucity of granular estimates of waste costs and pollution from waste, particularly in developing countries. We start with summarising the direct landfilling costs and then discuss the environmental value of the intervention. The OECD (2022) reports landfilling costs of 25 to 30 Euros per ton of waste per year. Directly applying these values and converting them with market exchange rates, reduced landfilling from increased segregation at source would amount to gross savings of Indian Rupees ₹165-198 per household per year (= 13.57% × 1.417/1,000 tonnes × 365 days × €25-30 × ₹94/€). While this gives a monetary value of the direct cost savings, it does not account for the environmental benefits from the intervention.

Segregated wet waste can be composted and dry waste can be recycled, leading to net environmental benefits that the direct landfilling savings do not account for. The environmental value of the intervention can be assessed from emission savings and has the advantage that it provides a market-based economic value of the intervention, which is rarely available for some other forms of pollution, such as soil and marine pollution. Naturally, this focuses only on the climate change impacts of the programme and we consider it as a lower bound of the environmental benefits that are likely to be higher on account of reduced

[38] The percentage of disposers per day also rises due to the intervention (Table A6E in the Appendix), and this is consistent with the self-reported evidence from the surveys in Table A5 in the Appendix suggesting reduced waste dumping. We check that this is not driven by increased periodicity of disposals (available upon request). The rise in the number of disposers makes a positive contribution to the overall valuation in this section. The magnitude depends on how the entering households were disposing of their waste previously. Assuming that they were openly dumping and it was being taken by street cleaners, then there is no additional saving because the waste was already being landfilled. If instead, the entering households were mismanaging their waste, such as through open burning, then there are additional annual savings but we assume these to be small because only 0.21 percent of households report burning their waste.

groundwater, soil and river pollution, but which are harder to evaluate due to a lack of standardised emission factors and monetary valuation factors.

Landfilling and composting/recycling emission factors for segregated wet waste (food and vegetable waste) and for landfilled unsegregated waste are taken from the US Environmental Protection Agency. Emissions factors for recycling of source-segregated dry waste (plastic, textile, paper, leather, glass and metal) is provided by life cycle assessments from Turner et al. (2015) that includes savings from reduced primary production due to recycling of materials. The composition of waste is taken from previous studies in Patna (Pandey 2019, Jha et al. 2020).

Reduced landfilling of segregated waste and material displacement from segregated recyclables yields greenhouse gas savings. The UK carbon credit price for firms in 2021-2022 averaged about £50 per tonne of carbon dioxide equivalent.[39] The Clean Development Mechanism and Joint Implementation under the Kyoto Protocol allow industrialised and transition countries to offset their own emissions by reducing those of another country. At the UK purchase price offered to firms, this amounts to potential benefits of 62.26kgCO2e $= 0.90 \times 69.53$ per household per year when the total emission saving before and after the intervention of 69.53kgCO2e is multiplied by the treatment effect in the total rise in the segregation rate (from Table 8).[40] At the market value of greenhouse gas savings, the benefit is 62.26kgCO2e × £50 × ₹112.61/£ = ₹351.

[39] The UK carbon price is considered here to compare directly with the social cost of carbon reported by the UK government later. Alternatively, the carbon price for the EU could also be used. The average carbon price under the EU Emissions Trading Scheme for the five-year period from April 1, 2021, to March 31, 2025, is taken to reduce volatility. From the International Carbon Action Partnership daily spot prices, the average is 72 euros per tonne and the average exchange rate from the IMF is 88 to the Indian rupee. This gives slightly higher magnitudes for the market values. The UK price data is taken from https://www.gov.uk/government/publications/determinations-of-the-uk-ets-carbon-price/uk-ets-carbon-prices-for-use-in-civil-penalties-2021-and-2022.

[40] The own and proximate treatment effects multiplied by the share of treated and control cluster households is divided by the overall post-pre difference in segregation rates of Panel B of Table 2.

The UK government however recommends using the social cost of CO2e for policy assessments, rather than the carbon credit price. At the recommended social value of £252 per ton of CO2e, the savings range from ₹1,766 per household per year (UK 2021). While this is at the top end of the range for social cost rates in US-based studies (Hahn et al., 2024), it is worth noting that the estimate is close to the shadow price of "undesirable" unsegregated waste for Chilean municipalities (Sala-Garrido et al., 2023).[41]

Economic Costs of the Intervention

The total cost for 5 months of training for 10,434 households was ₹2,581,000.[42] The variable cost component includes field staff and campaign tools that amount to ₹1,881,000. Part of the total expenditure - ₹700,000 - includes a senior manager and software support that have more of a fixed cost nature and can be spread across more households. Assuming no scaling up of the fixed costs, the estimated expenditure is a one-off cost of ₹247 per household.

Placing the overall expenditure in perspective, the Patna Municipal Corporation budgeted ₹2.57 billion solely for solid waste management in 2021-22 (or 34 percent of its revenue expenditure) for about 2 million residents. Therefore, the variable costs were about ₹1,000 per person. It also 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. The solid waste management grant included ₹0.5 billion for work on its landfill outside the city. To compare with other expenditures, roads and drains made up ₹1.25 billion and buses another ₹0.5 billion of the grants it received.

[41] The average shadow price in this study, inferred from recyclable material embodied in unsegregated waste, is 297.66 Euros per ton of waste, with a wide range of 0.045 to 2536.46 Euros per ton across municipalities.
[42] Some new households moved to the intervention areas after the census and they were covered too so the number of households is in practice slightly larger than that in the original census of intervention areas.

Net Valuation of the Intervention and Channels for Segregation Effects

A summary of landfill cost savings and emission savings, and benefit-to-cost ratios for the intervention are provided in Table 12. 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 3.3 to 4 (=165-198 × 5 / 247) if only landfill cost savings from increased segregation are accounted for in the benefits and to 7.1 when greenhouse gas emission savings at carbon credit prices are considered (= 351 × 5 / 247). Adding the direct landfilling cost savings and the emission savings at market value, the benefit-to-cost ratio ranges from 10.4 (=3.3+7.1) to 11.1 (=4+7.1) and, because the costs are incurred only once, one that could rise even further over a horizon longer than five years, thus offer strong testament to the citizen training programme on waste segregation as a high premium, cost effective policy for delivering environmental sustainability to local communities.[43]

Follow-up

The experimental analysis, and the previous cost-benefit calculations, focuses on the pre- and post-periods of the intervention before the last three clusters had started the intervention (13th April 2022). Once full treatment had occurred, data collection through waste observations continued again on a bi-weekly basis until 31st May 2021. A second household survey was also 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.

[43] The marginal value of public funds (MVPF) can also be determined (Hendren and Sprung-Keyser, 2020). The benefits ΔW that the policy provides to individuals in the population is the value of savings in greenhouse gas emissions from the programme and the related cost is the expenditure on citizen training net of the savings on reduced landfilling costs ($\Delta E - \Delta C$). Even under a conservative assumption of recurring training costs, the MVPF is between 4.3 to 7.1 – the high end of various policies impacting climate change - computed as ₹351 / (₹247 − ₹165 to ₹198). The denominator can arguably be larger if segregation increases time needed for waste management and hence reduces individual welfare, or if reduced landfilling increases property values and hence rents in the city. As discussed in the Appendix, time costs were minimal and previous work finds negligible impacts of waste site cleanups on housing valuations (Greenstone and Gallagher, 2008).

The data show that segregation rates continued to rise in these time periods after the experimental intervention was complete. Segregation rose from 10.88 percent (column (1) of Table 10) to 19.45 percent by 18th April 2022 when all households had started citizen training. Observations continued till May and segregation rates were 29.14 percent over the period between 19th April and 31st May.

Further environmental benefits from the intervention resulted through this build-up in segregation rates over time and this high level of segregation persisted in follow-up observations undertaken a couple of months afterwards. Bi-weekly observations between 27th July and 8th August showed that 32.31 percent of households continued to segregate waste (column (4) of Table 2). The citizen training programme therefore resulted in a persistent tripling of the segregation rate across households. This is important in light of several studies where effectiveness of the intervention relies on behaviour change but where the effects may fade away after the intervention has ceased (Della Vigna and Linos 2022 and Brandon et al. forthcoming).

Appendix Table A1 shows moreover that, once this extra time had permitted further direct improvements from the final treatments and temporal spillovers as time progressed, the timing of the roll-out of the intervention had not disadvantaged late treated clusters by four months after full rollout. Splitting the clusters into early treated phase 1 clusters (that started the training in the first half of the intervention schedule) and late treated phase 2 clusters (that started the training in the second half of the intervention schedule) shows very similar segregation rates with near convergence for the two groups by the follow-up observation dates as shown in Table A1 (33 percent for early first half treatments, and 31 percent for late second half treatments).[44] Thus, catch-up quickly occurred for the late treated

[44] The difference is small and statistically insignificant at -2.07 with an associated standard error of 5.55.

groups as they seemed to benefit from the spatial spillovers from early treated clusters in some cases as, even with staggered treatment dates, the fully rolled out programme ended up with similarly sized waste segregation improvements across the board. These, of course, cumulate up to generate even higher benefits from the programme than those from the double-digit benefit-cost ratios calculated for the experimental time window in the previous sub-section.

7. Conclusions

This paper studies a large-scale randomised intervention designed to examine whether citizen training in waste segregation can be a policy tool to reduce the urban waste footprint. Citizen training in waste management was offered to over 10,000 households in a research design that was staggered over time across clusters of buildings in neighbourhoods in the Indian city of Patna. Segregation-at-source increased substantially among households that received the intervention, based on staggered difference-in-differences and event study estimates. The analysis uncovers strong, robust and sizable magnitudes of estimated treatment effects that improved waste segregation for citizens in receipt of training and education.

Using features of the city's geography to look at spatial spillovers produces larger estimates of the economic and environmental benefits of the citizen training programme. Comparing outcomes in clusters that feature boundary discontinuities arising from both natural geographies and the built environment show additional benefits arising from positive spatial spillovers of the intervention. Estimates that exploit the non-crossing features of these boundaries are higher than those from the full sample, and the estimated spillovers from gravity and spatial decay models produce benefits that are of an additional half the size of the own treatment effect.

Waste segregation rates rose from relatively low initial levels (about one in ten) to more than triple (about one in three) four months after the full rollout of the citizen training programme. The post-programme levels can usefully be placed into comparative perspective. Most countries report the share of waste that is recycled rather than household segregation rates, because the composition of waste makes different forms of separation-at-source more appropriate. Although not directly comparable, it is worth noting that the share of municipal waste that is recycled in OECD countries has plateaued at about 30 percent (Fullerton and Kinnaman 2024). The citizen training intervention therefore pushed Patna's levels of waste segregation up to around the level currently operating in the average OECD country.

The experiment was highly cost effective and yielded economic benefits well above the costs. The value of increased segregation rates from the intervention can be translated to monetary values through the potential savings from reduced landfilling costs and reduced emissions at carbon credit prices, amounting to ₹516 to 549 per household per year at a one-off training cost of ₹247 per household (including fixed costs). Landfilling costs make up about a third of the benefits and emission savings the rest. Together these benefits break even the one-off costs of the training in less than a year, reaching at least double digit benefit-cost ratios. Increased waste segregation occurred after the programme had been fully rolled out and in the follow-up data collection four months afterwards the benefits had cumulated up to reach even higher economic and environmental benefits that notably ended up at very similar magnitudes for early and late receivers of citizen training. Overall, this very much shows that, through an effective design and implementation, the citizen training programme delivered a low-cost solution to ease Patna's waste burden.

The findings of this paper lend strong support to the argument that promoting community awareness can be a successful policy tool to alleviate the burgeoning waste problem in developing countries. Generating decentralised waste management from citizen training and education offers a low-cost solution with substantial economic and social benefits that both reduce the urban waste footprint and enhance local environmental sustainability. It also opens the door to wider participation in waste management activities and importantly offers scope to further deter the need for landfilling, a problem that is endemic and in need of effective solution the world over.

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Figure 1: Pre-Intervention Census Structure

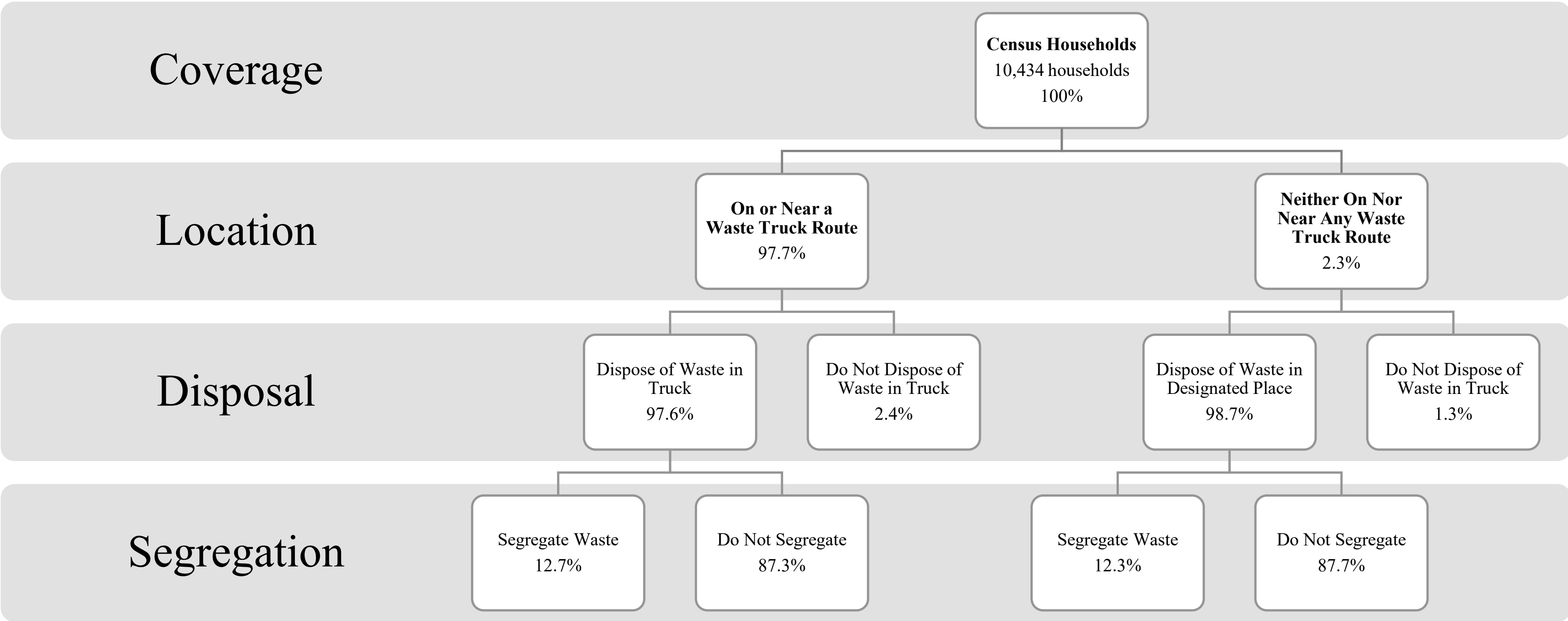
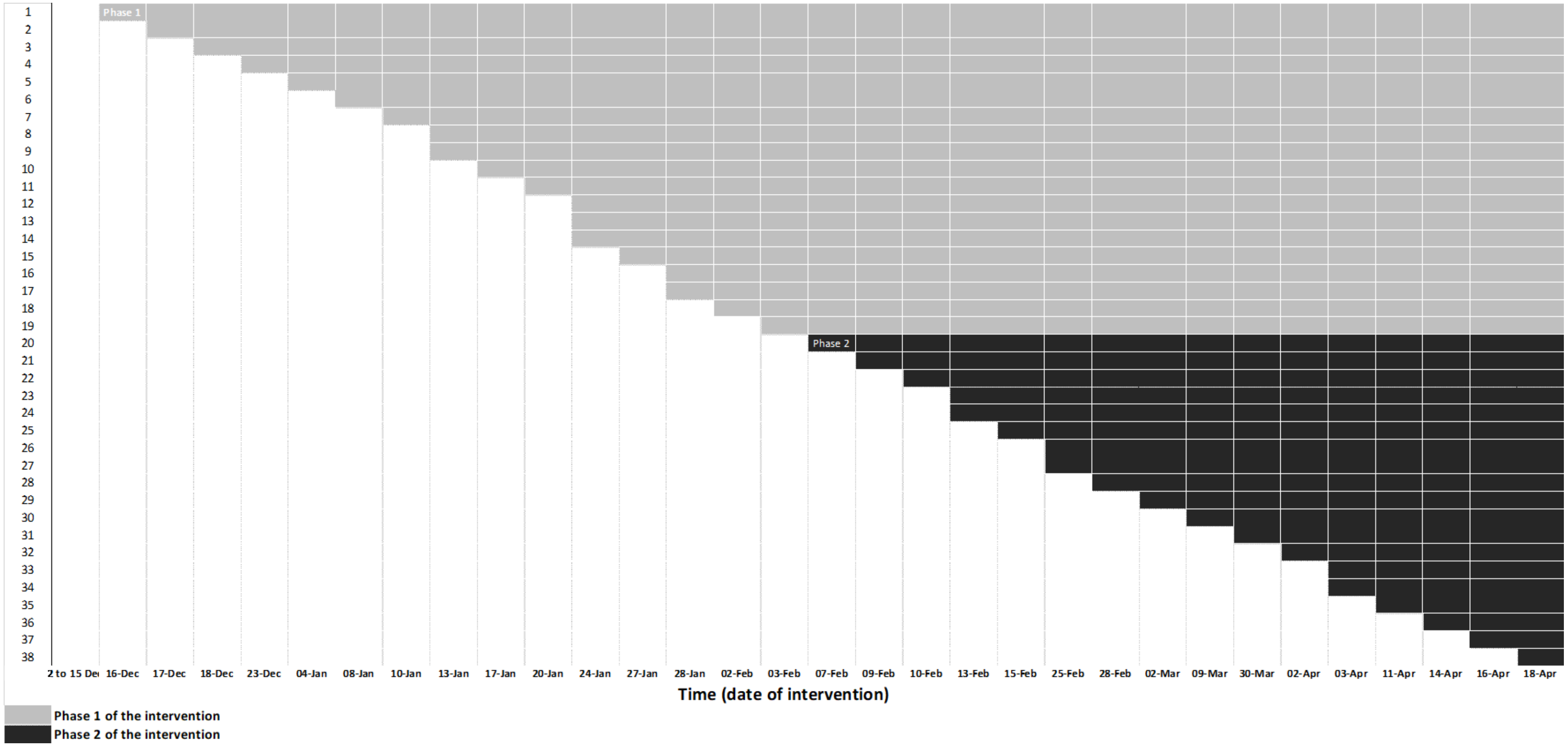


Figure 2: Treatment Order



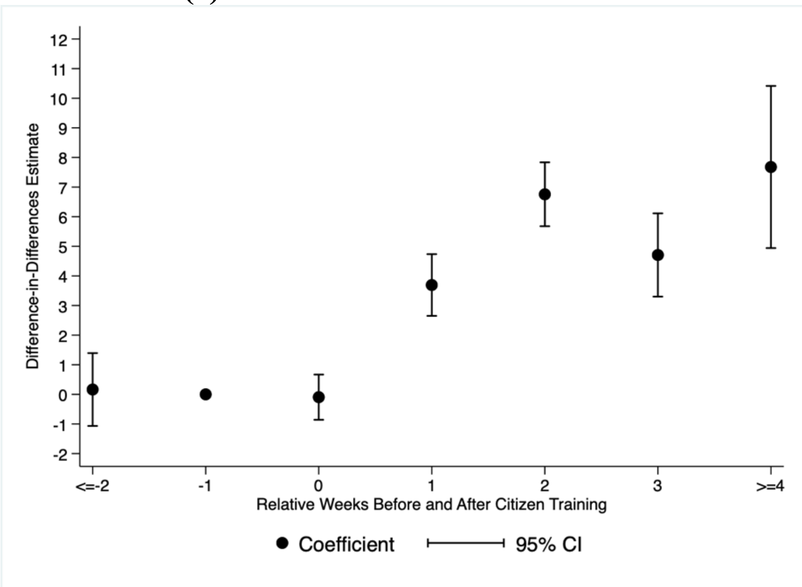
Notes: The rows denote calendar time and the columns denote clusters of buildings. The period 2nd to 15th December in the first column is the period of waste observations by enumerators before the start of any citizen training. Grey refers to Phase 1 of citizen training to the first half of clusters that starts after the waste observation of the first cluster to start citizen training (numbered in order of treatment from 1 to 19, and spatially corresponding to white squares on a chessboard). Black refers to Phase 2 of citizen training to the second half of clusters numbered from 20 to 38 and spatially corresponding to black squares on a chessboard. A switch from white to grey/black along a row shows that the cluster has started citizen training. A switch from white to grey/black along a column shows which clusters have (in white) and have not (in grey/black) started citizen training at a point in time.

Figure 3: Waste Training Material for Households

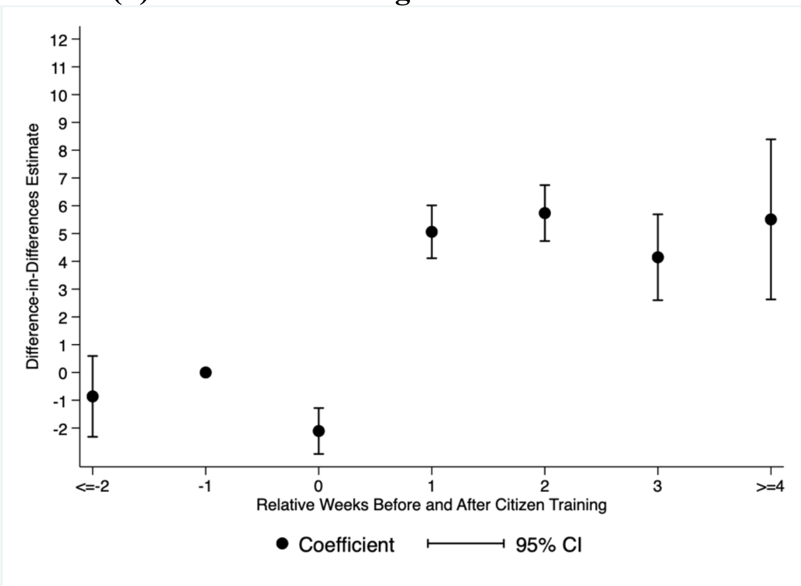
Notes: Picture to the left shows that wet waste (marked on the bin) is generated during cooking and can be easily kept separately from dry waste. Picture to the right is an information sheet for households showing common items that are under green (wet) waste, blue (dry) waste, e-waste and hazardous (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 4: Event Studies

(a) Balanced Stacks and Relative Time

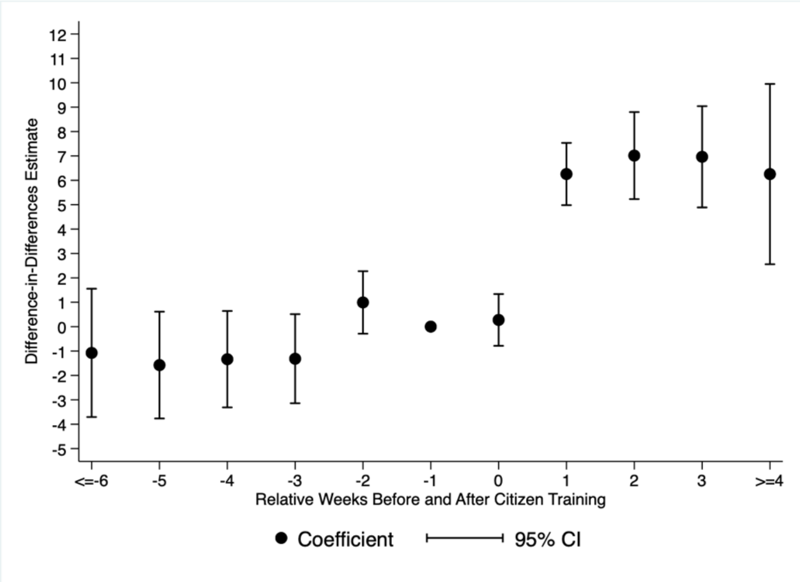


(b) Balanced Building Clusters and Relative Time



Notes: The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. Observations range from $\leq$-15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27, $\geq$28 relative days. 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 of each stack in (a). This balanced panel covers 257,060 disposer-day observations or 16,339 cluster-day observations. Panel (b) 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. DiD ATET coefficients are estimated for each stack-relative week and averaged across all stacks, with weights equal to the share of the stack in the clean control estimation sample to obtain the Staggered DiD ATET Estimate for each relative week. Weekly SDiD ATET estimates are normalised to zero in the week just before the start of the intervention, relative week, $r = -1$. Standard errors clustered two-way by building clusters and stacks. The event study coefficient estimates (and associated standard errors) comparable to Table 3 column (3) for (a) are 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) and for (b) 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).

Figure 5: Longer Duration Event Study



Notes: Same as Figure 4 (a) but with a longer duration of relative weeks before and after the start of citizen training. Clusters are fully balanced on weeks of ≤-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 3 column (3) 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).

Figure 6: City Canal Discontinuity

(A) Aerial view

(B) Photo of buildings on either side of the city canal

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.

Figure 7: Main Road Discontinuity

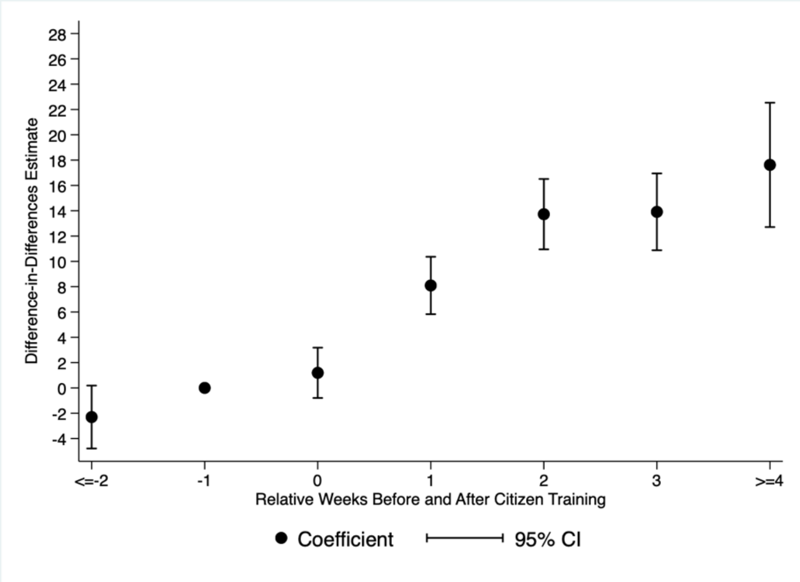
(A) Aerial view

(B) Photo of main road with buildings on either side of a metal barrier

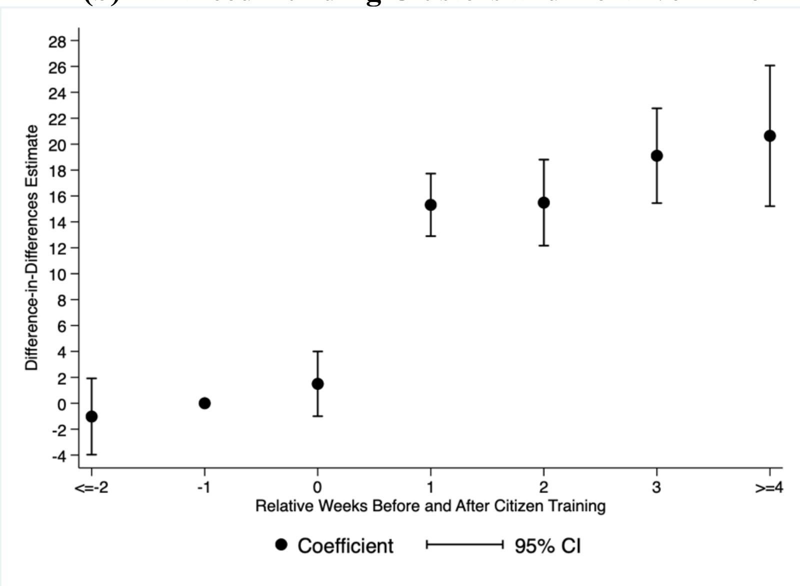
Notes: Panel (A) shows an aerial view of the main road, called Buddh Marg, in the centre of the city. Panel (B) shows buildings along the west side of the road are in the spatial discontinuity estimation sample with buildings on the east side of the road as their control clusters. The median of the road has a metal barrier to prevent crossings due to heavy traffic.

Figure 8: Event Study - Spatial Discontinuity

(a) Balanced Stacks and Relative Time

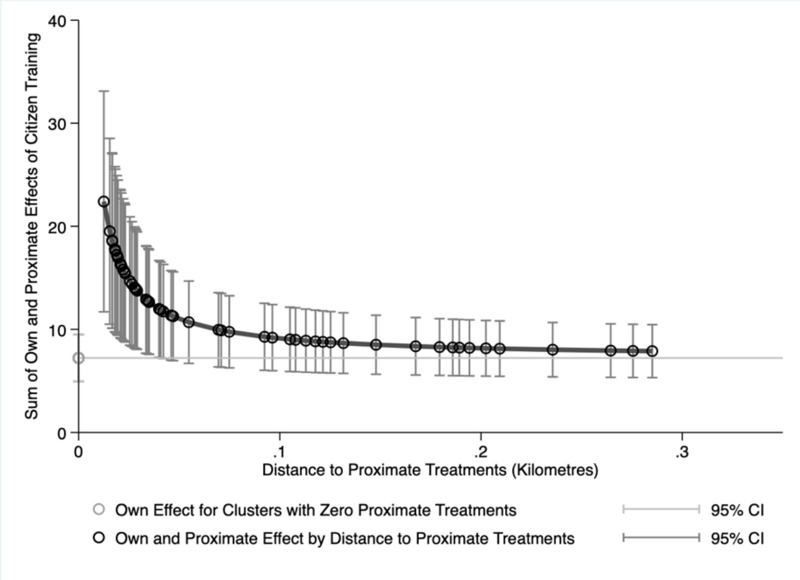


(b) Balanced Building Clusters and Relative Time



Notes: Same as Figure 4 (a) and (b), but for the spatial discontinuity estimation sample of Table 5. 105,570 disposer-days or 6,476 cluster-days in the balanced panel of (a) and 81,222 disposer-days or 4,865 cluster-days in the fully balanced panel of (b). Weekly SDiD ATET estimates are normalised to zero in the week just before the start of the intervention, relative week = -1. The event study coefficient estimates (and associated standard errors) comparable to Table 3 column (3) for (a) are -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) and for (b) 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 9: Spatial Decay and Spillovers



Notes: Derived from the column (3) specification of Table 8. Coefficients and confidence intervals for the sum of own and proximate treatment effects $\beta + \gamma I_{dcrs}$ are plotted against the distance to proximate treatments. Distance to proximate treatments is defined as the inverse of the I_{dcrs} measure in column (3) of Table 8, which is the sum of the inverse of bilateral distance of each not-yet-treated cluster to its 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 positive for not-yet treated clusters which are proximate to treated groups that start citizen training before them at each relative time, and is defined as zero otherwise. For reference, the horizontal line shows the (own) treatment effect β, that is also the sum of own and proximate treatment effects when there are no proximate treatments, $I_{dcrs} = 0$, and hence zero proximate treatment effects $\gamma I_{dcrs} = 0$. Distance to proximate treatments ranges from 0.01 to 0.29 for non-zero values and coefficient estimates in the plot are evaluated at each of the 56 distinct distance values.

Table 1: 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	Randomised order of citizen training across clusters	Authors at LSE
December 2 2021	Clustering of buildings	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 2: Waste Outcomes

Panel A: All periods of data collection	All Dec 2 - Aug 8	Pre Dec 2 - Apr 18	Post Dec 17 - May 31	Follow-up Jul 27- Aug 8
	(1)	(2)	(3)	(4)
Households that dispose of waste segregated into dry and wet waste (% of disposing households per day)	11.33	9.48	15.15	32.31
Segregated waste volume	154	141	181	342
Unsegregated waste volume	1263	1322	1139	1026
Waste disposed of in truck (gram per household per day)	1417	1463	1320	1368
Number of household-days	519,996	153,553	346,051	20,392
Number of building cluster-days	33,507	9,864	22,329	1,314

Panel 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	150	140	171
Unsegregated Waste	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. A stack consists of a group of building clusters that follow the same treatment schedule shown in Figure 1, consisting of 38 treated groups and their control clusters. All periods are divided into a Pre period covering observations days from 2/12/2021 to 13/4/2022 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 31/5/2022 and a Follow-up period covering observation days from 27/7/2022 to 8/8/2022 after all clusters have finished their citizen training. 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 Post period range is 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.[45]

[45] 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 cluster 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 3: 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	Days and Buildings
	(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 by regressing the waste outcome of a building cluster on the interaction between indicators for the stack, the clusters starting the citizen training in that stack and the relative week from the start of citizen training in that stack. 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 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 3. Standard errors in parentheses are clustered two-way by building cluster and stack.

Table 4: 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 2 for the spatial discontinuity estimation sample. The spatial discontinuity sample 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 5: 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	Days and Buildings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staggered DiD Estimate	13.37	13.84	13.53	16.72	19.61	12.94	20.11
	(0.92)	(0.89)	(0.89)	(1.57)	(1.38)	(1.28)	(1.69)
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 3, but for the spatial discontinuity estimation sample of Table 5.

Table 6: Staggered DiD Estimates, Spatial Discontinuity

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 as column (1) of Tables 3 and 6. 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 of Table 5 to treated and control clusters that are only on either side of the city canal flowing into the 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 the 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 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 5 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 7: Staggered DiD Estimates, Distance and Borders Gravity

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

	Sum of Proximity of Control Clusters to Treatments			
	Own	$1/\text{Distance}$	Borders	(1)×(2)
	(1)	(2)	(3)	(4)
A. Estimation of Gravity Model				
I. SDiD ATET (β)	4.50	7.91	9.23	8.20
	(0.85)	(3.06)	(1.49)	(1.23)
II. Proximity ATET (γ)				
Post×Control×Proximity (G_{dcrs})		0.09	1.54	0.17
		(0.08)	(0.39)	(0.05)
III. Proximity Effect ($\gamma\bar{G} = \gamma \times$ Mean of G_{dcrs} in Post)		3.17	4.35	3.46
		(2.89)	(1.11)	(0.93)
IV. Own β + Proximity $\gamma\bar{G}$ (I+III)		11.09	13.58	11.66
		(5.89)	(2.49)	(2.02)
Fixed Effects				
Stack-Building Cluster	yes	yes	yes	yes
Stack-Relative Week	yes	yes	yes	yes
Sample Size	261,839	261,839	261,839	261,839
B. Estimation of Post-Pre of Controls				
Post	5.20	-1.62	2.70	3.42
	(1.05)	(1.75)	(1.45)	(1.33)
Post×Gravity (G_{dcrs})		0.17	0.78	0.08
		(0.05)	(0.36)	(0.04)

Notes: Same as column (1) of Table 3 (reproduced in column (1) of Panel A) and adds Panel B of Post-Pre of Control Clusters (difference in means of the dependent variable between the Post and Pre periods within stack-building clusters, with standard errors in parentheses). The Staggered DID ATET estimate is reported in the row SDiD Own ATET. Additional variables are included to determine the spillover effects on control clusters that are more proximate to groups of households that have started citizen training. The Control cluster indicator is interacted with three different Proximity variables G_{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). Higher values of the proximity denote greater (multilateral) proximity of the control cluster to all treatments. The proximity effects are evaluated at the mean of the Control×Proximity variables, where the mean is over the entire sample (including treated clusters) during the Post period or $\gamma\bar{G} \equiv \sum_s \sum_{r>-1} \sum_{dc} \gamma G_{dcrs}(1 - D_{dcrs})\omega_{rs}$. Panel B shows the pre-post differences for control clusters in column (1) and adds in the gravity variables corresponding to each column in (2) to (4). Standard errors in parentheses are clustered two-way by stack and building clusters.

Table 8: Staggered DiD Estimates, Spatial Decay

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

	Own	Indicator	Value	(2) and (3)
	(1)	(2)	(3)	(4)
A. Estimation of Spatial Decay Model				
I. SDiD ATET (β)	4.50	8.89	7.22	9.29
	(0.85)	(1.34)	(1.12)	(1.29)
II. Spatial Proximity I_{dcrs} ATET (γ)				
a. Post×Control×Spatial Proximity Indicator		5.61		2.61
		(1.19)		(1.72)
b. Post×Control×Spatial Proximity Value			0.19	0.18
			(0.06)	(0.06)
III. Proximity Effect at Mean in Post ($\gamma\bar{I}$)				
Sum of γ × Mean of II.a,b. in Post		4.69	2.98	4.98
		(1.00)	(0.87)	(0.98)
IV. Own β + Proximity $\gamma\bar{I}$ (I+III)		13.57	10.20	14.27
		(2.21)	(1.84)	(2.14)
Fixed Effects				
Stack-Cluster	yes	yes	yes	yes
Stack-Relative Week	yes	yes	yes	yes
Sample Size	261,839	261,839	261,839	261,839
B. Estimation of Post-Pre of Controls				
I. Post	5.20	2.23	3.21	2.25
	(1.05)	(0.98)	(1.27)	(0.96)
II. Proximity Effect at Mean in Post ($\delta\bar{I}$)				
Sum of δ × Mean in II.a,b.		2.91	1.90	2.85
		(1.04)	(0.93)	(1.03)
Stack-Cluster Fixed Effects	yes	yes	yes	yes
Sample Size	146,693	146,693	146,693	146,693

Notes: Same as column (1) of Table 3 (reproduced in column (1) of Panel A) and adds Panel B of Post-Pre of Control Clusters (difference in means of the dependent variable between the Post and Pre periods within stack-building clusters, with standard errors in parentheses). Proximate treatment ATET (γ) on control clusters from equation (4) is estimated in row II and estimated effect is evaluated at the mean of the spatial proximity variable in row III, where the mean is over the entire population (including treated clusters) during the Post period or $\sum_s \sum_{r>-1} \sum_{dc} \gamma I_{dcrs}(1 - D_{dcrs})\omega_{rs}$. Spatial proximity I_{dcrs} is defined as positive for control clusters that share the same waste truck route or share a waste truck route border without a spatial discontinuity with clusters that have started citizen training at each relative time. Column (2) measures spatial proximity as an indicator for control clusters that are spatially proximate to treated clusters at each relative time ($I_{dcrs} > 0$). Column (3) measures spatial proximity as the sum of the bilateral proximity (or the inverse of the bilateral distance in kilometres) to proximate treatment groups at each relative time. Column (4) adds both measures. Panel B shows the pre-post differences for control clusters in column (1) and adds in the proximity variables corresponding to each column in (2) to (4). The proximate ATET is evaluated at the mean of the proximity variable in the post period in row III of Panel B. Standard errors in parentheses are clustered two-way by stack and building clusters.

Table 9: Summary of Findings

Household disposes of waste segregated into dry and wet waste (% of disposing households)		
Specification	Range of SDiD Estimates	
	Minimum	Maximum
Baseline	4.50	6.10
Current/Constant weights and Pure Controls	(0.85)	(1.41)
(Table 3, 1-4)		
Fully Balanced	4.46	4.94
-28,..,27/-42,..,41/-28,..,27 and Building Clusters	(0.82)	(0.90)
(Table 3, 5-7)		
City Geography:		
Spatial Discontinuities	13.37	16.72
(Table 5, 1-4)	(0.92)	(1.57)
Gravity	11.09	13.58
(Table 7, 2-4 IV)	(5.89)	(2.49)
Spatial Decay	10.20	14.27
(Table 8, 2-4 IV)	(1.84)	(2.14)

Notes: Summary of estimates from Tables 3, 5, 7 and 8.

Table 10: Comparison With Survey

Household disposes of waste segregated into dry and wet waste (% of disposing households)			
	Experiment	Survey, All Respondents	Survey, Same Respondent
	(1)	(2)	(3)
Panel A: All periods of data collection			
Pre	10.88	12.70	12.01
Post	29.14	29.17	29.49
Post – Pre	18.26	16.47	17.48
	(1.06)	(1.69)	(1.96)
Sample size	232,499	8,813	2,930
Panel B: Periods of experiment			
Pre	11.03	12.78	12.02
Post	30.22	29.25	29.67
Post – Pre	19.19	16.47	17.65
	(1.14)	(1.72)	(1.97)
Sample size	192,088	8,677	2,912

Notes: Pre is the period before the start of citizen training for each cluster and Post is after the programme. Post is matched as closely as possible to the survey, starting from 19/4 to 31/5. Column (1) reports segregation rates from the observations of waste disposal undertaken along the waste truck routes. Summary statistics from self-reported outcomes of surveyed households are shown in columns (2) to (5). Column (2) is the product of the indicator for 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 A reports summary statistics for all disposers and surveyed households. Column (1) of Panel A (Full Sample) contains 155,283 (Pre) + 77,216 (Post) unique disposer-day observations. It differs from column (1) of Table 3 because summary statistics are reported for the unstacked data, rather than the stacked data, to match with the survey data. Column (2) reports summary statistics for all households surveyed across two waves statistics consisting of 8,813 = 4,710 (Pre) + 4,103 (Post) survey responses, while column (3) reports the same for households where the same respondent answers the survey across both waves making up 2,930 = 1,465 (Pre) + 1,465 (Post) responses. Panel B reports the same statistics as Panel A, but for households in the estimation sample (excluding those that are pure control households that start their citizen training on the last three dates in the intervention schedule). Column (1) of Panel B contains 122,524 (Pre) + 69,564 (Post) unique disposer-day observations and columns (2) and (3) contain summary statistics from the household survey consisting of 4,639 (Pre) + 4,038 (Post) responses across two waves in column (2) and 1,456 (Pre) + 1,456 (Post) in column (3). Standard errors in parentheses are clustered by building clusters for the observation data and clustered two way by household and building group for the survey data.

Table 11: Reasons for Segregation Choice

	Household chooses as reason for segregation choice (% of surveyed households)		
	Time and ease of segregating	Care for community or local area	Concern for the environment
	(1)	(2)	(3)
Panel A: All			
Pre	50.40	25.66	10.26
Post	60.52	46.45	24.98
Post – Pre	10.12	20.79	14.72
	(3.59)	(4.11)	(2.52)
Sample size	8,206	8,206	8,206
Panel B: Household does segregate waste			
Pre	48.12	24.23	9.19
Post	60.57	59.82	34.34
Post – Pre	12.45	35.59	25.15
	(4.55)	(4.55)	(3.87)
Sample size	2,394	2,394	2,394
Panel C: Household does not segregate waste			
Pre	51.34	26.26	10.70
Post	60.50	40.95	21.13
Post – Pre	9.16	14.69	10.43
	(3.66)	(4.19)	(2.36)
Sample size	5,812	5,812	5,812

Notes: Summary statistics from self-reported outcomes of surveyed households are shown in columns (1) to (3). Panel A contains all households in the panel of the two survey waves with 4,103 households in each wave. Panels B and C separate the households into those that already segregate or start to segregate waste in Panel B and those that do not segregate waste in Panel C, where segregate is defined as in column (2) of Table 10. Column (1) is the share of households who choose time or ease of segregation as factors in their decision to segregate/not segregate waste. Column (2) is the share of households who provide community factors as reasons for segregating (including options saying care about my community/others do it/is or is not my job to do it). Column (3) is the share of households choosing environmental factors (including care about the environment or have children who care about the environment). Standard errors in parentheses are clustered two way by household and building group.

Table 12: 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)=(3)×5/247
(a) Landfilling Cost Savings	2,350 to 2,820 per ton of waste	70.18 kg of waste	165 to 198	3.34 to 4.01
(b) Greenhouse Gas Emission Savings				
Carbon market valuation	5,631 per ton of CO2e	62.26 kg of Co2e	351	7.10
Total = (a) + (b)			516 to 549	10.44 to 11.11

Notes: 2,350 to 2,820 is the 25 to 30 Euros of landfilling costs per ton of waste per year. This is multiplied by 70.18 kilograms of waste savings from landfilling per household per year, calculated as 13.57% SDiD ATET in column (2) of Table 8×1.417 kilogram of waste per household per day from column (1) of Table 2×365 days per year. 5,631 per ton of CO2e is from the carbon price of £50×112.61 to convert to Indian rupees and 28,378 is from the same for £252×112.61 for the social cost of CO2e. 62.26kg of CO2e is from 0.8955×69.53kg of CO2e. 69.53kg is saved per household per year from increased segregation calculated from emission factors for landfilling and recycling and 0.8955 is the SDiD ATET estimate divided by the actual pre to post change in segregation for all clusters. 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. 3.34 to 4.01 are added to 7.10 to arrive at the total benefit to cost ratios over a period of five years.

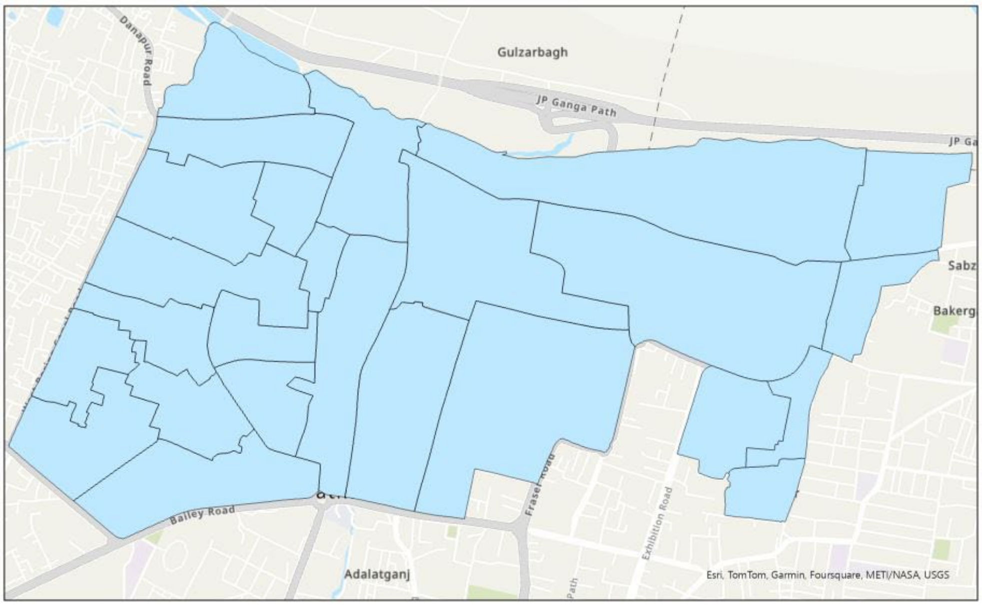
APPENDIX

Additional Figures

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

A. Photo of Waste Disposal

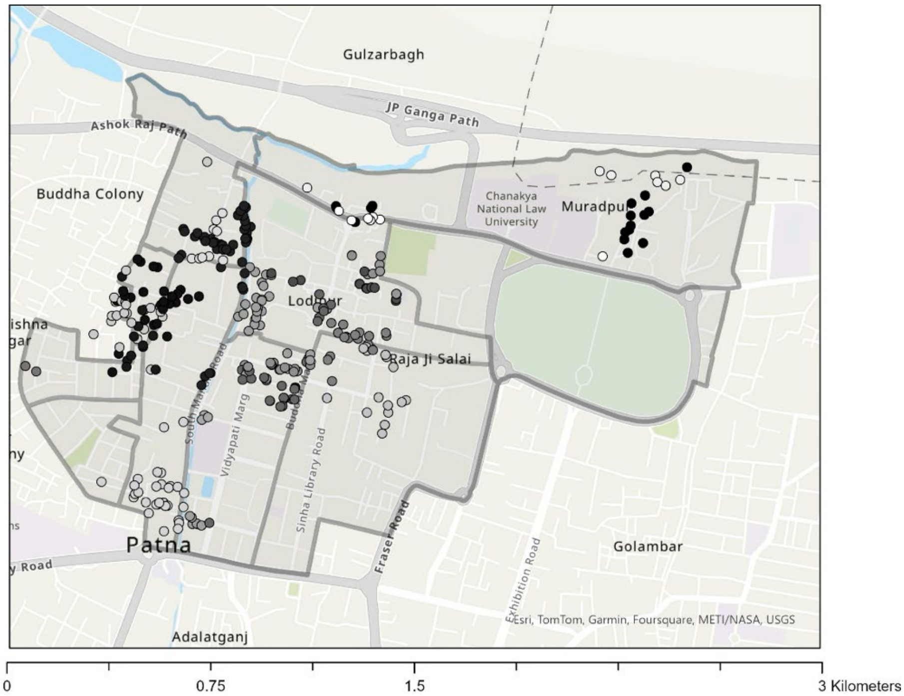
B. Maps of Areas Covered by Different Waste Trucks



Notes: The photo in Panel (A) is from instagram.com/cityofpatna. The map in Panel (B) is from coordinates provided by the Patna Municipal Corporation in 2021. Black boundaries marking the area covered by a unique waste truck route.

Figure A2: Order of Treatment

Building Clusters on Major Roads in the City Centre

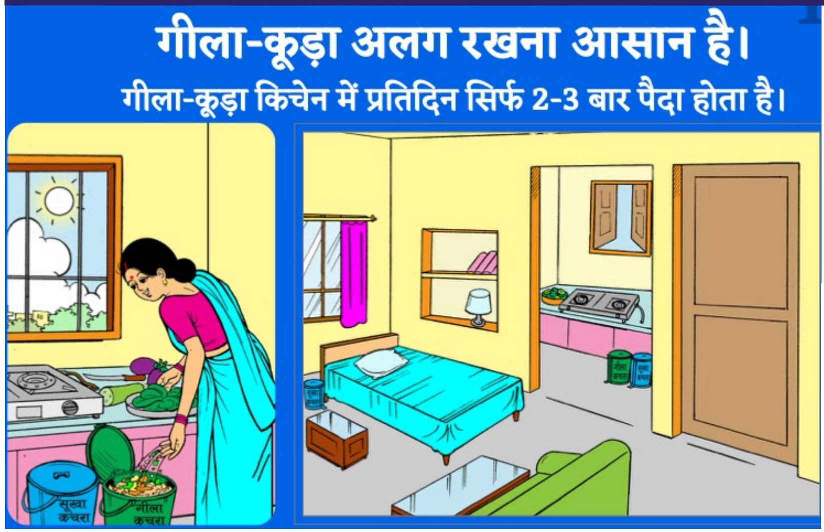


Notes: Map of a part of the City of Patna along the southern bank of the River Ganges. Grey outlines denote the boundaries of the area covered by a single waste truck route. Circles show clusters of buildings that are on the main roads. Lighter circles mark buildings that receive the treatment before the buildings marked by the darker circles that start citizen training later.

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.

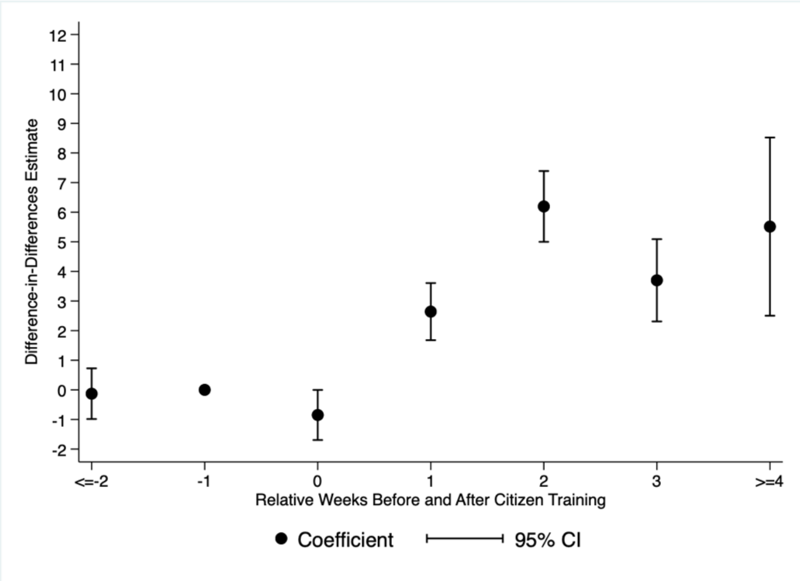
Figure A5: Examples of Enumerator and Training Activities

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.

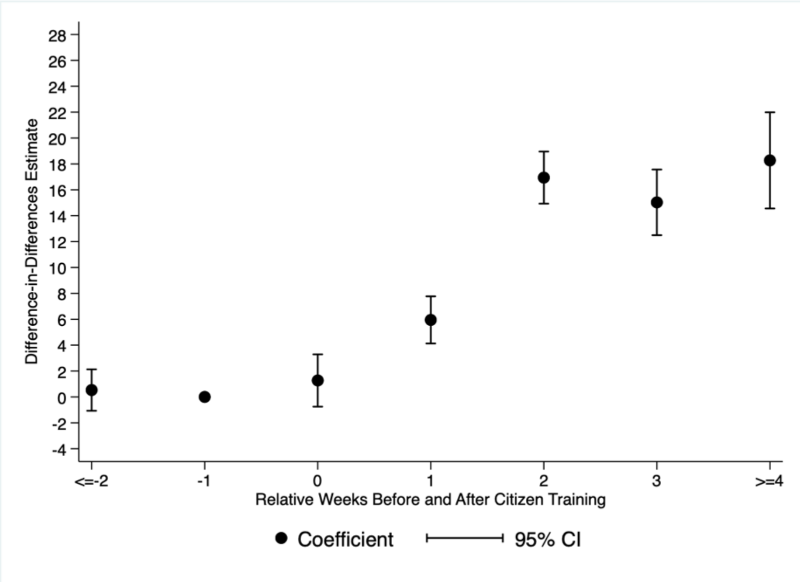
Photos of intervention teams conducting citizen training across different households. Consent taken for posting photos from individuals.

Figure A6: Event Study, Unbalanced



Notes: Comparable to event study, balanced, in Figure 4 (a). The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. Full estimation sample. 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. 261,839 disposer-day observations or 16,714 cluster-days. DiD ATET coefficients are estimated for each stack-relative week and averaged across all stacks, with weights equal to the average share of the stack in the clean control estimation sample in the period after the start of citizen training (to keep them fixed over relative weeks), to obtain the Staggered DiD ATET Estimate for each relative week. Weekly SDiD ATET estimates are normalised to zero in the week just before the start of the intervention, relative week = -1. Standard errors are clustered two-way by building clusters and stacks. The event study coefficient estimates (and associated standard errors) comparable to Table 3 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).

Figure A7: Event Study - Spatial Discontinuity, Unbalanced



Notes: Comparable to event study, balanced, in Figure 8 (a). The dependent variable is the share of households (percent per cluster per day) that dispose of waste segregated into dry and wet waste. Spatial discontinuity estimation sample. The observations range from $\leq$-15, -14 to -8, -7 to -1, 0 to 6, 7 to 13, 14 to 20, 21 to 27, $\geq$28 relative days. 134,334 disposer-days or 8,306 cluster-days. DiD ATET coefficients are estimated for each stack-relative week and averaged across all stacks, with weights equal to the average share of the stack in the clean control estimation sample in the period after the start of citizen training (to keep them fixed over relative weeks), to obtain the Staggered DiD ATET Estimate for each relative week. Weekly SDiD ATET estimates are normalised to zero in the week just before the start of the intervention, relative week = -1. Standard errors are clustered two-way by building clusters and stacks. The event study coefficient estimates (and associated standard errors) comparable to Table 3 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).

Additional Tables

Table A1 shows segregation rates of stacks of early phase 1 and later phase 2 treated households and their control groups for the full sample of all periods of data collection (panel A) and for periods of the experiment (in panel B). The early phase 1 treatments are for the first 19 stacks consisting of early treated clusters that start their citizen training in the first half of the intervention schedule and the later phase 2 treatments are for the remainder 19 stacks consisting of the late-treated clusters.

Table A1: Waste Segregation By Treatment Phase

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

Panel A: All periods of data collection	All Dec 2 - Aug 8	Pre Dec 2 - Apr 18	Post Dec 17 - May 31	Follow-up Jul 27- Aug 8
	(1)	(2)	(3)	(4)
Phase 1	11.40	8.91	13.80	33.46
Number of household-days	241,816	56,885	212,677	8,618
Number of building cluster-days	17,727	3,676	13,496	554
Phase 2	11.26	9.82	20.29	31.39
Number of household-days	278,180	96,668	133,374	11,774
Number of building cluster-days	15,780	6,188	8,833	760

Panel 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 as Table 2. Phase 1 is the first half of 19 stacks of treated households that start citizen training in the first 19 treatment groups and their controls, and Phase 2 the remainder 19 stacks of the second half of 19 treatment groups and their controls.

Observable Characteristics of Households by Timing of Intervention

As noted earlier, household characteristics are available from longer interviews of households across different clusters. A 50 percent random sample of buildings was selected for household interviews from the census listing of intervention areas (see research protocols at the end of the paper). In the tables to follow, self-reported characteristics are from interviews conducted before the start of any intervention. Each survey interview typically required twenty minutes with the resident. The interviews collected information on households' waste practices from the member of the household who usually engaged in waste management for the household, wherever possible. Typically, this is the daughter or the daughter-in-law of the head of the household and in certain cases, the domestic help (in which case, the interview also involved other members such as the head of the household who would know more about the family).

While self-reported waste practices could be another source of evidence on waste behaviour, a baseline survey revealed that self-reported segregation rates were systematically higher than rates observed by enumerators in each area. The paper therefore focuses on qualitative responses to questions that are less likely to be misreported. The questions cover household characteristics (household size, religion, social group and education), household asset ownership to proxy for wealth (whether owns a refrigerator, air cooling unit, washing machine, motorcycle/scooter, car, residence), waste management characteristics (whether bins are disposed of in the vehicle as reported by the households, whether reports segregating or willing to segregate waste, whether knows how to segregate waste and the product of the three), other waste management characteristics (the number of waste bins/bags in the household, when waste had been last disposed of to measure frequency, willingness to pay more than Rupees 30 per month for segregated waste collection and disposal).

The willingness to pay question gave a randomised amount between Rupees 30 to 180 and asked whether the respondent would be willing to segregate their waste and pay that amount to get segregated waste collection in exchange for free compost. The reported statistic is the fraction of households that were willing to pay for segregated waste disposal. As seen in other studies (Kayamo 2022, Basistha et al. 2024), there is some but generally quite low willingness to pay for waste management among households.

The waste management characteristics also include the gender of the waste manager, the distance to the waste truck stop from their home, whether waste is not disposed of in designated area/vehicle) and questions on household attitudes towards the environment and waste workers (whether the effects of the environment crisis are exaggerated,[46] whether finds it hard to change own habits to be more environmentally-friendly,[47] whether waste workers should be paid more and be provided better working conditions, whether waste workers are discriminated against in society and whether Covid-19 has made us value essential workers such as waste workers more).

The survey reports enable an examination of household characteristics covered by the citizen training programme in two halves. Table A2A compares households that received the training in the first half of the intervention schedule with those that received it in the second half. Overall, the households look highly similar to each other across a number of different household characteristics that could matter for waste behaviour.

The mean household size, the share of households with a college-educated member and the share that own a refrigerator, air cooling unit, washing machine and motorcycle/scooter are similar across clusters in the two halves of the intervention. Waste management characteristics are also highly similar.

The share of households that self-report segregating their waste into dry and wet waste is about a quarter in both halves, which is about fifteen percentage points higher than the observation data from the waste enumerators. The mean number of bins is about one in clusters across both halves of the intervention. While this might seem too low, many households have no designated waste bins and use other household items, such as plastic bags or buckets, to store and dispose of their waste. The share that disposed of their waste the previous day or the same day as the survey is about 95 percent in each half of the clusters.

One way of measuring waste dumping that households might be reluctant to reveal is to ask them the ways in which they dispose of their waste: (a) collected by government/formal or informal waste collectors/disposed of in designated areas, (b) remainder categories that include disposed of within the household yard or plot (often meaning it has been buried or scattered around), burned or buried, or "disposed of elsewhere (road, water body, open dump etc.)" or (c) don't know (which is less than 0.5 percent of all responses). Waste not disposed of at designated pick-ups is constructed as an indicator for responses in (b), and this category is less than ten percent of all households. It

[46] Adapted from Public Opinion and the Environment: The Nine Types of Americans, 2014. Available at: https://apnorc.org/wp-content/uploads/2020/02/Segmentation-Topline_FINAL.pdf

[47] Adapted from Huebner et al. (2015).

almost entirely consists of disposed of elsewhere. In textual explanations, households often report this to mean that the vehicle does not come close to their home and they report leaving it on the road for the municipality to pick up.[48]

About a fifth of the households report some problems with mosquitoes or flies. This might affect their waste practices and we find that the shares reporting this are highly similar across both halves of the intervention.

Household attitudes towards the environment are very similar, with no strong opinions in either direction. Households' opinions on waste workers are also very alike, with strong agreement on better pay and working conditions for waste workers and their value being appreciated since Covid, but with some disagreement on whether waste workers are discriminated against in society.

There are differences across clusters in the first and second half of the intervention in terms of a couple of characteristics - car ownership and the share of households by religion (Hindu/Muslim/Others) and social group (General/Scheduled Caste/Others). The car ownership difference seems to be largely driven by the small shares of households that own a car across all clusters. Finally, there is a higher share of Hindu and general caste households in the clusters that get the intervention in the second half, suggesting spatial sorting based on caste as is known from previous studies in India. Though the differences are not statistically significant, we account for this in Table A4 below by re-estimating Table 8 with controls for these household characteristics interacted with the relative time indicators.

The main findings on balance in household characteristics achieved from the chessboard design of the staggered intervention is corroborated in Table A2B. It focuses on households in sub-experiments where only contiguous treated and control clusters that are one either side of a spatial discontinuity are examined. The households in these sub-experiments in phases 1 and 2 have similar household characteristics to the full sample and sometimes show greater balance, though some slight differences in the shares of households by caste across groups remain.

Table A2A: 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			

[48] Open dumping is not uncommon in middle income countries. For example, Garg et al. (2018) find over 9 percent of villages in Indonesia in their study primarily dump their trash in the river.

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	3.20	3.16	0.04 (0.18)
I find it hard to change my habits to be more environmentally-friendly	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 households interviews before the start of any citizen training. 2,139 households in Phase 1 of the intervention and 2,571 in Phase 2. Standard errors are clustered by building group.

Table A2B: 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 5. 1,878 households in Phase 1 of the intervention and 2,319 in Phase 2.

Bilateral Proximity Results

For completeness, Table A3 shows results based on bilateral proximity between the treated group in a stack and its control clusters. Column (1) reproduces the baseline estimate from column (1) of Table 3. In column (2), only control groups that do not share a waste truck route or a waste truck route border with the treated group of a stack are included. Residents from these control groups are unlikely to directly encounter treated households at a truck stop. Column (3) combines physical distance with bilateral borders. An indicator for whether the treated and control groups share a border with each other is interacted with the inverse of the geographical distance between them (Border/Distance). Proximate control clusters, with greater than the mean value for control clusters, are excluded in column (3). The SDiD ATET estimates rise from 4.5 to 5.15.

Table A3: Staggered DiD Estimates, Distance and Border Sub-Samples

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

	Baseline	Bilateral Borders and Distance	
		Control cluster borders treated group	(2) divided by distance from treated group
	(1)	(2)	(3)
Staggered DiD Estimate	4.50	5.15	5.15
	(0.85)	(0.87)	(0.87)
Fixed Effects			
Stack-Building Cluster	yes	yes	yes
Stack-Relative Week	yes	yes	yes
Sample Size	261,839	261,839	261,839

Notes: Same as column (1) of Table 3, repeated for ease of reference in column (1) above. Columns (2) and (3) exclude control clusters with bilaterally proximity to the treated cluster in each stack. Column (2) excludes control clusters that shares a waste truck route or share a border with the waste truck route of the treated cluster in each stack. Column (3) combines the waste truck route border and the distance between a treated cluster and its control cluster. An indicator for whether the treated and control clusters share a truck route or a border with each other is interacted with the inverse of the geographical distance between them (Border/Distance). Control clusters with higher values than the mean of control clusters are excluded in column (3).

Spatial Decay with Controls for Household Characteristics

Table A4 considers different household characteristics and interacts them with relative time indicators to add as independent variables in the specification of equation (4). The main household characteristics of interest are car ownership, religion and social group where there are some differences across clusters that received the intervention in the first and second half of the interventions schedule in Table A2A. The main findings are similar to those in Table 8 (without additional independent variables from household characteristics). Additional specifications, such as with education and gender of the waste manager controls, are almost identical to the estimates in Table 8 and hence not reported here.

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

Household disposes of waste segregated into dry and wet waste (% of disposing households)			
	(1)	(2)	(3)
A. Estimation of Spatial Decay Model			
I. SDiD ATET (β)	7.27	8.65	8.04
	(1.75)	(1.61)	(1.33)
II. Post×Control×Spatial Proximity Indicator ATET (γ)	5.84	5.42	6.16
	(1.31)	(1.30)	(1.26)
III. Proximity Effect (γ × Mean of II in Post $\bar{I}$)	4.88	4.53	5.15
	(1.09)	(1.09)	(1.05)
IV. Own β + Proximity $\gamma\bar{I}$ (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 (3) of Table 8 but with additional independent variables for household characteristics interacted with indicators for the relative time in each stack. Household characteristics are the means of the household characteristic variable for each group of building clusters. Column (1) adds the share of Hindu families interacted with the relative time indicators and the share of Muslim families interacted with the relative time indicators as independent variables to the specification of equation (4). The household characteristics in column (2) are the share of General Caste families and the share of Scheduled Caste families, and in column (3) is the share of households that own a car.

Pre-Post Differences in Other Survey Outcomes

Table A5 shows the pre- and post-intervention outcomes and attitudes from the self-reported survey data. The first four rows show the variables for the segregation measure from the survey. Another objective measure of segregation is the mean number of bins in the cluster and a rise in this provides another measure of the rise in waste segregation.

Waste disposal frequency shows a rise, but this is small and from already high shares of people disposing their waste that day or the day before. Mean disposal time per week is almost the same and there is a tiny fall in waste dumping. This occurs along with a drop in the willingness to pay for segregated waste disposal, possibly because households find it easy to do so themselves.

There is some indication that households become more likely to disagree that the environmental crisis is exaggerated and more likely to agree with changing their habits to be more environmentally-friendly. Attitudes towards waste workers are more sympathetic on pay and working conditions, but there is a reduced perception of discrimination faced by waste workers, possibly following from their higher and increased value to society shared by households after the pandemic.

Table A5: 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 A2A, 8,813 randomly sampled households before and after the citizen training intervention.

Waste Outcomes

Tables A6A to A6E contain a summary of SDiD estimates, corresponding to Table 9, but for waste outcomes other than segregation by households. These are the share of segregated waste in total waste per disposer, the volume of segregated waste per disposer per day, the volume of unsegregated waste per disposer per day, the volume of total waste per disposer per day, and the number of disposers per building per day.

Table A6A: 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	4.04	5.55
Current/Constant weights and Pure Controls	(0.86)	(1.35)
Fully Balanced	3.65	4.95
-28,..,27/-42,..,41/-28,..,27 and Building Clusters	(0.85)	(0.93)
City Geography:		
Spatial Discontinuities	11.52	14.77
	(0.89)	(1.47)
Gravity	10.42	13.34
	(5.77)	(2.57)
Spatial Decay	9.82	14.18
	(1.69)	(2.08)

Notes: Same as for Table 9 covering 260,177 unique disposer-day observations.

Table A6B: Summary of Findings, Segregated Waste Volume

Segregated waste volume (gram per disposer per day)		
Specification	Range of SDiD Estimates	
	Minimum	Maximum
Baseline	39	65
Current/Constant weights and Pure Controls	(15)	(17)
Fully Balanced	43	69
-28,..,27/-42,..,41/-28,..,27 and Building Clusters	(15)	(13)
City Geography:		
Spatial Discontinuities	126	143
	(15)	(26)
Gravity	43	185
	(111)	(46)
Spatial Decay	83	177
	(29)	(46)

Notes: Same as for Table 9 covering 260,177 unique disposer-day observations.

Table A6C: 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	-160	-228
	(74)	(50)
Spatial Decay	-88	-132
	(39)	(73)

Notes: Same as for Table 9 covering 260,177 unique disposer-day observations. Own ATET reported in the first column of the last two rows because proximate treatment effects are small and statistically insignificant.

Table A6D: 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	-20	13
	(26)	(40)

Notes: Same as for Table 9 covering 260,177 unique disposer-day observations. Own ATET reported in the last row because proximate treatment effects are small and statistically insignificant.

Table A6E: Summary of Findings, Disposers

Disposers (number per building per day)		
Specification	Range of SDiD Estimates	
	Minimum	Maximum
Baseline	0.16	0.51
Current/Constant weights and Pure Controls	(0.03)	(0.08)
Fully Balanced	0.37	0.56
-28,..,27/-42,..,41/-28,..,27 and Building Clusters	(0.05)	(0.07)
City Geography:		
Spatial Discontinuities	0.26	0.82
	(0.06)	(0.11)
Gravity	0.33	0.97
	(0.09)	(0.22)
Spatial Decay	0.21	0.40
	(0.09)	(0.08)

Notes: Same as for Table 9 covering 367,056 unique household-day observations (that includes zeros filled in for non-disposers).

Additional Information

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

Listing Protocol

1. Introduction –

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.

Before starting the survey:

2. 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.

3. Listing will be done in two steps:

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

- Step 2 – Families, businesses, shops.

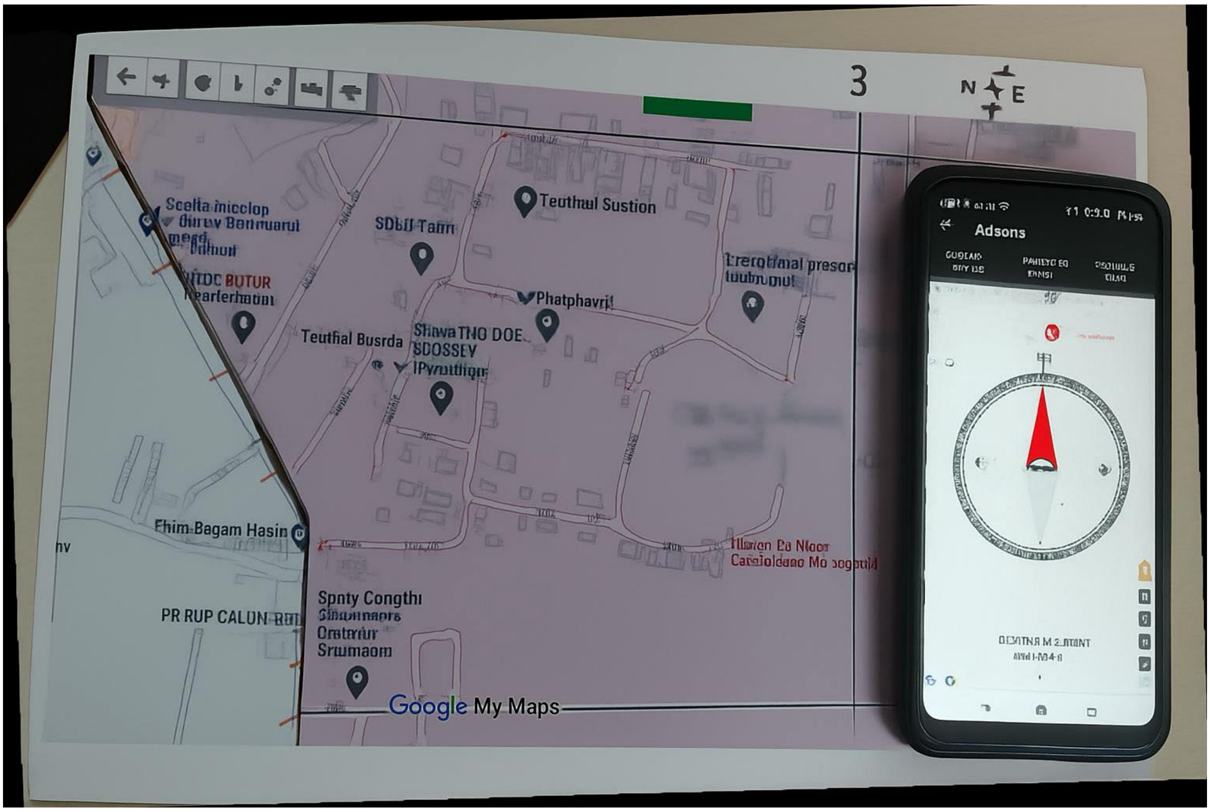
Important points to remember during the survey:

For a single house, the following forms may 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:

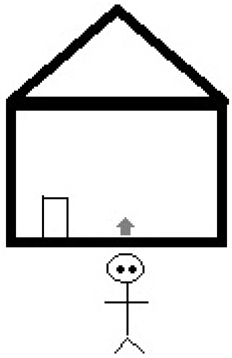
- When writing the road number, always use our internal road number already provided on the map.
- If a new road is found that is not marked on the map, label it as A1, A2, A3 etc., and record the same road number in the house/apartment/business/shop survey forms.
- If a house faces two roads, write 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.



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.



Additional Notes:

- If individuals in the house cook separately, they should be listed as separate families.

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.

Note: 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:

No. of families in a building	No. 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

- Only families that agree to participate will be surveyed.

Selection of Respondents

- Any adult member of the family.
- Preferably an adult responsible for waste disposal.

People Not to Be Surveyed

- 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

First 15 – 20 mins

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?”

Next 10 minutes

4. Detailed explanation of the composting process (how wet waste can be transformed into compost)

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

Last 5 minutes

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