Trading Trash on Tricycles*

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Abstract

Low regulatory and fiscal capacity limit the set of policy instruments available for municipal governments to control the externalities arising from density. Citizens resort to unregulated markets for service provision, but these leave externalities unaddressed. We build a structural model of solid waste collection and disposal, and estimate it using experimental variation and bespoke data we collect in Accra; through surveys with households and informal collectors, and a self-developed smartphone application. We estimate households' discrete choice demand system using BDM, TIOLI, and stated preference experiments. We estimate waste collectors' routing problem using a field experiment in which we subsidise disposal at waste transfer stations. Downstream subsidies at transfer stations can correct environmental externalities unpriced by the market. Counterfactual price subsidies of 50% at current transfer stations achieve socially optimal levels of waste pollution for the set of active disposal sites. Their gains in terms of pollution reduction exceed that of new infrastructure development. Our results suggests that in settings with low fiscal and regulatory capacity, limited pricing policy can help internalise environmental costs, effectively delivering public services by leveraging informal markets.

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1 Introduction

Urbanisation gives rise to Pigouvian problems such as pollution, disease spread, crime, or traffic congestion (Bryan et al. 2020), which left unaddressed generate large welfare losses. Addressing such negative externalities requires a combination of pricing policies, bans, quantity regulations, and the provision of urban public goods/services.[1] However, low regulatory and fiscal capacity limit the set of policy instruments available for municipal governments.[2] Decentralised unregulated markets for the provision of environmental public services aimed at tacking pollution –such as sanitation and solid waste management–, have expanded across cities in the developing world, pushing a public goods problem onto private provision.[3] These markets provide private value to citizens but fail to control externalities. What levels of environmental quality can different types of environmental regulation sustain in developing cities? Answering this question requires understanding how individual behaviour and private markets will respond to regulation. We take this question to solid waste disposal in Accra.

In the Greater Accra Metropolitan Area, as in many developing cities, door-to-door refuse collection and disposal are largely delivered by unregulated private actors. The government licenses, in a public-private-partnership, collection services and the management of engineered disposal sites (waste transfer stations and landfills) to one integrated company.[4] However, this utility reaches only a small share of households. Instead, a rapidly-expanding unregulated market serves most citizens. Over 70% of household waste is collected by informal waste collectors on motorised tricycles (known locally as Borla Taxis), who travel the city daily in search for customers, and dispose of the collected waste

[1] Examples of these policies abound in the transportation sector. Kreindler 2024 explores peak-spreading pricing policies to regulate traffic in Bangalore, Conwell 2025 studies how to improve the market for informal privatised transit in Cape Town, several papers examine the delivery of public transportation networks (Balboni et al. 2020), (Kreindler et al. 2023), (Tsivanidis 2023), (Zárate 2024), and how private and public provision interact (Björkegren et al. 2025).

[2] Weak institutions challenges setting the right incentives in the market through Pigouvian taxes or subsidies (Ashraf et al. 2016).

[3] Decentralised, private on site approaches to sanitation such as ventilated pit latrines are common in many lower-income cities that lack waterborne sewerage systems. Houde et al. 2024, and Deutschmann et al. 2024 provide details on the market for sanitation services in Dakar, analyse how these markets fail, and explore market improvements to increase service adoption.

[4] In door-to-door collection, a small set of companies licensed by the municipal assemblies co-exist. Still, formal collection is largely dominated by one company, which also manages disposal.

at waste transfer stations and illegal dumpsites. While the market has filled gaps in collection coverage and expanded service rates by 37% in the last decade, concerns remain around its reliance on final disposal at uncontrolled dumpsites, where waste pollution is not mitigated.

This paper documents the structure of Accra's waste market, examines what the unregulated private sector is delivering, and quantifies the market response to public intervention focused on pricing waste pollution. We collected new data from households, waste collectors, and disposal sites, through a variety of exercises across the Greater Accra Metropolitan Area. The data allows us to identify the main features of a market that, to the best of our knowledge, has not been quantitatively studied before. Second, we build and estimate a structural model of waste collection and disposal that allows to explain the high usage of collection services provided by the market, identify the causes of unaddressed pollution, and quantitatively evaluate the market impacts of government policies in the form of subsidies and public infrastructure. To estimate our model, we leverage two sets of experimental exercises. To estimate the demand curve for door-to-door collection, we conducted BDM (Becker et al. 1964) and take-it-or-leave-it (TIOLI) demand elicitation exercises. Households also participated in a stated preference survey experiment, which we use to estimate a richer discrete choice demand structure. To estimate waste collector choices, we run a field experiment, subsidising waste disposal at government transfer stations, and measuring how collectors value time, commuting costs, and daily profits.

Our novel primary data collection allows us to overcome challenges that widespread informality in waste markets of low-income cities poses for the availability of secondary data. In our setting, no up-to-date data existed beyond aggregated census information on household disposal choices.[5] We designed a series of primary data collection exercises that allow us to generate novel insights into solid waste management in developing cities and estimate our model. We conduct a survey of 1,800 households across 150 enumeration areas (EA), documenting collection and disposal choices. To assess the impact of neighbourhood waste pollution, we took 6,000 images of gutters and drains near surveyed households, which we classify manually, according to the amount of waste detected. We mapped the location of all disposal sites in the city, and gathered observational data on collector flows at each site. Leveraging these, we ran a survey of 400 Borla Taxis covering

[5]Ghana Population and Housing Census, 2010, and 2021 (Ghana Statistical Service).

the entire metropolitan area. This allowed us to construct collection-disposal commuting routes and learn about the characteristics of disposal sites. We designed a smartphone application that collectors were invited to use as part of this survey, for a period of two weeks to one month. They were incentivised to register their collection transactions, providing us with geolocated, timestamped transaction data. This detailed information allows for a careful description of the characteristics of the waste collection market, and for validation of our survey data.

A set of descriptive facts on the market guide our model. Access to formal collection trucks and containers is restricted spatially, while Borla Taxis serve most areas in the city. Borla Taxis charge a lower price and provide collection at a higher frequency. We observe that households predominantly choose Borla Taxi services when available. Despite the large expansion of the collection market, local waste pollution remains a challenge. We estimate that a 1% increase in the count of trash objects in gutters and drains is associated with a 0.075 percentage point increase in the share reporting flooding, 0.082 in malaria, and 0.024 in diarrhoea (among other symptoms). Our transaction data reveals a competitive door-to-door collection market. We observe stable prices with very low dispersion around the times when most collectors are searching for customers. This coincides with low search times between transactions and a fairly constant tricycle loading rate, which again exhibits low variation across areas in the city. Our count data at disposal sites indicates that disposal is highly concentrated at dumpsites, with the four illegal dumpsites in the city accounting for approximately 75% of disposal activity in the market. This alone suggests that in the absence of pricing policies, the market displaces externalities from upstream to downstream of waste generation. The geolocated collection transactions and our survey data suggest the formation of catchment areas around disposal sites (i.e. Borla Taxis collect relatively close to disposal sites, trading off commuting and disposal costs), driving spatial differentiation in disposal, consistent with local market power.

Our model combines two discrete choice systems ruling household waste disposal choices and collectors routing decisions. It introduces market power in disposal, with disposal sites competing in a Nash-Bertrand pricing game. Upstream of the waste flow, households demand waste collection services, which collectors supply by choosing collection locations and the number of customers to serve. Downstream, collectors demand options to dispose of their collected waste, which are supplied by disposal sites (either government transfer stations or uncontrolled/illegal dumpsites). Waste uncollected at source and disposed of at illegal dumps generate external environmental and health costs. Through the model we characterize and quantify optimal urban waste management policy given environmental externalities and the structure of waste markets in collection and disposal. Consistent with Pigou 1932, we find that a social planner would set downstream disposal price minus sites' marginal costs equal to the marginal environmental externalities at dumpsites (downstream) and neighbourhoods (upstream), addressing both market power and pollution.

We then take the model to the data. We estimate the demand for Borla Taxi waste collection using BDM and TIOLI elicitation exercises, in which we offer households the option to purchase a collection service during the interview. We estimate high price elasticities at low prices and a high take-up rate of Borla Taxi services at equilibrium attribute values. 70% of households are willing to have their waste collected at the current market price of 18 Ghana cedis (GHS) per week. A 50% price reduction to 9 GHS would raise this share to around 90%. We cannot reject that the price elasticities we estimate with BDM and TIOLI (on different random samples) are the same.

We run a stated preference survey experiment, using choice cards with exogenously varying attribute values, to understand how households choose between different disposal options when multiple alternatives (Borla Taxi, formal collection, communal container, burning, or dumping) are available, and they can differ across dimensions like price, frequency, or time involvement. Our estimates show that beyond prices, households value frequency of collection. Using the estimated preferences to predict demand in each location, we find that Borla Taxis capture a market share close to 70%, with about 20% of households burning or dumping their waste, and the remainder opting for either formal truck collection or communal containers. These predicted market shares align with the results from the BDM and TIOLI exercises, with survey responses on main and secondary waste disposal choices, and with the spatial variation in waste pollution we measure using the images of gutters and drains.

To estimate collectors' routing choices, we run a field experiment, where we subsidise disposal at waste transfer stations by 80 GHS. [Estimates of price elasticity, and of probability of formal disposal go here. This is currently at field-work stage. Current structural estimates leverage a Nested Fixed Point strategy over collection and disposal prices, with MLE estimation of taste parameters and SMM estimation of disposal costs]. We use the experimental variation in route profits to structurally estimate all parameters governing collectors' route choices via Generalised Method of Moments (GMM).

In our final calibration step, we estimate via Simulated Method of Moments (SMM) the site-specific cost parameters that govern disposal sites' endogenous pricing choices. We simulate sites' pricing game and match model-generated disposal flow shares and prices to our observed data. Our estimating procedure exploits model-implied variation in collector flows and disposal fees, and leverages the parameter estimates of household and collectors discrete choice problems. Intuitively, sites with higher costs attract fewer collectors and charge higher fees in equilibrium, with spatial differentiation through travel costs allowing some degree of market power. We estimate marginal costs for dumpsites between 0.15-0.65 and GHS per waste bag. Consistent with the different technologies used, transfer stations exhibit higher costs, between 1 and 2.4 GHS per bag.

Our counterfactual exercises show that downstream subsidies of 50% at transfer station can achieve the same level of controlled pollution as the socially optimal allocation, that which internalises environmental and health damages at source and at dumpsites. This means that for the current set of disposal sites in the city, the government can rely on the door-to-door collection market and deliver waste disposal at its optimal level, albeit at a higher cost, by halving the prices at stations. The construction of planned infrastructure achieves smaller reductions in illegal disposal shares and risks crowding out existing stations. Free disposal at transfer stations would almost eliminate illegal disposal at open dumps. These results point to the possibility of co-delivery of environmental public services by the government and informal markets in settings with low fiscal and regulatory capacity. Markets effectively reach the bulk of waste generation and competitive forces drive collection prices down. The role of government becomes to price the unaddressed externalities where its feasible to do so.

Waste collection and disposal in developing cities is an important empirical setting. Inadequate disposal generates substantial negative externalities: waste burning creates air and water pollution, uncontrolled dumpsites degrade soil and groundwater while emitting greenhouse gases, and blocked drainage systems cause flooding that disproportionately affects the urban poor and facilitates disease transmission. Notably, waste disposal has proven remarkably hard to regulate effectively across cities in the developing world.[6]

[6] Historically this has been the case throughout the world. Unregulated dumpsites, labelled as "human-made disasters" by the United Nations Environment Programme, were the main disposal choice globally until the middle of last century. Many of them last for decades, reach very large sizes, and become the

In Sub-Saharan Africa, 86% of waste remains uncontrolled (UNEP 2024). Yet, there is limited knowledge on how these waste systems function, and the economics of urban waste management in developing countries remains broadly understudied (Bryan et al. 2020). An earlier wave of work in the 1990s, focused on the U.S., examined optimal pricing instruments (e.g. Fullerton and Kinnaman 1996, Fullerton and Wolverton 2000, Fullerton and Kinnaman 1995, Kinnaman and Fullerton 2000, Fullerton and Wu 1998, Palmer and Walls 1997). Recent empirical studies have focused on specific improvements to solid waste management in developing countries. Using randomised-controlled-trials, they have examined the effectiveness of informal regulation leveraging norms change using collective action incentives at the neighbourhood level targeting street cleanups (Jakob and Coccia 2024) or reduced waste burning (Buntaine et al. 2024), and information treatments to increase household sorting and recycling (Dhingra et al. 2024) and reduce indiscriminate dumping in drains and gutters (Leffers 2024). We are the first to study the problem at a city scale using a quantitative model that covers the behaviour of households, collectors, and disposal sites' operators –tracing waste from generation to collection, transportation, and final disposal.[7]

The remainder of the paper is organised as follows. Section 2 provides details on our setting. Section 3 describes our data sources and data collection exercises. Section 4 gathers the descriptive evidence that informs our modelling strategy. In Section 5, we develop a structural model of waste collection and disposal, which captures the behaviour of households, waste collectors, and disposal sites. Sections 6 and 7 characterise the decentralised equilibrium and social planner allocation. Section 8 describes our estimation strategy and results. It provides details on our survey experiments to elicit demand and our field experiment to estimate waste collectors' disposal demand system. In Section 9, we analyse counterfactual waste management policies. Section 10 concludes.

2 Setting: The growth of an unregulated market

In Accra solid waste management is privatised, and largely unregulated. Solid waste is collected from households or commercial areas by a combination of informal tricycle collectors, referred to as "Borla taxis", and regulated private contractors licensed by

de-facto method for providing waste disposal services.

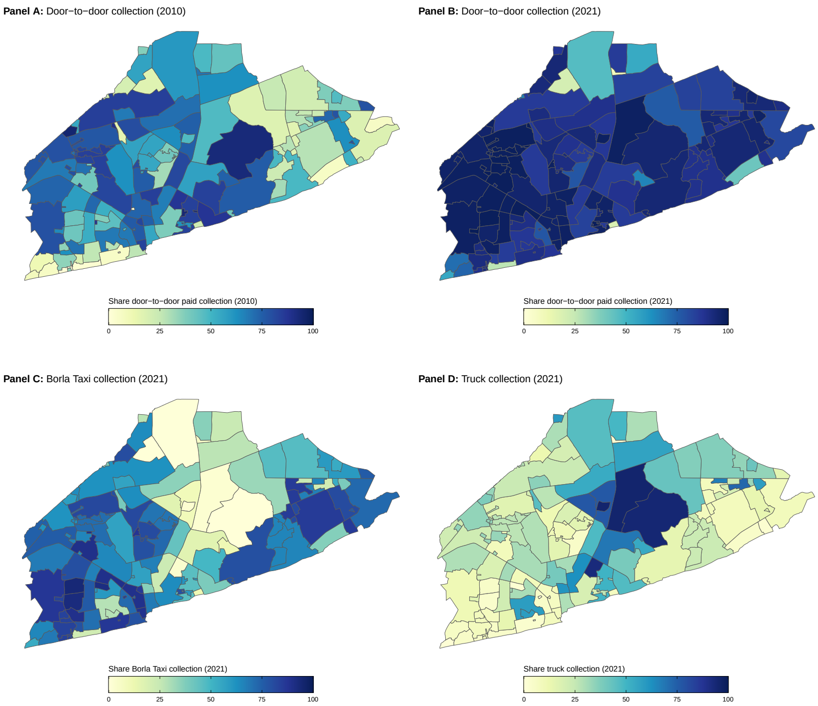
[7]Previous quantitative structural work has focused on how intermediation affects market efficiency on New York City' commercial waste industry (Salz 2022).

the city authorities. During the last couple of decades, the city has become increasingly reliant on unregulated private service provision. The share of households in urban Greater Accra that report paying for their waste to be collected (to licensed trucks or Borla Taxis) grew from 51% to over 70% between 2010 and 2021 according to the respective nationwide population and housing censuses. Figure 1 shows the expansion of paid door-to-door collection in Accra between these years. The map in Panel A indicates significant heterogeneity back in 2010, with big areas of the city showing low to moderate coverage (light yellow to medium blue). Panel B (2021) reveals the large widespread expansion of the market over the last decade, with most localities now hosting a large share of households paying for formal or informal waste collection services (dark blue).

It is worth noting that the areas where paid collection increased the most did so through increases in the market share of tricycle collection (Panel C). In 2021, around half of households in urban Greater Accra report using tricycle collectors ("Borla taxis") as their main solid waste disposal method. This share increases to 60% when restricting ourselves to the main area of the city depicted in Figure 1. Panel D shows that formal truck collection on the other hand is very clustered in higher-income residential areas along the airport, with many localities in the city exhibiting very low shares of formal collection (for an aggregate share of 28% in 2021).

Borla Taxis transport collected waste to transfer stations or dumpsites for disposal. At both types of disposal sites collectors need to pay a disposal fee and there is limited recycling. Transfer stations are funded with assistance from municipal governments, and operated by a private company. There, waste is compacted and sent to engineered landfills. Transfer stations include leachate containment systems to prevent water pollution, covered storage to avoid air pollution, and paved surfaces to prevent soil pollution. Unregulated, or illegal dumpsites are large pieces of cleared land with no infrastructure to control pollution. Waste is dumped indiscriminately. Some is separated by informal waste pickers; the rest is burned. Figure A1 shows examples of transfer stations and illegal sites, and Appendix A.1 provides more background details on the structure of the market for waste collection and disposal, which leverage statistics we generate from our primary data.

Figure 1: Waste collection market expansion



Notes: We plot data on the main solid waste disposal option at the locality level, obtained from the 2010 and 2021 Population and Housing Census (Ghana Statistical Service, 2010, and 2021). The maps employ the same colour gradient from light yellow (0% coverage) to dark blue (100% coverage) across all panels, showing the share of households that report each option as their main choice of solid waste disposal. Panel A shows the share of households that report paying for solid waste disposal in 2010. In the 2010 census, the question was not disaggregated across waste disposal options. It only documented whether a household uses paid collection services. In Panel B we construct the equivalent measure to that in Panel A, by adding the share of households that pay for formal truck collection and the share that pay for Borla Taxi services using the 2021 data. The 2021 census asked specifically about the main solid waste disposal method used by the household. In Panel C and D we report the share of households using Borla Taxis and formal truck collection as their main solid waste disposal method respectively.

3 Data

3.1 Geography and samples coverage

We constructed a new dataset on demand and supply for waste collection and disposal across the Greater Accra Metropolitan Area (GAMA)[8] through several exercises over a

[8]The whole metropolitan area had a population of 4,992,911 people in 2021 and an area of 3,959.059 km^2, divided in 25 municipal districts.

year.[9] In October-December 2024, we collected data on household demand for waste collection for 1800 respondents in 150 EAs within the city of Accra[10]. Our enumeration areas are highlighted in red in Figure 2, which illustrates the geospatial coverage of our data. In March-May 2025, we collected data for 400 collectors to understand the supply of waste collection and demand for disposal at dumpsites and transfer stations. We sampled at disposal sites (yellow dots), according to the collector traffic we estimated at each site. In Figure 2, we highlight in blue the areas where collectors in our sample report collecting waste. It is important to note that they cover most of the built-up area in the metropolitan area, which we display as the light grey area.[11] The overlap between the collection areas and built-up area makes us confident that we capture most of the spatial variation in collection with the 400 respondents in our sample –16% of the estimated number of collectors working in the GAMA.

3.2 Demand for waste collection

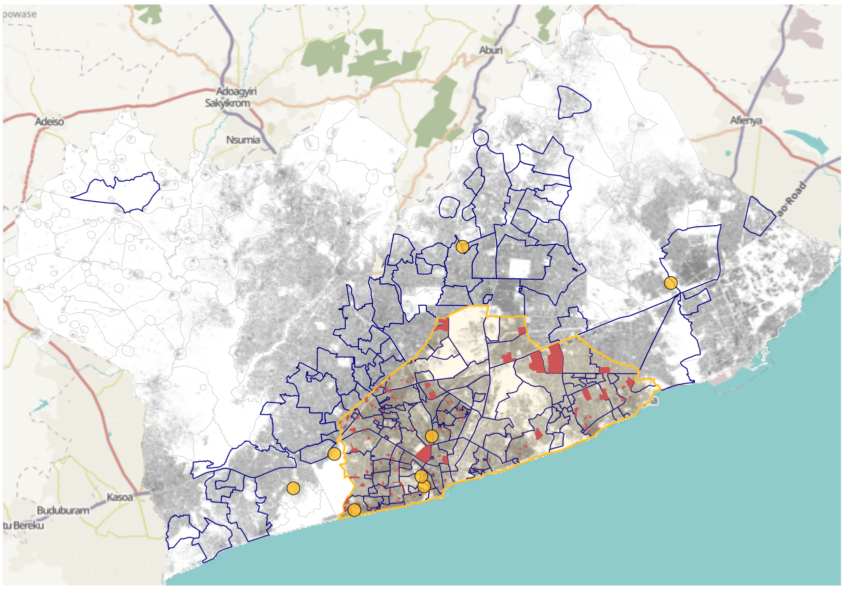
We surveyed 1800 households across 150 enumeration areas (EA) within Accra (main city-area). We randomly selected 50 EAs within different housing income stratum, and randomly surveyed 12 households within each EA via door-to-door interviews, to form a sample of 1800 households. Further details on the sample are in Appendix A.2.1. The survey included questions on the availability of waste disposal options in the neighbourhood and their attributes or characteristics (frequency of collection, average price, waiting times for formal and informal collection, and walking times to communal containers). We also asked about individual main and secondary waste disposal choices and recorded details such as average price paid, frequency of collection, and payment arrangements, among

[9] We complement our survey data with administrative census data from the Ghana Statistical Service. We obtained classified 2021 census data at the locality level on the main solid waste disposal choice made by households and key household characteristics. We also leverage 2010 publicly available census data at the enumeration area level. We use the 2021 data to calibrate access to formal collection and communal containers and to validate our model predictions.

[10] The city of Accra is the territory that existed as the unified Accra Metropolitan District until 2008. It covers almost 200 km^2 now divided in 13 municipal districts (Ablekuma Central Municipal, Ablekuma North Municipal, Ablekuma West Municipal, Ayawaso Central Municipal, Ayawaso East, Ayawaso North Municipal, Ayawaso West Municipal, Korle Klottey, Krowor Municipal, La Dadekotopon Municipal, Ledzokuku, Okaikoi North, and Accra Metropolitan Area (AMA)), 124 localities, and 2820 census enumeration areas. It is home for 1,782,150 inhabitants (2021 Census)

[11] To represent the settled area, we use Global Human Settlements data (GHSL), downloaded from https://human-settlement.emergency.copernicus.eu.

Figure 2: Geospatial coverage of primary data



Notes: Household survey enumeration areas are highlighted in red. The area enclosed within a yellow boundary is the city of Accra –Accra Metropolitan District until 2008. This area corresponds to the following 2021 municipal districts: Ablekuma Central Municipal, Ablekuma North Municipal, Ablekuma West Municipal, Ayawaso Central Municipal, Ayawaso East, Ayawaso North Municipal, Ayawaso West Municipal, Korle Klottey, Krowor Municipal, La Dadekotopon Municipal, Ledzokuku, Okaikoi North, and Accra Metropolitan Area (AMA). The yellow dots are the main disposal sites in GAMA, where we conduct the collector sampling. The polygons in blue are the localities where collectors in our sample report collecting waste in. The grey shaded area is the settlements layer from the Global Human Settlements data (GHSL) for 2023. The area in white is the Greater Accra Metropolitan Area (GAMA). The background map tiles are rendered using the Humanitarian OpenStreetMap Team style.

others. Finally, we asked households about their experiences with symptoms and formal diagnostics for a wide range of health indicators. We also inquired about the occurrence of flooding in their neighbourhood and own street. We closed the survey by asking about waste dumping and burning, through a set of questions regarding norms, neighbours' behaviour, and own behaviour, using a randomised-response technique. We recorded key household characteristics following the format of questions in the Census.

To construct an objective measure of local waste pollution faced by households in our sample, we took pictures of gutters and drains near surveyed households following a simple protocol.[12] We obtained a total 6000 pictures (between 5 and 10 per household).

[12] Pictures had to be taken perpendicular to the gutter, pointing directly towards it, and every 5 steps. We took a total of 5-10 pictures for each household. In some instances, there were no gutters near a

We inspected and manually counted the number of trash objects in each picture, averaged image-level counts at household-level first and EA-level second, and thereby constructed a measure of waste pollution in the 150 areas we surveyed.[13] In Figures A3 and A4, we provide examples of pictures for neighbourhoods with low and high waste pollution levels. Figure A5 displays the spatial variation in local waste pollution across our survey areas.

3.3 Supply of waste collection and disposal

3.3.1 Disposal sites inventory and collector flow counts

To design our sample of waste collectors, we conduct an inventory of all disposal sites in operation within the GAMA and measure the flow of collectors arriving to each of them. We visited all disposal sites –both transfer stations and illegal or uncontrolled dumpsites– that we had identified in a pilot survey with 50 collectors, online newspapers, and reports on solid waste management in Accra. Some of the sites we found across these sources were no longer in operation or had been decommissioned. On active sites, we counted the number of tricycle collectors arriving during the day, since early in the morning until the early afternoon. We cross-checked our numbers with the personnel working at the sites to arrive to our final estimates of collectors flows to each site. Table A1 provides details on the sites inventory, including the rationale for sample inclusion or exclusion for each site

Our final list includes 8 sites where collectors operating in Accra dispose of their waste. The list includes 4 formal transfer stations/recycling sites, and 4 unofficial, uncontrolled dumpsites. The 4 formal sites and the estimated rounded collector traffic (in parentheses) are the Ashaiman-Adjie Kojo transfer station (150 collectors), the Pantang transfer station (100 collectors), the Korlebu Recycling Plan (IRECOP) (100 collectors), and the Kokomlemle Mini Transfer Station (Britania Mini Waste TS) (10 collectors). The unofficial dumpsites are the Mallam/Tetegu dumpsite (150 collectors), the Glefe dumpsite (100 collectors), the Agbogbloshie Sikkens dumpsite (350 collectors), and the McCarthy

survey household or they were closed. In those cases enumerators had to take a photo of the close gutter or the ground as proof.

[13] We tried using deep-learning techniques relying on YOLO models we trained on existing waste images (TACO dataset). The models struggled to detect waste objects in turbid water, which are of particular importance in our application.

dumpsite (400 collectors). We allocate our sample of 400 collectors proportionally to the traffic at each site.

3.3.2 Borla Taxi survey

We surveyed 400 collectors disposing of their waste in our 8 sampling disposal sites.[14] The questionnaire included general questions on waste collection practices, a time use survey to understand time spent searching for customers, commuting, recycling, and disposing of waste, and several detailed modules: on main and secondary collection localities, on disposal and recycling choices, and on daily/weekly accounting (costs and revenue breakdown, and total profits).

The information gathered allows us to characterise our choices of interest (i.e. collection area, number of customers, and disposal site) and the attribute values governing them. First, daily commuting flows (from home to collection area, and from collection area to disposal site) reveal collectors' choice of collection area and disposal sites, as well as commuting distances. Second, through the module on disposal we gather information on the attributes of disposal sites beyond commuting costs (daily fee, waiting time, and recycling price). Third, our general questions on collection practices give us information on the distribution of daily customers. And fourth, our accounting module allows us to measure daily profits, collection and recycling revenues, and total costs.

3.3.3 Transactions data

We complement our survey with real-time, geolocated data on waste collection transactions. Upon recruitment, surveyors invited collectors to download a smartphone app we designed for the study.[15] This meant that collectors had to own a GPS-enabled smartphone to participate in the survey, but most collectors we approached owned a basic smartphone and were willing to download the app.[16] The data collection app required active engagement. We instructed collectors to register all their daily collection transac-

[14] Enumerators arranged in-person interviews at disposal sites, after informing informal Borla Taxi leaders, personnel at transfer stations, and high-level members of the waste collector associations. In some instances, Borla Taxi leaders helped coordinate interviews at the sites or near collectors' home locations.

[15] Figure A6 shows the timing of app registrations over the survey period.

[16] There were no operating system restrictions. We made the app available in the Apple Store, Google Playstore, and downloadable directly using an APK

tions for a period of two weeks, indicating the agreed price and whether they received any of the waste already separated/sorted. In Figure A7, we include the app screens with the main functionalities. The app automatically retrieved the geolocation and time of the transaction. To incentivise usage, the app included a simple reward system through which collectors redeemed compensation via mobile money at the end of each week.[17]

There are a total of 25840 transactions and 1752 collector-day observations from the start of April until the end of May. We classify each collector in a given day according to their usage. We identify "normal users" as those who record a number of transactions close to their reported daily average number of customers in the survey. And abnormal/low-users as those who either report too many transactions (very small number) or do not engage with the app and register numbers well below their stated number of daily customers.[18] Out of the total collector-day observations, 43% are classified as normal users. Figure A8 shows the basis for our classification –the relationship between number of daily customers and the number of transactions registered in a day. Except for those reporting customers over 50 (small percentage of the total sample), our classification seems reasonable, with recorded transactions scattered around the 45-degree line, in a clear upward-sloping relationship. Conversely, those that we classify as low-usage show no relationship between the number of customers in the survey and the number of recorded transactions, which remain always low.

A number of additional descriptive facts validate our approach. First, the distribution of customers in the survey for both type of users is very similar, hence the different behaviour using the app is not driven by differences in the number of customers. Moreover, for each date, the average number of transactions registered by *normal users* is very

[17]Enumerators helped collectors download the app into their smartphones and register a few trial transactions to show them the app functionalities. We organised a system of daily callbacks to incentivise collectors to fill the data and validate the information registered in the day. We paid collectors to register transactions for a period of 2-4 weeks in total. After the incentivised period, many collectors kept using the app.

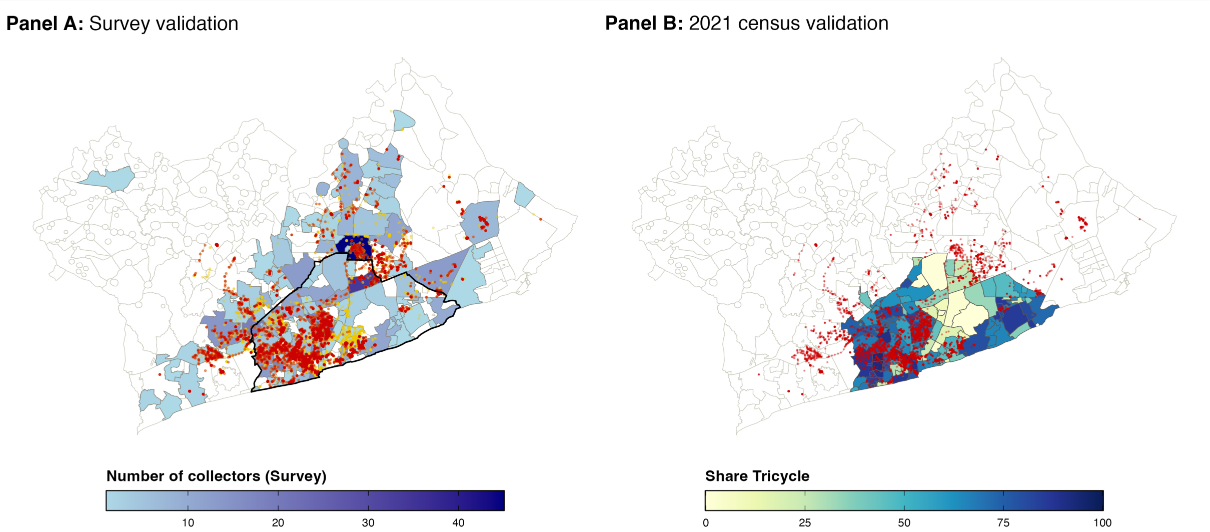
[18]This means that a collector can be classified as normal user in a date and as abnormal/low-user in another. For example collector A, reports an average number of daily customers in the survey of 25. In day one, collector A registers 21 transactions in the app, in day two, reports 31 transactions, and in day three reports 23 transactions. All of these are classified as *normal usage* collector-days. The same collector A registers 8 transactions on day four. In this case, we classify the same collector in day four as *low-usage* due to the difference between the registered transactions in that particular day and the average daily number of customers reported in the survey.

similar to the number of customers in the survey for both *normal users* and *abnormal/low users*. The number of transactions registered by the latter is significantly below for each date. These again suggests that the two types of users are not systematically different in the number of customers. Figure A9 illustrates these two facts. Second, the spatial distribution of transactions is very similar across the two types of users. And this spatial distribution is consistent with the data reported in our Borla Taxi survey, and the data included in the 2021 Population Census. The map in Panel A of Figure 3 shows in yellow all registered transactions and in red the transactions that correspond to normal usage. The two display a remarkably similar and comprehensive spatial coverage, strengthening our case for the representativeness of the data registered by *normal-users*. Additionally, the registered transactions overlay well with the information on collection areas we gather in the survey. The same map displays in blue the localities where collectors in the survey report collecting waste in, with darker shades of blue indicating higher collector density. The transactions data cover almost all the localities identified in the survey, and its density coincides reasonably well with that derived from the information in the survey. Finally, the 2021 Population Census allows us for an additional cross-validation of the transactions data. In Panel B, for the main city-area, we display the share of households that relied on Borla Taxi collection in 2021. The higher density of transactions (normal-usage only) corresponds clearly with areas with higher shares of Borla Taxi/tricycle collection.[19]

Our final sample of geolocated transactions strengthens our analysis in four ways. First, it provides an accurate measure of collection prices across neighbourhoods in the GAMA, a key equilibrium outcome that our model ought to generate. Second, it helps us validate the information on collection areas reported in the survey. Third, it informs our understanding of the downstream and upstream structure of the market, as we describe in Section 4. And fourth, it allows us to estimate the costs of searching and filling up the tricycle, as explained in Section 5.2.2.

[19]The East of the city seems to be an exception. It is possible that a small number of collectors serve the high shares of households using these services. Alternatively, the closure of the Teshie transfer station has changed collection flows. At the time of our survey, the Teshie transfer station, located in this area, was closed. Anecdotally, collectors at the Adjie Kojo transfer station up north reported that they used to dispose of at Teshie transfer station when it was open. If disposal, and possibly collection flows have diverted further north, this may explain the difference between the transactions and the census data.

Figure 3: Transactions against survey and census data



Notes: The map in Panel A includes the location of transactions by those classified as *normal users* (small red dots), and of all transactions (small yellow dots). The map also indicates, as the colour of each locality polygon, the number of collectors in the survey that report collecting in that locality. Light blue indicates numbers lower than 10, dark blue numbers higher than 40 collectors. The total area represented in white corresponds to the GAMA. The map in Panel B includes the location of transactions by those classified as *normal users* (small red dots), as in Panel A. It also includes information on the share of households in the 2021 Population and Housing Census that report using Borla Taxis/Tricycles as their main solid waste disposal method. The data is at the locality level for the area that forms the city of Accra (within the GAMA). The map employs a colour gradient from light yellow (0% coverage) to dark blue (100% coverage). In Panel A, the area corresponding to the city of Accra is indicated using a thicker black boundary.

4 Descriptive facts

We present four facts that motivate our model and experimental exercises. These stylised facts document the structure of the collection and disposal markets as well as the trade-offs faced by households and collectors when choosing disposal options or collection areas and final disposal sites, respectively.

Fact 1 – *Access to formal collection trucks is highly restricted, while Borla Taxis serve most areas in the city. Borla Taxis charge lower prices and provide collection at a higher frequency. Households predominantly choose Borla Taxi services.*

Access: Only 29% of households in our sample report that formal truck collectors operate in their area. Figure A10 shows in white the survey enumeration areas with no access to formal trucks.[20] These tend to be further from main roads, and notably within the city slums and other areas with high levels of housing poverty (see Figure A2). Consistently, in our sample, those that report availability of truck collection in their area tend to also report higher incomes (Figure A11). Panel D in Figure 1, which shows formal collection shares at the locality level in 2021, is also consistent with this variation in access to licensed collection services. In contrast to this, only 9.8% of households report that Borla Taxis do not collect in their area, with access being less dependent on income (Figure A11). Our collector survey and transaction data confirm that collectors serve most of the metropolitan area, as illustrated earlier in Figure 3.

Choices and attributes: Among the households that have access to formal collection, 32% use the service. Conversely, 92% of households use Borla Taxi services if they are available in their area. In Figure A12 we present the raw numbers, which illustrate both differences in access and household choices. To explain these choices, we gathered information on the attribute values of all disposal options available to households. Table 1 summarises this information. Average weekly payment to Borla Taxis is 17 GHS. For formal collection, the arranged fees amount to 23.8 GHS a week on average. Borla Taxis collect waste much more frequently. 99% of households in the whole sample (users and non users) report them collecting waste at least once a week, with a large majority collecting every day. In contrast, 62% report that formal trucks collect at least once a week. Beyond door-to-door collection, only 16% of households report having access to a communal container in their area. On average they pay 6 GHS and have to walk 10 min to get to a container. 47% of those reporting access to a container in their area use it. Anecdotally, non-users mentioned long walking distances and the convenience of Borla Taxi services.

Fact 2 – *Despite the large expansion of Borla Taxi collection, neighbourhood waste pollution remains a challenge, contributing to the prevalence of diseases and increased flood risks during the rainy season.*

In our survey, around 80% of households report using Borla Taxis/Tricycle collection as their main waste disposal option. Figure 4 disaggregates this statistic at the EA level; Figure A13 shows the distribution of main waste disposal choices across localities using 2021 census data and our survey. Informal tricycle collection (dark blue) is the dominant method across most areas, typically representing 50-90% of disposal. However,

[20]The lines in blue we represent the network of highways, primary, and secondary roads.

Table 1: Household waste disposal options: availability and attributes

	Mean	SD	N
Availability of formal collection only	0.029	0.169	1813
Availability of formal and Borla Taxi collection	0.263	0.440	1813
Availability of Borla Taxi collection only	0.639	0.480	1813
Availability of waste container in the area	0.162	0.369	1813
No door-to-door collection available	0.069	0.253	1813
Use formal waste collection service	0.323	0.468	529
Use Borla Taxi collection service	0.922	0.268	1635
Use communal container	0.466	0.500	294
Borla Taxi weekly payment	16.993	29.559	1444
Formal collection weekly payment	23.765	35.356	118
Formal collection $\geq$ once week	0.625	0.485	456
Borla Taxi collection $\geq$ once week	0.987	0.114	1601
Disposal fee at container	6.017	4.083	177
Walking time to container (minutes)	9.976	6.295	293

Notes: The underlying data is from the household survey. There are 1813 survey participants across 150 EAs. All variables are reported based on knowledge about availability and attributes in the neighbourhood except weekly prices, which are reported for users of the service. We report, in three columns, the mean, standard deviation, and number of observations for each variable.

there is substantial variation across localities –some areas show nearly complete reliance on informal collection, while in others, options like formal collection (light blue), containers (yellow), and burning/dumping (red) gain importance. Burning and dumping also emerge as the secondary disposal choice for several households across our survey EAs. These numbers are likely and underestimate of the amount of local waste pollution (i.e. household burning and dumping). Despite the relatively low expressed choices, 40% of people expressed seeing others burning waste in their neighbourhood, and 24% have seen others dumping waste in gutters or drains. In Appendix A.3.1, we provide details on a small randomised response exercise we conducted with households, designed to reduce social desirability bias or non-response for sensitive questions like waste dumping or burning. Our objective was to obtain a better measure of the underlying probability of burning/dumping in the city. The results however reflect that burning and particularly dumping are potentially very stigmatised behaviours and hence obtaining accurate estimates of their prevalence via survey responses is challenging. In Section 8.2, we will turn instead to model-implied shares of burning/dumping in Accra, based on our demand estimates and measured values of the attributes of waste disposal options.

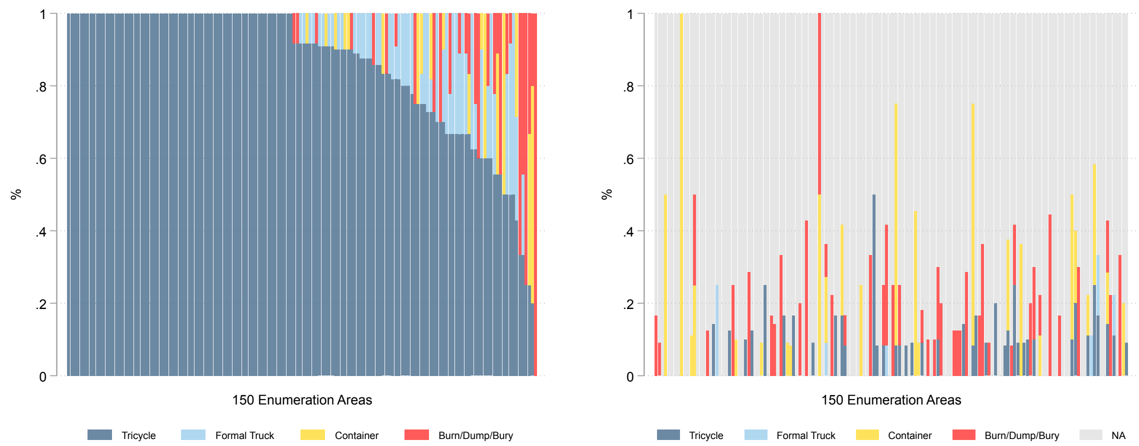
Our objective measures of waste pollution however allow us to assess the extent to which there is incomplete collection in the current collection market equilibrium and what are its welfare consequences. Table 2, provides suggestive evidence on the effect of local waste pollution on health outcomes and the incidence of flooding. We find a consistently positive and statistically significant association between trash accumulation and adverse outcomes. Specifically, a 1% increase in the count of trash in gutters/drains is associated with a 0.075 percentage point increase in the share reporting flooding, 0.082 in malaria, 0.024 in diarrhoea, 0.018 in vomiting, 0.041 in coughing, and 0.027 in skin problems, with all coefficients significant at the 5% or 10% level. Regressions include controls for door-to-door collection access, district fixed effects, and altitude, which is negatively associated with flooding.

Fact 3 – *The Borla Taxi collection market is competitive and clears by noon. Search time between two transactions is constant throughout the day and across neighbourhoods.*

We turn to our high-frequency data to document how the waste collection market operates over the course of a day. Panel A in Figure 5, shows that most collectors search and match with customers between 6am and 10am (red solid line). This is consistent with the fact that 97% of households reported having their waste collected by 10 am. During

Figure 4: Household collection/disposal choices (main and secondary)

(a) Survey Main Choice (EA) | (b) Survey Secondary Choice (EA)



Notes: Panel A shows survey responses to the question on main waste disposal option. There is a total of 1813 households participating in the survey. We calculate shares at the enumeration area level. The figure plots the shares for each disposal option stacked, at the EA level. EAs have been sorted based on the share of Tricycle/Borla Taxi collection share. In dark blue, we present tricycle collection shares, in light blue, formal truck collection shares, in yellow, the share of households using containers as their main option, and in red the share using burning/dumping/burying trash. In Panel B we represent the answers to the second waste disposal option used occasionality by households. The order and colour schemes are preserved. When households in an EA report not using a second waste disposal option occasionally we leave it as NA in a light gray colour.

this period, average transaction prices (in blue) remain stable, with narrow confidence intervals. Later in the day, the number of collectors and transactions drop sharply, and prices and their dispersion rise. This pattern suggests that the market is competitive during the main operating hours across and within neighbourhoods, with collectors offering similar prices.[21] Panel B in Figure 5 confirms the timing of market clearing we see in the transactions data. It shows collector responses to the time use module in the survey. Collectors commute from 4:00 to 6:00 am (yellow dotted line), search and collect between 6:00 and 10:00 am (red solid line), and then start their commute to disposal (gray dotted line) and home locations (black dotted line).

Panel C presents the time between transactions. After 10 am searching becomes harder, consistent with the observed higher and more volatile prices observed in Panel A, which adjust to a lower supply and higher search costs. During the market concentration

[21] The increase in prices at later hours likely reflects reduced supply and thus greater pricing power for those still operating.

Table 2: **Waste pollution damages**

	(1) Flooding	(2) Malaria	(3) Diarrhea	(4) Vomiting	(5) Coughing	(6) Skin problems
Log (trash count)	0.0749**	0.0819**	0.0238**	0.0183**	0.0412*	0.0267*
	(0.032)	(0.033)	(0.010)	(0.008)	(0.021)	(0.016)
Borla Taxis access	-0.0957	-0.0233	0.0127	0.0347	-0.0483	0.0488
	(0.119)	(0.074)	(0.023)	(0.035)	(0.070)	(0.040)
Formal collection access	-0.0427	-0.0452	0.0177	0.0304	-0.0886*	0.0235
	(0.076)	(0.066)	(0.026)	(0.032)	(0.053)	(0.037)
Altitude	-0.00181***					
	(0.001)					
Observations	143	143	143	143	143	143

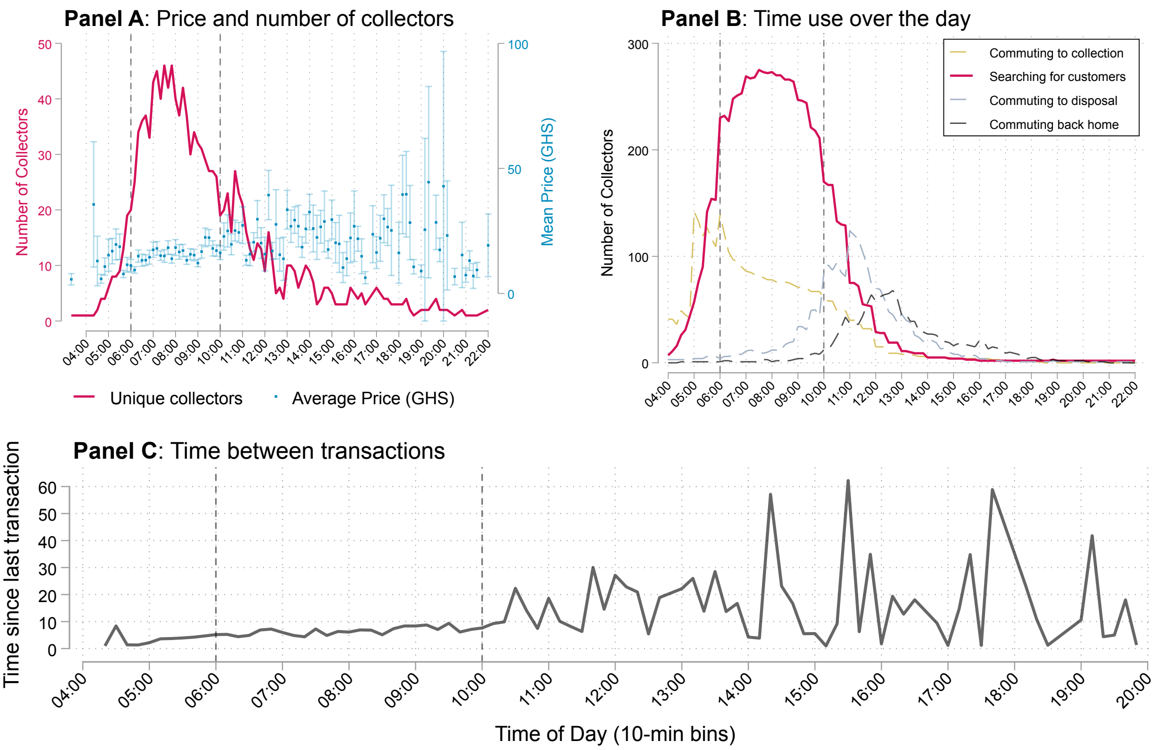
Notes: * 0.1 ** 0.05 *** 0.01. To calculate trash count averages at the EA level, we first average at the household level based on 6000 images of gutters and drains near surveyed households. We then compute EA-level averages. We include as controls population density, a housing poverty index constructed using census data, the share of pictures that are of drains (instead of gutters), and altitude when using flooding as the outcome variable. For the rest of the outcomes, the coefficient for altitude is very small and not significant. Regressions include district fixed effects.

period (6-10 am), the average time observed between transactions is low, and increasing very slowly until 10 am. This implies that the rate at which collectors load their tricycle is fairly constant on average during the period they are active in the market (i.e. before commuting to dispose of the collected waste). At every 10 min bin, collectors are making transactions 5-15 min after the last one. Furthermore, Figure 6 shows little dispersion in the times reported in Panel C, pointing towards similar loading rates across areas. The three panels are consistent in showing a competitive collector market with constant with no significant search frictions that clears before noon.

Fact 4 – *Disposal sites appear to have distinct catchment areas, likely due to the substantial travel costs faced by collectors.*

Our count data indicates that disposal is concentrated at dumpsites. The four informal dumpsites together account for approximately 75% of all disposal activity, with two of then dominating the market (Panel B in Figure 7 shows the market shares for disposal sites in the GAMA –the Mc Carthy and Agbogbloshie Sikkens dumpsites in dark and light red cover more than half of the market). Panel A of the same Figure shows the locations of disposal sites (large, coloured circles). The sites are spread across different parts of the city, with market shares varying from around 8% to nearly 30%. In Panel A we also

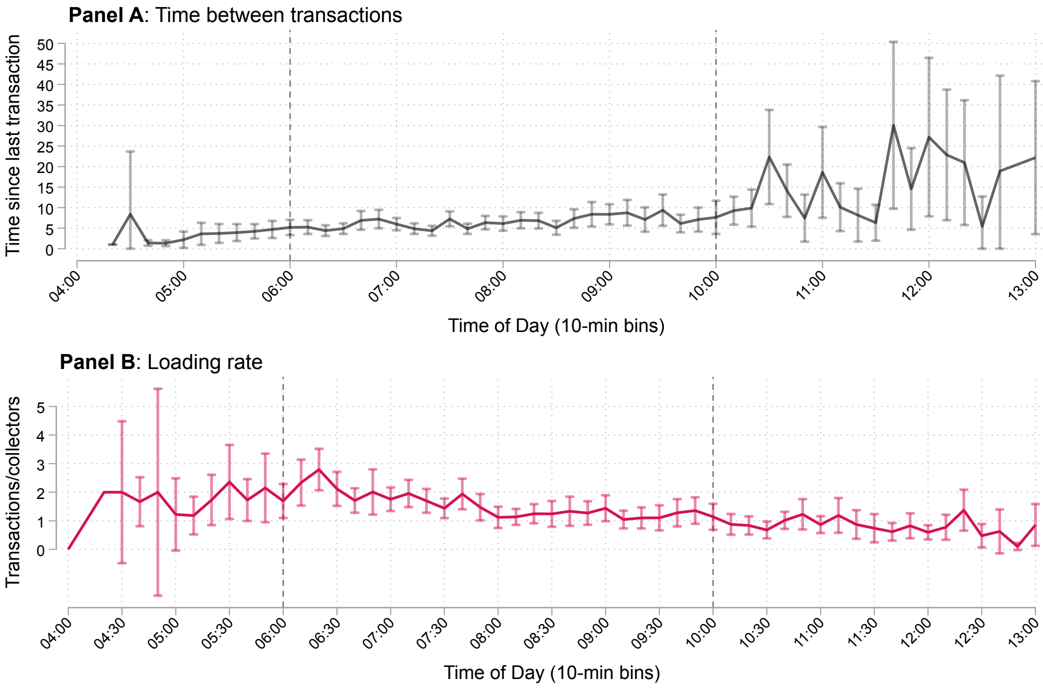
Figure 5: Collection market



Notes: Panel A shows in red the number of collectors transacting in each 10-min bin, according to the transaction data collected through our smartphone app. The left y-axis in red indicates the numbers. In blue, we represent the average price of the transactions registered in the app at every 10-min time bin. We include 95% confidence intervals also in blue. In Panel B we represent the number of collectors engaging in each of four activities at each point in time. In red the number of collectors searching for customers; in a dotted yellow line the number commuting to collection areas, in a dotted gray line the number commuting to disposal sites, and in a black dotted line the number commuting back home. The underlying data comes from our survey with 400 collectors. We asked start and end time for each of these activities, and construct the figure based on these data. In Panel C we add the time between transactions registered by active (i.e. transacting) collectors in the smartphone app. We calculate average time since last transaction for the transactions registered in each 10-min time bin.

represent the location of collection transactions (small dots), which take the colour of the disposal site where the collected waste was disposed. Notably, most household waste is collected relatively close to the site where it is ultimately disposed, forming catchment areas around disposal sites. This is particularly the case for transfer stations (blue, light green, and dark green), where spatial differentiation is clearest. For the cheaper dump-sites, collectors can afford to travel longer distances, with some waste being transported across the city –Panel A reveals several cases where waste collected in eastern parts is taken to Glefe (yellow) or McCarthy (dark red), both located in the west. Figures A14

Figure 6: Loading rate

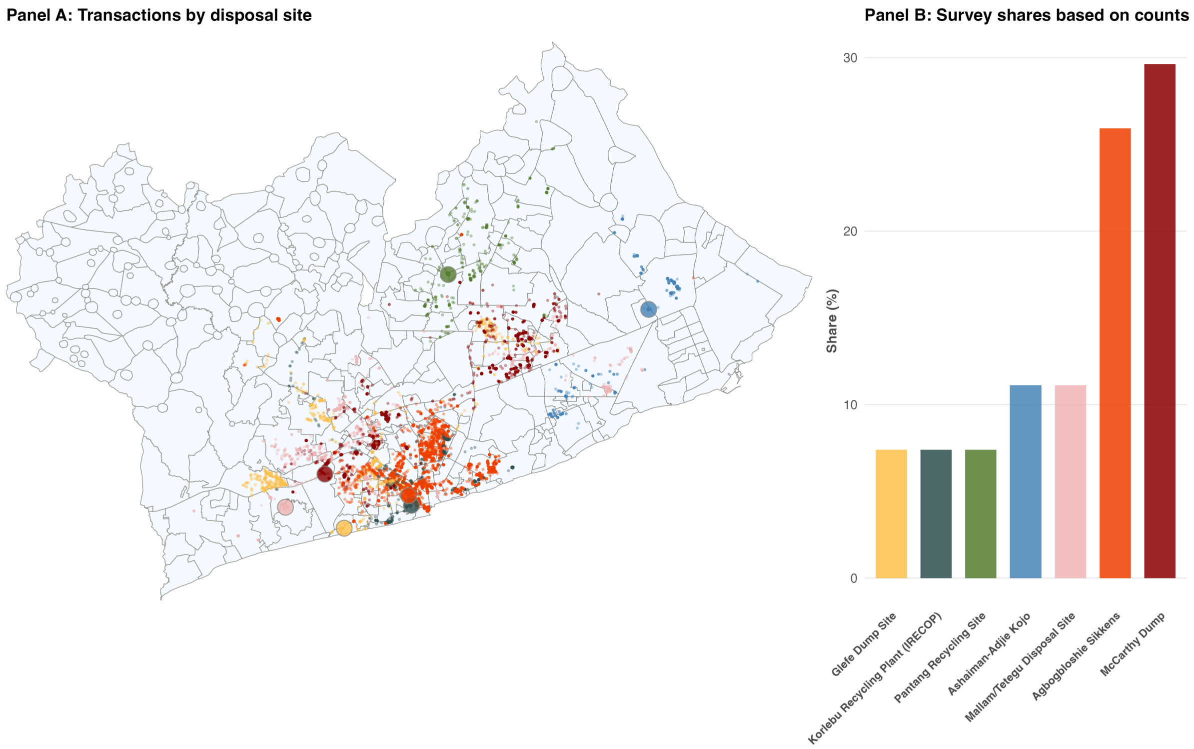


Notes: The figure shows the time between transactions registered by collectors in the smartphone app. We calculate average time since last transaction for the transactions registered in each 10-min time bin. 95% confidence intervals are displayed in gray. We calculate loading rates as the number of transactions over the number of searching collectors (in red), first at the locality level, and then averaged at the time-bin level. 95% confidence intervals are displayed in red.

and A15, show, using survey data on collection areas, a very similar spatial differentiation pattern. The spatial dispersion of sites and the formation of localised catchment areas points to local market power, whereby commuting costs limit the extent to which collectors can arbitrage across disposal sites.

These patterns raise questions about how collectors choose disposal sites and how operators establish disposal fees in competition with each other. Table 3 provides descriptives on the factors behind this choice. Informal sites tend to charge lower fees, involve shorter waiting times, and are often closer to collectors' homes. However, they offer fewer opportunities to sell recyclables. Collection outcomes such as prices, number of customers, revenue, measured with the survey and app transaction data, as well as collectors' overall profits do not differ significantly for those disposing at formal and informal sites, suggesting that collectors are broadly profit-maximising and that potential

Figure 7: Collection transactions by disposal site



Notes: Panel A shows the geolocation of collection transactions registered in the smartphone app as small dots. The colour of each dot corresponds to the disposal site chosen by the collector registering the transaction. We observe the disposal site choice in the survey. The bigger circles display the location of disposal sites and are coloured using the same palette. We include a total of 15425 transactions. These are the transactions for which the disposal site is clearly identified in the survey, excluding Kokomlemle Mini Transfer station and other sites mentioned in small number by collectors. Panel B shows the disposal shares for each site as measured in the sites inventory exercise, where we manually counted the flow of collectors arriving to each site on a given day. Relative to the app data, Agbogbloshie Sikkens in under-represented and McCarthy is over represented in the count data. The rest of the patterns remain very similar.

gains are arbitraged away, with price differences compensating for commuting costs (Table A2).

5 A Model of Waste Collection and Disposal

Our model consists of three types of agents. First, households that choose between waste disposal options: formal trucks, Borla Taxis, communal containers, and illegal disposal via burning or dumping. Their choice is governed by the characteristics of each option, namely price, frequency of access, time involved, and the need to sort. Second,

Table 3: Disposal and recycling

	(1) Unofficial	(2) Formal	(3) Δ	(4) Ha: $\Delta < 0$	(5) Ha: $\Delta \neq 0$	(6) Ha: $\Delta > 0$
Disposal						
Payment to dispose (each visit)	43.06	123.86	-80.81***	0.000	0.000	1.000
	(N= 283)	(N= 96)				
Total time at disposal site	25.18	139.54	-114.35***	0.000	0.000	1.000
	(N= 287)	(N= 97)				
Total time commuting back home (min)	29.91	43.75	-13.84***	0.000	0.000	1.000
	(N= 287)	(N= 97)				
Recycling						
Sorts from collected waste	0.55	0.67	-0.12**	0.014	0.028	0.986
	(N= 286)	(N= 97)				
Sells recyclables	0.56	0.69	-0.13**	0.010	0.021	0.990
	(N= 287)	(N= 97)				
Total time recycling (min)	30.23	27.11	3.12	0.782	0.437	0.218
	(N= 283)	(N= 97)				
Daily recycling revenue	23.62	44.72	-21.10***	0.000	0.000	1.000
	(N= 287)	(N= 97)				
Selling price for a small bag of recyclables	21.65	51.62	-29.98***	0.003	0.006	0.997
	(N= 68)	(N= 48)				
Selling price for a big bag of recyclables	85.61	373.23	-287.61***	0.000	0.000	1.000
	(N= 98)	(N= 62)				
Daily average % of household sorted waste (app)	60.62	52.02	8.60	0.809	0.382	0.191
	(N= 69)	(N= 23)				

Notes: The table reports mean outcomes for waste collectors at Unofficial (col. (1)) and Formal (col. (2)) disposal sites. Δ (col. (3)) is the difference in means for collectors disposing at unofficial and formal sites. Sample sizes (N) for each group appear in parentheses below the means. Stars on Δ denote significance from two-sided Welch t-tests: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Columns (4)–(6) give one-sided p-values for the hypotheses $H_a: \Delta < 0$, $H_a: \Delta \neq 0$, and $H_a: \Delta > 0$, respectively. Formal sites are the Ashaiman-Adjie Kojo transfer station, the Pantang transfer station, the Korlebu Recycling Plant (IRECOP), the Kotoku Trash Site/Amasaman, and the Kokomlemle Mini Transfer Station. Unofficial or illegal sites are the Mallam/Tetegu dumpsite, the Glefe dumpsite, the Agbogbloshie Sikkens dumpsite, and the McCarthy dumpsite. All variables in the table are winsorised (1st and 99th percentiles).

informal waste collectors that choose collection-disposal routes by trading off commuting distances, time spent at disposal sites, and collection profits net of disposal costs. This route choice involves selecting an area for collection and a site (transfer station or dumpsite) for disposal. We also model collectors' choice of number of customers based on a costly search process. Third, disposal sites exercising market power locally, internalising their demand, and playing a pricing game in setting disposal fees. The actions of these three types of agents together determine the amount of uncontrolled waste in the city (i.e. waste not collected or collected but disposed of at illegal dumpsites), which translates into pollution and its associated damages.

5.1 Households

When deciding how to dispose of their waste, households choose between formal collection (F), Borla Taxis (BT), communal containers (C), or burning and dumping (BD). The set of available options may vary across neighbourhoods, and household i living in neighbourhood $a \in \mathcal{A}$ chooses the disposal option $o \in \mathcal{O}_a$ that maximises utility

$$U_{iao} = \kappa_o + \kappa_1 \, p_{ao} + \kappa_2 \, f_{ao} + \kappa_3 \, w_{ao} + \kappa_4 \, s_{ao} + \mu_H \, \varepsilon_{iao} \tag{1}$$

Each disposal option is characterised by its price p_{ao}, collection frequency f_{ao}, waiting time w_{ao}, and waste sorting requirement s_{ao}. The selection of these attributes was informed by our conversations with households and Borla Taxis during focus groups. The taste parameters $\boldsymbol{\kappa}$ govern how each attribute affects household's utility. We allow for level-differences across waste disposal options κ_o to enter the deterministic component of utility. All things equal, these capture differences in preferences across disposal options, which may be driven by social norms, or environmental and health considerations, perhaps even lead to partial internalisation of damages.

We assume the idiosyncratic utility component ε_{iao} to be iid and to follow a Gumbel distribution. The logit choice probabilities for each option o in area a are

$$\pi_{ao} = \frac{\exp\big(\kappa_o + \kappa_1 \, p_{ao} + \kappa_2 \, f_{ao} + \kappa_3 \, w_{ao} + \kappa_4 \, s_{ao}\big)^{\frac{1}{\mu_H}}}{\sum_{h \in \mathcal{O}_a} \exp\big(\kappa_h + \kappa_1 \, p_{ah} + \kappa_2 \, f_{ah} + \kappa_3 \, w_{ah} + \kappa_4 \, s_{ah}\big)^{\frac{1}{\mu_H}}} \tag{2}$$

This modelling choice further implies that the expected utility of a household living in area a can be expressed as

$$\mathcal{U}_a^H = \mu_H \,\Gamma + \sum_{o \in \mathcal{O}_a} \pi_{ao} \left(\kappa_o + \kappa_1 \, p_{ao} + \kappa_2 \, f_{ao} + \kappa_3 \, w_{ao} + \kappa_4 \, s_{ao} - \mu_H \ln\left(\pi_{ao}\right)\right) \tag{3}$$

where Γ is the Euler–Mascheroni constant (see Appendix A.7 for derivations).

Neighbourhood pollution: We can calculate the share of waste that is burned or dumped indiscriminately for equilibrium attribute levels $\pi_{a,BD}$ using (2). We assume that waste uncollected at source leads to environmental and health damages, which take the following form

$$E^{\mathcal{A}} \equiv \iota \sum_{a \in \mathcal{A}} N_a^H \pi_{a,BD} \tag{4}$$

where the parameter ι translates waste pollution into a monetary welfare metric and N_a^H is the number of households living in location a.

We assume that only prices are subject to endogenous adjustments and assume that the remaining attributes of the disposal options (frequency $\mathbf{F}$ and time $\mathbf{T}$) are exogenously determined. We fix them at the levels observed in our household survey. Note that in (1), we also abstract from social interactions in waste disposal choices.

5.2 Borla Taxis

5.2.1 Collection-disposal route choice

An informal waste collector living in home location $h \in \mathcal{H} \subseteq \mathcal{A}$ chooses a collection-disposal pair aj from the full set of combinations of residential neighbourhoods and disposal sites $\mathcal{C} = \{(a, j) : \ a \in \mathcal{A}, \ j \in \mathcal{J}^F \cup \mathcal{J}^I\}$, where $\mathcal{J}^F$ is the set of waste transfer stations available and $\mathcal{J}^I$ is the set of unregulated dumpsites. The home locations of collectors are exogenously determined and the number of waste collectors living in each location denoted as N_h^{BT}.[22] The utility of collector i living in h, collecting in a, and disposing at site j is

$$U_{ihaj} \;=\; \nu_1 \underbrace{\Pi_{aj}}_{\substack{\text{route}\\ \text{profit}}} - \nu_2 \underbrace{\tau_{hajh}}_{\substack{\text{travel}\\ \text{distance}}} - \nu_3 \underbrace{T_j}_{\substack{\text{wait}\\ \text{time}}} + \mu_C \, \varepsilon_{iaj} \tag{5}$$

[22]In Appendix A.7 we present a model extension where the home locations and total number of collectors in the city are endogenously determined.

Collectors need to incur commuting costs determined by the total route distance τ_{hajh}; from home h to area a, to site j, and back home. If they choose to dispose at site j they need to wait T_j time units at the site. Waiting time is not a feature of congestion but of the type of site (the technology and procedures at transfer stations involve longer wait times).

Collectors take the collection price in each area $p_{a,BT}$, disposal fee p_j^d they need to pay, and per-unit recycling revenue r_j at site j as given. Their route profits take a simple form

$$\Pi_{aj} = (p_a - p_j^d + r_j)\, q_{aj} \; - C(q_{aj}) \tag{6}$$

where q_{aj} denotes the number of customers and $C(q_{aj})$ the search/tricycle fill-up costs. $C(q_{aj})$, and hence the choice of optimal number of customers q_{aj}^* are determined by the matching process through which collectors find customers, which we describe in Section 5.2.2 below.

We allow for idiosyncratic collector-route shocks ε_{iaj}, which are iid and follow a Gumbel distribution. The route (pair $\{a, j\}$) choice probabilities for collectors living in area h are

$$\phi_{haj} = \frac{\exp\left(\nu_1 \Pi_{aj} + \nu_2 \tau_{hajh} + \nu_3 T_j\right)^{\frac{1}{\mu_C}}}{\sum_{(b,k)\in\mathcal{C}} \exp\left(\nu_1 \Pi_{bk} + \nu_2 \tau_{hbkh} + \nu_3 T_k\right)^{\frac{1}{\mu_C}}} \tag{7}$$

Similarly to households, the expected utility of a collector with home location h can be expressed as

$$\mathcal{U}_h^{BT} = \mu_C \,\Gamma + \sum_{(b,k)\in\mathcal{C}} \phi_{hbk} \left(\nu_1 \Pi_{bk} + \nu_2 \tau_{hbkh} + \nu_3 T_k - \mu_C \ln\left(\phi_{hbk}\right)\right) \tag{8}$$

5.2.2 Search costs and quantity choice

In each area a collectors incur in costly search, traveling to find households looking for their waste to be collected. The time it takes a collector to find a customer is governed by the loading rate, which is defined as the average number of transactions m_{at} per active collector c_{at} at each point in time

$$\vartheta_{at} = \frac{1}{T} \frac{m_{at}}{c_{at}} \tag{9}$$

where T is the duration of the time interval. It follows that the average time between transactions is given by

$$\Delta_{at} = \vartheta_{at}^{-1} \tag{10}$$

As discussed in Section 4, the transactions per active collector and the time between transitions do not vary substantially throughout the main operating hours of Borla Taxis and do not exhibit considerable spatial heterogeneity. In particular, Figure 6 suggest that $\frac{m_{at}}{c_{at}} \approx 1.5$ and $\Delta_{at} \approx 7$ during all 10 minute intervals ($T = 10$) of the main operating hours. These numbers are consistent with (9) and (10) suggesting that $\vartheta_{at} \approx 0.15$ for all time periods and locations. In the following we threat the loading rate as physical parameter $\vartheta_{at} = \vartheta = 0.15$ reflecting the speed at which a waste collector can load the waste, handle the transaction, and drive to the next building. The evidence in Figure 6 suggests this process to take about 7 minutes, which we believe to be a reasonable value. While the descriptive evidence in Section 4 does not provide definitive evidence of the loading rate being exogenous, it is suggestive and consistent with this assumption.

Given a constant loading rate ϑ, collecting waste from q customers requires a total time $T(q) = \frac{q}{\vartheta}$. We further assume that time increases costs in a non-convex way, as fuel costs per minute, exhaustion, and opportunity costs increase as the tricycle fills up, taking the following quadratic functional form

$$C(q) = \frac{\theta}{2} (T(q))^2 = \frac{\delta}{2} \left(\frac{q}{\vartheta}\right)^2 \tag{11}$$

This functional form ensures unique optima. The parameter θ translates search time into monetary units. Collectors choose the number of customers maximising collection profits net of disposal fees. Despite the physical limits of the tricycle, we abstract from a rigid capacity constraint.[23] Collectors report rarely reaching the true physical maximum of the tricycle. They also often increase the height of the tricycle using wooden boards they attach to its sides to fit more bags. The solution to the FOC for route profits is

$$q^*_{aj} = \frac{\left(p_a - p^d_j + r_j\right) \vartheta^2}{\delta} \tag{12}$$

The optimal profits conditional on choosing collection area a and disposal site j are therefore $\Pi^*_{aj} = \frac{\delta}{2} \left(\frac{q^*_{aj}}{\vartheta}\right)^2$.

Lastly, we model the search process to be costly for collectors, but not subject to any inefficiencies leading to excess demand or supply. Therefore collection markets will clear

$$\pi_{a,BT} N_a = \sum_k \sum_m \phi_{kam} N_k q_{am} \tag{13}$$

[23]Indeed, we do not observe any bunching in the distribution for the number of customers that would suggest collectors reaching a capacity constraint.

Whereby the above expression follows from (2) and (7).

5.3 Formal trucks and containers

We assume that the availability of formal collection trucks $\mathcal{F}^{\mathcal{A}}$ and communal containers $\mathcal{C}^{\mathcal{A}}$ in neighbourhood a is exogenously determined and calibrate it using geolocated 2021 census data. As these two waste collection options are provided in cooperation with, or directly by, local authorities, we abstract from any inefficiencies in these two sectors. We model the pricing to follow a Pigouvian rational, setting the price equal to the marginal provision cost $mc_{a,o}$ minus the averted environmental damages ι

$$p_{a,o} = mc_{a,o} - s\,, \qquad \text{for} \quad o \in \{F, C\} \tag{14}$$

by imposing the per unit subsidy of $s = \iota$. In the quantitative analysis we calibrate these prices to the values reported by households in our survey data. Providers of formal collection and communal container services receive profits

$$\Pi_a^o = (p_{a,o} - mc_{a,o})\, Q_{a,o} - F_{a,o}\,, \qquad \text{for} \quad o \in \{F, C\} \tag{15}$$

where $F_{a,o}$ are the fixed costs of providing the service in location a. We further assume that the government owns these firms and can provide any quantity $Q_{a,o}$ even if the providers do not break even.

5.4 Disposal sites

We have documented that disposal sites seem to have considerable market power driven by the commuting costs collectors face. We model disposal sites as behaving strategically, internalising the effect of their pricing choices on collector flows, following similar applications (Nevo 2001). Profit-maximising sites with spatially differentiated access to demand compete for collector flows in prices à la Nash–Bertrand, given the parameters governing collectors' route choices, their marginal costs, and the set of disposal sites in the city. Let $\mathcal{J}$ be the set of active disposal sites and $\mathcal{S}$ the set of candidate sites as $\mathcal{S}$. Each site operator $j \in \mathcal{J}$ selects a price p_j^d to maximise profits

$$\Pi_j^D = (p_j^d - \zeta_j) \cdot \lambda_j(\mathbf{p}^d) - F_j \tag{16}$$

where ζ_j is the site-specific marginal cost of processing waste. In the case of transfer stations this involves compacting it and transporting it to landfills, ensuring no contamination throughout the process. In the case of dumpsites, this involves burning it or allocating it a space in the available land. $\lambda_j(\mathbf{p}^d)$ is the total inflow of waste arriving to site j via collectors, defined as a function of optimal route choice shares and quantities collected

$$\lambda_j = \sum_h \sum_a N_h^{BT} \phi_{haj} q_{aj} \tag{17}$$

This flow of collectors depends on the full vector of disposal prices $\mathbf{p}^d = (p_k^d)_{k \in \mathcal{J}}$, which determine collector route choices $\{a, j\}$ according to the specification of route utility in (5).

Under the existence of a pure-strategy Bertrand-Nash equilibrium in prices, and strictly positive prices supporting it, the disposal price p_j^d for each site j must satisfy the first-order condition

$$\lambda_j(\mathbf{p}^d) + (p_j^d - \zeta_j)\,\frac{\partial \lambda_j(\mathbf{p}^d)}{\partial p_j^d} = 0 \tag{18}$$

Fixed costs discipline which dumpsites remain in the market. In our counterfactuals we will allow exit of unprofitable dumpsites, implying that $\mathcal{J} \subseteq \mathcal{S}$. We bound fixed costs based on equilibrium prices, market shares, and our expression for sites' profits. Transfer stations may exist at negative profits, as they are supported by the government. We do not model disposal sites' entry, as entry is very restricted. We assume that dumpsites are currently in the areas where its feasible for them to operate (near cleared land and water bodies, as documented in Figure A16).[24]

Dumpsite pollution: At dumpsites there are no measures in place to control soil and water pollution. All waste that cannot be recycled is burned. And waste is left standing for long periods of time leading to air pollution and GHG emissions. The negative environmental and health consequences arising from open dumps have been documented in public health and environmental science. We model aggregate damages arising from disposal at dumpsites as follows

$$E^{\mathcal{I}} \equiv \sum_{j \in \mathcal{J}} \varrho_j \lambda_j \tag{19}$$

where ϱ_j translates tons of waste in open dumps into a monetary welfare cost. As at transfer stations waste is treated properly, no pollution arises there implying that $\varrho_j = 0$ for $j \in \mathcal{J}^{\mathcal{F}}$. We calibrate ϱ_j at dumpsites using estimates from the literature on the social costs of open dumpsites in developing countries (Table 6 provides details)

[24] Agbogbloshie Sikkens is located close to one of city's biggest slums and by the Korle Lagoon. The rest of the dumpsites are located in low-density areas, by large surfaces of free land near water bodies.

6 Equilibrium

We now characterize the general equilibrium of the model. Informal waste collection and disposal are determined by the parameters $\{\boldsymbol{\kappa}, \mu_H, \boldsymbol{\nu}, \mu_C, \vartheta, \delta, \iota, \varrho\}$, model geography $\left\{\mathcal{A}, \mathcal{S}, \boldsymbol{\tau}, \boldsymbol{\xi}, \mathbf{N^H}, \mathbf{N_h^{BT}}\right\}$, availability of formal collection and communal containers $\left\{\mathcal{F}^{\mathcal{A}}, \mathcal{C}^{\mathcal{A}}\right\}$, exogenous collection option attributes $\{\mathbf{P}, \mathbf{F}, \mathbf{T}\}$, and characteristics of disposal sites $\left\{\boldsymbol{\zeta}, \mathbf{T^d}, \mathbf{R^d}\right\}$.

Given these primitives, the endogenous variables $\left\{\boldsymbol{\pi}, \boldsymbol{\phi}, \mathbf{q}, \mathcal{J}, \mathbf{p_{BT}}, \mathbf{p^d}\right\}$ adjust such that household demand is given by (2), Borla Taxi's route choices and collection quantity follow (7) and (12), collection markets clear (13), disposal sites set their profit maximising prices (18), and only profitable disposal sites remain in the market.

7 Welfare and social optimum

We define welfare Ω as the sum of the expected utility of households (3) and collectors (8) in monetary terms, together with profits of the disposal sites (16) as well as of formal collection and communal container providers (15), net of neighbourhood waste pollution (4) and dumpsite pollution (19) to obtain

$$\Omega \equiv \sum_a N_a^H \frac{\mathcal{U}_a^H}{|\kappa_1|} + \sum_h N_h^{BT} \frac{\mathcal{U}_h^{BT}}{\nu_1} + \sum_j \Pi_j^D + \sum_a \Pi_a^F + \sum_a \Pi_a^C - E^{\mathcal{A}} - E^{\mathcal{I}} \tag{20}$$

The above is a monetary welfare metric. Dividing $\mathcal{U}_a^H$ by $|\kappa_1|$ and $\mathcal{U}_h^{BT}$ by ν_1 yields the monetary equivalent of the expected utility of households and collectors, respectively, while profits and environmental damages are already defined in monetary units. Unlike private actors, the social planner accounts for the two types of market failures. First, the planner internalises the environmental damages associated with uncollected or improperly disposed waste. Second, the planner corrects the distortions arising from market power of disposal sites.

The social planner's problem can be decomposed into two steps. In the first step, the planner chooses the allocations $\left\{\tilde{\boldsymbol{\pi}}, \tilde{\boldsymbol{\phi}}, \tilde{\mathbf{q}}\right\}$ that maximise welfare for a given set of disposal sites $\mathcal{J}$, subject to collection and disposal market clearing, as well as all shares being non-negative and summing up to one at the relevant levels of aggregation. In the second step, the planner then chooses the set of active disposal sites $\tilde{\mathcal{J}}$ that maximises welfare Ω. We define $\tilde{\mathbf{p}} = \left\{\tilde{\mathbf{p}}_{BT}, \tilde{\mathbf{p}}_F, \tilde{\mathbf{p}}_C, \tilde{\mathbf{p}}^d\right\}$ as the set of prices that the planner needs to impose to decentralise the socially optimal allocations for a given set of disposal sites $\mathcal{J}$, that is to achieve that $\{\boldsymbol{\pi}(\tilde{\mathbf{p}}), \boldsymbol{\phi}(\tilde{\mathbf{p}}), \mathbf{q}(\tilde{\mathbf{p}})\} = \left\{\tilde{\boldsymbol{\pi}}, \tilde{\boldsymbol{\phi}}, \tilde{\mathbf{q}}\right\}$. A formal characterisation of the social planner's problem as well as all derivations are detailed in Appendix A.7.2. It follows that a simple Pigouvian policy implements the socially optimal allocations.

Proposition 1. *Given a set of active disposal sites $\mathcal{J}$, the social optimal allocations can be implemented by setting the disposal price at site j to*

$$\tilde{p}^d_j = \zeta_j + \varrho_j - \iota\,, \tag{21}$$

by setting the prices of formal collection and communal containers to

$$\tilde{p}_{a,o} = mc_{a,o} - \iota\,, \tag{22}$$

and the Borla Taxi prices $\tilde{\mathbf{p}}_{BT}$ being determined as the vector of prices ensuring collection market clearing (13). Whereby demand, route choices, and collection quantities are governed by (2), (7), and (12), respectively.

This result reveals that the planner corrects three aspects. First, monopolistic price setting at disposal sites is eliminated and prices are instead set to equal marginal costs ζ_j. Second, disposal prices at dumpsites incorporate the pollution damages ϱ_j they generate, thereby correcting waste flows and collection quantities. Third, the planner lowers the unit costs of all waste collection options that reduce neighbourhood waste pollution by the value of averted damages ι. Together, these adjustments address market failures arising from environmental externalities and the market power of disposal sites. We obtain the standard Pigouvian result that prices must equal marginal costs plus marginal environmental damages. For the formal collection and communal container options we had assumed that status quo pricing regime already follows this rationale (14), therefore no additional adjustments are required in those sectors. Expression (21) further highlights the trade-offs faced by the planner in regulating dumpsites. On the one hand, they are desirable because they contribute to reducing neighbourhood pollution; on the other hand, they generate pollution themselves and should therefore be costly to use.

Since both the Borla Taxi prices and the disposal price in the competitive equilibrium can only be obtained numerically, an analytical comparison with the prices that implement the socially optimal allocations is not feasible. We therefore conduct this comparison as part of our quantitative analysis in Section 9.1.

8 Estimation

8.1 Strategy

We divide the estimation of the structural parameters governing households', collectors', and sites' choices in four stages, circumventing endogeneity issues at each stage. We present our estimation strategy in this section and empirical details and results in Sections 8.2, 8.3, and 8.4.

We estimate the parameters $\boldsymbol{\kappa}$ that govern the demand of households for waste collection in (1) using three survey experiments. To estimate the price elasticity (κ_1), we run incentivised BDM and TIOLI demand elicitation exercises with 60% and 40% of the households in our sample, respectively. Incentive compatibility ensures that respondents' dominant strategy is to bid their true maximum willingness-to-pay. We estimate the remaining parameters in (1), determining the sensitivity of households' choices to the other attributes of waste disposal options using a stated preference survey experiment, where we randomly vary the values of disposal options' attributes. Due to the controlled nature of the experiment, we can estimate the parameters independently from the rest of the model.

Estimation of the matching elasticities governing the matching process that determines collector tricycle loading rates (Equation A.17) reduces to a simple linear IV regression. For this, we leverage our app transaction data and our survey, where we register collectors home locations, with which we construct an instrument for the number of active collectors over time and locations we observe in the app data.

We estimate the taste parameters $\boldsymbol{\nu}$ on collectors' discrete choice problem in two steps. We use experimental variation in the price of disposal at transfer stations to directly estimate collector disposal choice price elasticity (ν_1). We then use our treatment assignment as an instrument for route profits to jointly estimate the remaining taste parameters governing collectors' route choices in (5) via GMM. We assume that commuting distances and waiting time at disposal sites are exogenous. Based on our observations, waiting times are not determined by congestion at sites or limited capacity. Instead, they are a feature of sites' technology. At transfer stations processes take longer because tricycles' weight is measured at a loading platform, and waste is unloaded and compacted following environmental standards. At dumpsites, collectors wait briefly to pay, unload some recyclables, and find a space to dump their waste over existing piles of refuse.

The parameters estimated in the steps so far determine the flow of collectors (and total waste) to each site for given disposal prices. We use SMM to structurally recover the marginal costs for each active disposal site. We simulate sites' pricing game, recomputing collector flows until reaching Bertrand equilibrium in disposal pricing, and matching observed disposal prices and collector flow shares.

8.2 Survey experiments: demand for waste collection

We randomly allocated 60% of households in our sample to conduct an incentivised willingness-to-pay demand elicitation exercise following Becker et al. 1964 (BDM). The remaining 40% made an incentivised take-it-or-leave-it (TIOLI) choice and participate in a stated preference survey experiment. We now provide details and results for each of these exercises.

8.2.1 BDM

We used the BDM mechanism to estimate willingness to pay (WTP) for waste collection services. To create real incentives in both our BDM and TIOLI experiments we offered households to collect their waste and arranged it in collaboration with Borla Taxis or community members.[25] We asked household members to state their bid for having their waste collected at the end of the interview through the collection service we provide. Enumerators were instructed to bargain progressively until respondents stopped increasing their bid. Respondents drew a random price from a sealed envelope, containing uniformly distributed prices with varying support based on enumerators' assessments of the size of the waste bag. If the drawn price was lower or equal to the bid, the individual had to purchase our waste collection services at the drawn price and we collected their bag of waste. If the random price turned to be higher than the household's bid, we did not take the bag of trash. BDM is incentive compatible (i.e. individuals' dominant strategy is to bid their true maximum WTP for waste collection services) because the reported WTP does not affect the price paid. Only whether the individual gets their waste collected.

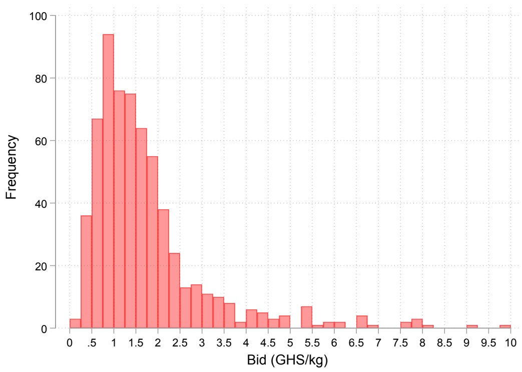
Unlike in many of its applications, in our BDM mechanism we are not measuring WTP for the same standard good across households. At the moment of the experiment,

[25]When this was not possible, winning respondents were given cash to pay for next day collection at the end of BDM exercise.

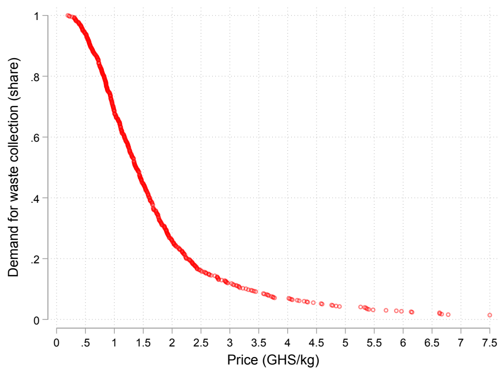
different households may have different quantities of waste accumulated and hence different WTP for our waste collection service. To adjust for differences in the quantity of available waste at the time of the survey, we weighted every bag of waste using identical scales (see Figure A18 for an example) and estimate willingness to pay in GHS/kg.[26] This allows us to obtain a consistent measure of WTP accounting for differences in the size of available waste.[27] We include the distribution of measured waste bags' weights in Figure A20. As expected, the randomisation of participation across demand elicitation mechanisms yields very similar distribution of waste bag's weights for TIOLI and BDM respondents. In Figure A21 we present the intuitive upward relationship between respondent bid and the weight of the waste bag. Both the variation observed in the weights distribution and the positive relationship between weights and bids justify our approach. Figure 8 displays the distribution of participants' bids per kg of waste and the resulting raw cumulative demand. We provide formal estimates of the demand curve in the next section.

Figure 8: Bids and cumulative demand

(a) *BDM bids (GHS/kg)*



(b) *Cumulative demand*



Notes: Panel A represents the histogram of raw respondent bids in the BDM demand elicitation exercise per kg of waste, as measured for each respondent using identical scales. Panel B displays the resulting cumulative demand, obtained by aggregating the number of respondents willing to pay at each price or higher. 1080 households participated in the BDM elicitation exercise.

[26]If enumerators could not weigh respondents' waste bags, either because it was too heavy or it was arranged in a way that made it challenging, survey participants were asked to participate in the stated preference experiment instead. In each of these cases, enumerators took pictures of the waste bag. We include examples that illustrate the challenge in obtaining weight measures in Figure A19.

[27]Informal Borla Taxis price based on their estimates of the weight of waste bags, so this is a relevant measure.

8.2.2 Take-it-or-leave-it (TIOLI)

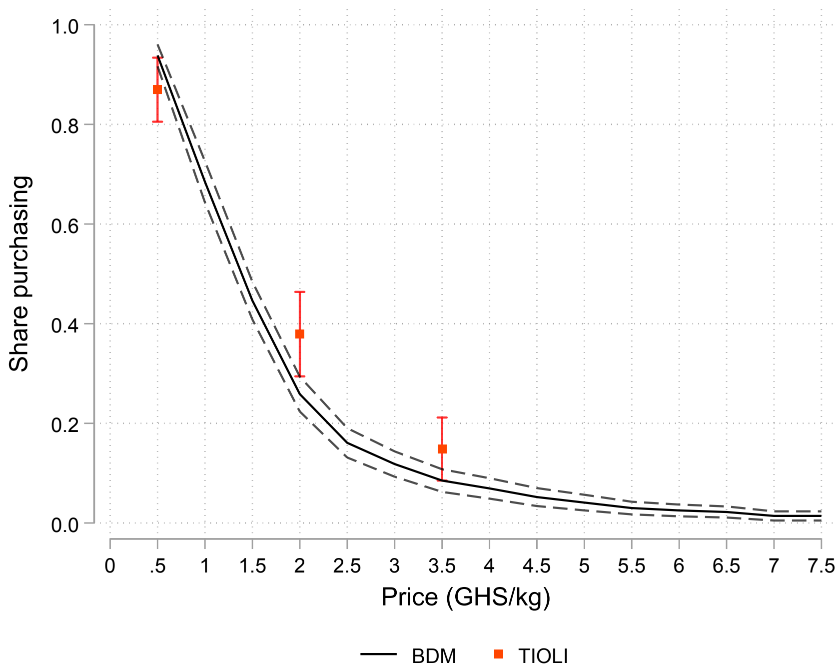
With the remaining 40% of households we conducted an incentivised TIOLI demand elicitation exercise and an un-incentivised stated preference survey experiment. For the TIOLI exercise, we selected three points in the GHS/kg distribution. We chose the points based on the 2023 Ghana Annual Household Income and Expenditure Survey, where households report some information on their expenditures for solid waste collection. Respondents were instructed to draw prices per kg from previously prepared envelopes with uniform distributions. Enumerators weighted respondents waste bags and registered both the drawn price and the bag's weight in the tablet used in the survey. The software then calculated the total price (GHS), which interviewees then had to accept or reject, with no bargaining allowed. We offered respondents the same collection service used with BDM participants. Hence accepting the offered price meant that we took respondents waste and they had to pay the accepted price.

In Figure 9 we present the demand estimates for both the BDM and TIOLI mechanisms, generated using data from a total of 685 BDM final bids, and 394 TIOLI accept/reject observations (115 at 0.5 GHS/kg, 124 at 2 GHS/kg, and 155 at 3.5 GHS/kg). The BDM estimates reflect for each price/kg (on the x-axis), the share of households bidding a value greater or equal than such price. The TIOLI point estimates in red indicate the share who chose to purchase at each of the three selected price points after random selection.

Our BDM and TIOLI estimates are statistically indistinguishable. While TIOLI estimates appear slightly higher at greater prices, we cannot reject the null hypothesis that BDM and TIOLI estimates are the same at any of the TIOLI price points (0.5 GHS/kg, 2 GHS/kg, and 3.5 GHS/kg), using 95% confidence intervals and standard errors clustered at the survey EA-level for each mechanism. We use different samples for each mechanism, as respondents were randomly assigned to conduct the *BDM* (60%) or *"stated preference + TIOLI"* (40%) experimental exercises. The fact that our estimates for the two elicitation exercises coincide gives reassurance on their accuracy.

Second, it is worth noting that while over 80% of respondents are willing to pay for door-to-door waste collection at 0.5 GHS/kg, prices would need to drop even further to get to full collection. For an average waste bag of 4 kg this means dropping below 2 GHS for a one-time collection. For context, in our app transaction data only 3% of transactions are below 2 GHS. Demand at low prices is very elastic, with around a 50% decline in the share purchasing when prices increase from 0.5 to 1.5 GHS/kg. At higher prices demand is inelastic but the share willing to purchase collection services drops below 20% at a price of 2 GHS/kg. We split our sample based on self-reported monthly household income and report estimates for the BDM and TIOLI for the resulting three income groups in Figure A22. While noisier, the analysis does not support notable differences in willingness to pay across income groups. However, for prices significantly higher than equilibrium levels, it might be hard to capture heterogeneity in WTP with an incentivised mechanism if the good/service for which households are bidding is readily available outside of the experiment.

Figure 9: BDM and TIOLI demand estimates



Notes: BDM demand curve, with a 95% confidence band and standard errors clustered at the survey enumeration area level. TIOLI demand at three price points (GHS/kg) –0,5, 2, and 3.5, with 95% confidence intervals and EA-level clustering of standard errors. The BDM demand curve reflects the share of households that bid higher or equal than the indicated price in GHS/kg. The TIOLI point estimates reflect the share of households that accepted the price (i.e. purchased the collection service) at each of the random price points. We use point-wise inference from logit regressions at prices/kg going from 0.5 to 7.5 with 0.5 increments. There are a total of 685 clean BDM final bids, and 394 TIOLI accept/reject observations (115 at 0.5 GHS/kg, 124 at 2 GHS/kg, and 155 at 3.5 GHS/kg).

As detailed later in Section 8.2.4, we scale up our one-time GHS/kg estimates using our measures for daily waste generation per household and households' chosen frequency of collection, to obtain demand estimates with respect to weekly costs of collection for total weekly waste generation. These estimates suggest that while about 70% of households are willing to have their waste collected at the current market price of 18 GHS per week, a 50% price reduction to 9 GHS would raise this share to around 90%.

8.2.3 Stated Preference Experiment

We designed an stated preference survey to estimate all parameters determining household demand for waste disposal/collection services in (1). Namely, monetary values of time costs, frequency, and the need for sorting, the sensitivity to collection prices, and the utility cost or benefit of each utility option with respect to Borla Taxis (κ_o in Equation 1). We asked respondents to picture a hypothetical choice across all waste disposal options commonly available, and used a series of choice cards (i.e. choice sets) with exogenously-varied fees, frequency, time cost, and sorting requirements. Households were asked to choose their preferred option amongst informal collection (Borla Taxi), formal truck collection, communal disposal at containers, or burning/dumping their waste indiscriminately. We always included all four options in each choice card, and the same four attributes of waste disposal options. Respondents made eight choices each across eight cards with randomly varying attribute values. Figure 10 provides an example of the choice cards we used. We chose the values of the attributes based on the 2023 Ghana Annual Household Income and Expenditure Survey, which provides some measures of expenditure on solid waste disposal, as well as on focus groups discussions we conducted with households in two neighbourhoods (low and middle income) and with waste collectors (close to one of the main open dumpsites), in January 2024.

Using the stated preference data we estimate the demand parameters for household waste disposal choices. Respondents faced choices among disposal alternatives or options o in a choice set $\mathcal{S}$. Options in each choice scenario vary exogenously in their price p_o, frequency f_o, waiting time t_o, and sorting requirements s_o. An individual i chooses waste disposal option o in a choice set $\mathcal{S}$ with probability

$$\pi_{io} = \frac{\exp\left(\kappa_o + \kappa_1 p_o + \kappa_2 f_o + \kappa_3 w_o + \kappa_4 s_o\right)}{\sum_{h\in\mathcal{S}} \exp\left(\kappa_h + \kappa_1 p_h + \kappa_2 f_h + \kappa_3 t_h + \kappa_4 s_h\right)} \tag{23}$$

The option-specific constants κ_o capture intrinsic preferences for each disposal method

Figure 10: Stated preference survey example choice set

	Borla Taxi	Formal Truck Collector	Communal Container/ Open	Burn/Dump
Frequency	**Everyday**	**Every 14 Days**	**Everyday**	**Everyday**
Weekly Collection Price	**10**	**10**	**5**	**0**
Time Lost	**10 min**	**5 min**	**15 min**	**5 min**
Need to Sort	**No**	**No**	**Yes**	**No**
Your Choice	☐	☐	☐	☐

Notes: This figure shows an example of a choice card (choice set) from our stated preference survey. It includes a hypothetical choice across four waste disposal options/alternatives (the four columns). The rows correspond to the attributes/characteristics of waste disposal options. In the cells we include the randomly assigned values of the attributes for each waste disposal option. These vary across choice sets but are the same across respondents.

relative to the normalized option (Borla Taxi). These parameters reflect unobserved attributes including social norms, environmental concerns, and health considerations that affect disposal choices beyond the explicitly modelled attributes. The ratio $\left|\frac{\kappa_o}{\kappa_1}\right|$ measures the monetary equivalent of these intrinsic (dis)utilities in GHS terms. The price coefficient κ_1 identifies households' sensitivity to collection/disposal prices, with $\left|\frac{1}{\kappa_1}\right|$ identifying the Gumbel shape. The attribute coefficients κ_2 through κ_4 capture preferences for the remaining service attributes, with ratios $\left|\frac{\kappa_k}{\kappa_1}\right|$ being households' willingness-to-pay for marginal improvements in collection frequency, reduced waiting time, and no sorting requirements, respectively.

We estimate via maximum likelihood the multinomial logit discrete choice model in (23), which is consistent with the choice probabilities in (2). The sample includes all households interviewed in our stated preference module, who also participated in the TIOLI elicitation exercise.

In the estimation, we assume that idiosyncratic taste shocks are independently and identically distributed across respondents, but allow them to be correlated across the choices made by a given respondent. We test for attribute interactions to identify whether time cost sensitivity varies with disposal options. The intuition being that waiting time at home for door-to-door collection yields less disutility than the walking time to a container or more importantly than the time involved in burning waste. We also test for whether a nested logit specification is desirable.[28]

Table 4 reports the estimates. Consistent with the demand curves in Figure 9, households display a strong collection/disposal price elasticity. In the pooled logit (Column 1), the price coefficient of -0.0633 implies that a GHS 10 increase in weekly costs reduces the probability of choosing a service by roughly 46%.[29] In the nested logit (Column 7), the corresponding coefficient (-0.0518), yields a 41% reduction in probability for the same price change. Collection frequency also matters for waste collection/disposal choices. In Column 1, the coefficient of -0.0265 means that a one-day delay in collection per week reduces the probability of choosing a service by about 2.6% at the baseline price. Translating this into monetary terms, the ratio $\left|\frac{\kappa_2}{\kappa_1}\right| = 0.42$ implies households are willing to pay about 0.42 GHS/week for each additional collection day. Moving from once-a-week collection to daily collection (6 extra collections) is therefore worth about 2.5 GHS/week to the average household –equivalent to 14% of the average weekly Borla Taxi collection price.

Time costs do not appear to influence choices on average across disposal options in the baseline logit model (Column 1). However, Column 2, reveals differences in the disutility of time across disposal methods. While households are not sensitive to the time involved in door-to-door collection options or in walking to a container, they are so for burning/dumping. The negative coefficient of -0.0330 in Column 2 implies that households are willing to pay $\left|\frac{-0.0330}{-0.0624}\right| \approx 0.53$ GHS/week to avoid each an extra minute of active disposal time via burning or indiscriminate dumping. Ten additional minutes of burning/dumping is thus valued at about GHS 5.3/week in disutility. This is consistent with the direct pollution and unpleasantry involved in the activity, and the increasing risk

[28] As nests we include 1) door-to-door options vs the rest, and 2) Polluting options vs the rest.

[29] $e^{-0.0633\times10} - 1 \approx -46\%$

Table 4: Stated preference estimates

	Logit					Nested-Logit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-0.0633***	-0.0624***	-0.0607***	-0.0640***	-0.0453***	-0.0350*	-0.0518***
	(0.003)	(0.003)	(0.007)	(0.006)	(0.005)	(0.020)	(0.007)
Frequency	-0.0265***	-0.0272***	-0.0187**	-0.0135*	-0.0122*	-0.0160*	-0.0216***
	(0.004)	(0.004)	(0.008)	(0.007)	(0.007)	(0.008)	(0.004)
Time	0.000111						
	(0.002)						
Time × Door-to-Door		0.00290	0.0154**	0.00945	0.00818	-0.0000665	0.00434
		(0.003)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)
Time × Communal		0.00622	0.0330**	0.0184	-0.000851	0.00399	0.00796
		(0.005)	(0.015)	(0.012)	(0.012)	(0.003)	(0.005)
Time × Burn/Dump		-0.0330***	-0.0389***	-0.0213**	-0.0332***	-0.0244***	-0.0291***
		(0.005)	(0.010)	(0.011)	(0.012)	(0.008)	(0.006)
Sort	-0.0233	-0.0185	0.206***	-0.0217	0.0244	-0.0148	-0.0130
	(0.028)	(0.028)	(0.055)	(0.059)	(0.049)	(0.018)	(0.024)
Constants							
Formal	-0.260***	-0.262***	-0.269**	-0.350***	-0.115	-0.146*	-0.215***
	(0.047)	(0.047)	(0.106)	(0.088)	(0.089)	(0.083)	(0.044)
Communal	-1.249***	-1.310***	-1.734***	-1.502***	-1.422***	-0.745*	-1.394***
	(0.069)	(0.104)	(0.273)	(0.232)	(0.220)	(0.404)	(0.098)
Burn/Dump	-2.358***	-1.988***	-0.970***	-1.991***	-2.282***	-2.102***	-1.966***
	(0.108)	(0.125)	(0.205)	(0.235)	(0.279)	(0.126)	(0.121)
Respondents	963	963	211	250	258	963	963
Observations	7704	7704	1688	2000	2064	7704	7704
Income category			Lowest	Low	Middle		

Notes: * 0.1 ** 0.05 *** 0.01. We cannot reject the null of no correlation within either "door-to-door vs rest" or "burn/dump vs rest" nests. We therefore use the logit model as our preferred specification.

of being caught. For communal containers, the time coefficient is smaller and statistically insignificant. For door-to-door services, the time coefficient is near zero and not significant, consistent with the idea that passive waiting at home is much less burdensome than active travel or burning. The sorting requirement is generally insignificant, meaning recycling efforts do not generate disutility for households.

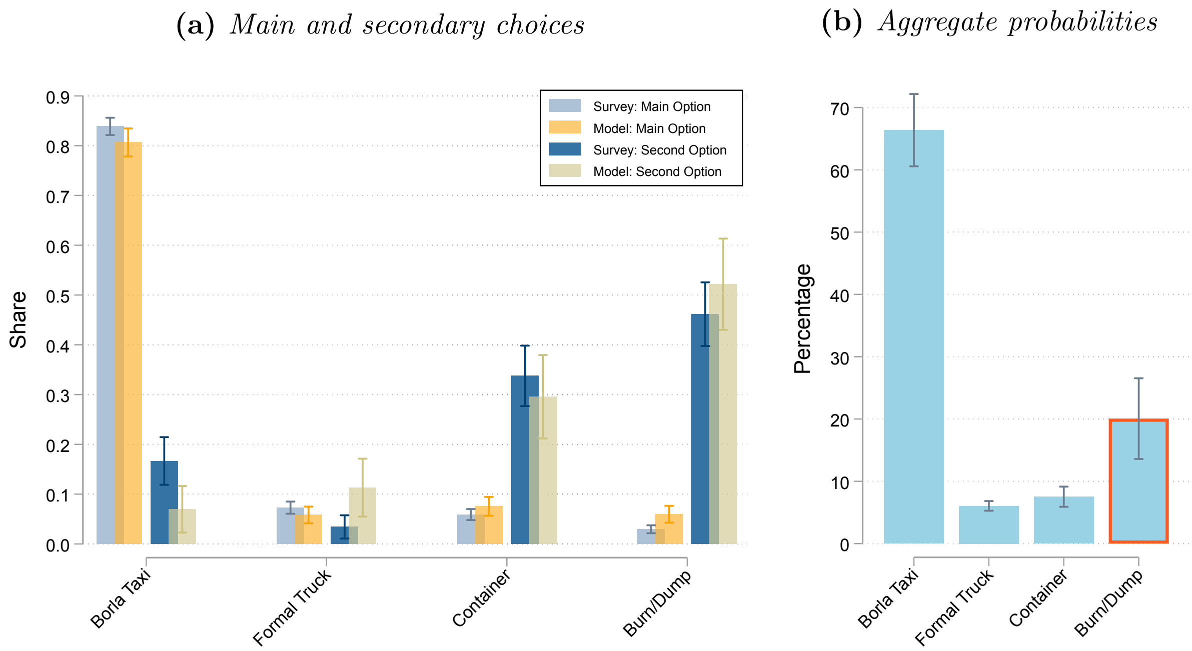
The option-specific constants (κ_o) capture intrinsic preferences relative to Borla Taxi (informal door-to-door). In Column 1, the constant for formal truck collection is -0.260, implying that a price reduction of 4.11 GHS/week in formal services are needed to make households indifferent between formal trucks and Borla Taxi, all else equal. While perhaps surprising, formal services require registration, are often less reliable than Borla Taxis, and may involve additional costs not modelled explicitly. For communal containers, the intrinsic penalty is larger (-1.249, about GHS 19.7/week lower WTP). These are often congested and also unreliable. For burning/dumping, the utility cost is are significantly greater (-2.358, or about GHS 37.3/week lower WTP). These point to utility costs associated with more polluting, less reliable/convenient, or morally acceptable disposal methods.

8.2.4 Aggregate predictions and validation

We use our stated preference estimates to predict demand for each disposal option, based on the observed equilibrium attribute levels reported by survey respondents for the options available to them, and excluding alternatives not available in their area. We compute the choice probabilities in (2) for each respondent and option and aggregate these probabilities to obtain city-wide estimates for Accra. Figure 11 (Panel A) presents the predicted primary and secondary disposal method choices from the stated preference experiment, together with survey responses on main and secondary disposal choices. Overall, the predictions closely match the survey responses across disposal options for both main and secondary choices. Around 80% in both the survey and our model predictions rank Borla Taxis as their main choice. Formal trucks and containers are the main choice for around 5% of respondents and burning/dumping constitutes the main disposal choice for between 2–4% of households in data and model respectively. Figure 11 (Panel B) displays the predicted market shares at the city level. We estimate that Borla Taxis capture approximately 65% of the market, and importantly around 20% of households burn or dump their waste. The remaining households use either formal collection services or communal containers (both options covering less than 10% of the market).

Two additional validation exercises support the robustness of our estimates. First, we scale up the BDM and TIOLI estimates (with respect to GHS/kg) to compare them with the stated preference estimates (with respect to weekly GHS cost). To do this, we rely on our bag weight measures, and construct an average daily waste generation per capita rate of 0.62 kg. We use the per capita weight for those that express daily collection frequency, and half of the per capita weight for those that express collection frequency every two days,

Figure 11: Predicted and survey choice shares



Notes: Panel A compares predicted choice shares from the stated preference model with survey responses for main and secondary disposal options. Panel B presents aggregate predicted market shares based on all choice probability predicted data. The predictions are generated using the estimates in Table 4, which we obtain from the data we gather in the stated preference experiment. It covers 963 respondents and 7704 observations. The number of respondents is determined by the random assignment of 40% of total survey respondents to participate in the TIOLI mechanism and stated preference experiment. Additionally, those respondents originally assigned to conduct the BDM mechanisms, but whose waste bags could not be weighted in the interview were assigned to participate in the stated preference experiment as well. To generate the figure in Panel A, we select the first and second probability for each respondent. To generate the figure in Panel B, we use all predicted probabilities across individuals and disposal options.

because Borla Taxis tend to serve neighbourhoods daily. We do not know for how long those that express once-a-week collection frequency have had their waste accumulating by the time of the interview. However, the similarity in the weight-per-capita measures across groups expressing different collection frequencies is reassuring. Figure A23 provides details on the data behind our average daily per capita waste generation estimate.[30] To convert the BDM and TIOLI estimates, we multiply the prices in GHS/kg times the average household size of 4, the estimated daily waste generation per capita (0.62), and the number of days in a week. This gives us BDM and TIOLI estimates with respect to weekly costs in GHS, which we can compare to our stated preference estimates. This

[30] As reference figures, in 2020, the daily waste generation per capita was 0.51 kg in peri-urban and low-income areas, 0.69 kg in middle-income areas, and 0.91 kg in affluent neighbourhoods.

is well understood graphically in Figure A24, where we overlap the demand curve we construct with the stated preference estimates and measured attribute values with our BDM and TIOLI estimates for weekly costs. We cannot reject the null that the predicted market shares at equilibrium prices are the same using stated preferences, BDM, and TIOLI estimation. Moreover, at two of the three price points in the TIOLI exercise, the estimates for stated preference and TIOLI coincide. The sample of households for the TIOLI and stated preference experiment are the same, lending credibility to the accuracy of our estimates. Methodologically, this comparison between incentivised elicitation and stated preference surveys may help validate similar exercises in future research.

We close this section with an extra validation exercise. In Figure A25, we present the correlation between the predicted dump/burn shares across enumeration areas and our measure of waste pollution. For each bin of the trash count measure we represent the average predicted burn/dump probability. The positive correlation suggests that our predictions are capturing actual behaviour, which we measure via our objective waste pollution data.

8.3 Collector route choice

To estimate the parameters governing collectors' route choice we conduct a field experiment. The objective of the experiment is double. First, to document in a reduced form whether subsidising transfer station increases the share of disposal at these sites. Second, the experimental variation allows us to structurally estimate the taste parameters of collectors discrete choices.

8.3.1 Experimental design

In collaboration with transfer stations, we subsidised their disposal price for a subset of collectors. We randomly assigned a sample of collectors into either a control (200 collectors) or a treatment group (200 collectors). Collectors in the treatment group were offered a 100 GHS discount on their total disposal fee at any transfer station everyday for the total period of the experiment. The average payment per disposal visit in our initial survey is 123.86 GHS at transfer stations and 43.06 GHS at dumpsites. We set up a stand near transfer stations to make payments and communicated its location to treated collectors. We collect a mix of real-time transaction data throughout the entire period of the experiment, and baseline and endline survey data.

Transaction Data. We incentivised collectors to register collection and disposal transactions on our app on a daily basis during a month. Enumerators monitored in-person, on the app, and via callbacks the data registration process and filled daily collector reports in the app, complementing the collector self-registered data. We construct the history of collection transactions (number and price), as well as disposal transactions (site and fee), for all collectors in our experimental sample.

Collector Surveys. We conducted an in-person baseline collector survey in August 2025. And two in person and phone-based endline survey waves in September 2025 and October 2025. The surveys serve as a complement to the real-time transaction data obtained via the app. We focused on two set of outcomes, related to both sides of the collection-disposal market. We gathered information on the number of customers served by collectors, the areas where they collect, and the prices they charge. On the other hand, we ask about the choice of disposal site, and the price paid for disposal. The main outcome of interest is the chosen disposal site. At baseline, we also collect basic demographics and key variables related to the operations of being a waste collector to assess balance.

8.3.2 Summary statistics for the experimental sample

[To be filled once fieldwork is completed]

8.3.3 Experimental results on formal disposal

[To be filled once fieldwork is completed]

8.3.4 Structural Estimation of Route Choice Parameters

Endogeneity in the structural equation for route utility (5) arises from the route profit term, Π_{aj}. Profits are a function of collection prices p_a, determined in equilibrium between households and collectors, and disposal prices p_j^d, set in a Nash-Bertrand pricing game among disposal sites. The latter depend on collector route choices, introducing simultaneity, as profits Π_{aj} are jointly determined with route utility U_{haj}. In addition to simultaneity, the route utility specification may omit route-level characteristics unobserved to the researcher but known to collectors. If these unobservables are correlated with profits–e.g., disposal sites with better unobserved amenities charging higher prices–then standard estimators would be biased. We rewrite route utility (5) as

$$U_{haj}^{(i)} = \underbrace{\nu_1 \Pi_{aj} + \omega_{aj}}_{\delta_{aj}} - \nu_2 \tau_{hajh} - \nu_3 T_j + \varepsilon_{iaj} \tag{24}$$

where ω_{aj} denotes the unobserved component of route utility, ε_{iaj} is a random shock, and the route-specific mean utility is $\delta_{aj} \equiv \nu_1 \Pi_{aj} + \omega_{aj}$. Note that δ_{aj} does not vary by origin h, while travel costs τ_{hajh} do. This specification allows us to separately identify the travel cost parameter ν_2. We estimate the structural parameters (ν_1, ν_2, ν_3) using a BLP-style nested fixed point with GMM approach. We proceed in the following two steps.

Step 1: Inversion of Mean Utilities. For any given values of (ν_2, ν_3), we recover route-specific mean utilities that match observed route shares. Under the Logit formulation, the share of collectors from origin h selecting route $\{a, j\}$ is

$$\phi_{haj} = \frac{\exp\left(\delta_{aj} - \nu_2 \tau_{hajh} - \nu_3 T_j\right)}{\sum_{a',j'} \exp\left(\delta_{a'j'} - \nu_2 \tau_{ha'j'h} - \nu_3 T_{j'}\right)}$$

Let s_{haj} denote the observed share of active collectors from origin h choosing route $\{a, j\}$. For a given (ν_2, ν_3), we use the contraction mapping à la Berry et al. 1995 to find the unique vector $\boldsymbol{\delta}(\nu_2, \nu_3)$ that satisfies

$$\phi_{haj}(\boldsymbol{\delta}; \nu_2, \nu_3) = s_{haj} \quad \forall (h, a, j)$$

The recovered mean utilities $\boldsymbol{\delta}(\nu_2, \nu_3)$ depend on the assumed values of (ν_2, ν_3) (even though the true $\delta_{aj} = \nu_1 \Pi_{aj} + \omega_{aj}$ does not)

Step 2: Nested Fixed Point GMM Estimation. We search over values of (ν_2, ν_3) to minimize the GMM objective function following this procedure. 1) For each candidate (ν_2, ν_3), we (a) solve the share inversion in Step 1 to obtain $\boldsymbol{\delta}(\nu_2, \nu_3)$, and (b) Given these recovered mean utilities, estimate ν_1 via the IV regression

$$\hat{\nu}_1(\nu_2, \nu_3) = \arg\min_{\nu_1} \left\| \sum_{i,a,j} Z_{iaj} \cdot \left(\delta_{aj}(\nu_2, \nu_3) - \nu_1 \Pi_{aj}\right) \right\|^2 \tag{25}$$

Where $Z_{iaj} = D_i \times S_j$ is our experimental instrument, with D_i indicating treatment assignment (at collector level) and S_j indicating treatment disposal sites (i.e. transfer stations). 2) We obtain the optimal parameters $(\hat{\nu}_2, \hat{\nu}_3)$ by minimising the GMM objective

$Q(\nu_2, \nu_3) = g(\nu_2, \nu_3)' W g(\nu_2, \nu_3)$, where W is a positive definite weighting matrix, and moments follow from the exclusion restriction

$$g(\nu_2, \nu_3) = \sum_{i,a,j} Z_{iaj} \cdot (\delta_{aj}(\nu_2, \nu_3) - \hat{\nu}_1(\nu_2, \nu_3)\Pi_{aj}) . \tag{26}$$

The parameters are identified through distinct sources of variation. ν_1 (profits) is identified by the experimental variation. Treated collectors at subsidized sites face exogenously lower disposal costs, shifting route profits Π_{aj} while being orthogonal to unobserved route quality ω_{aj}. ν_2 (travel cost) is identified by comparing route choices of collectors from different origins. For the same route $\{a, j\}$, collectors living closer choose it more frequently than those living farther away. This differential response to distance identifies how much collectors dislike commuting. Finally, ν_3 (waiting time) is identified by variation in waiting times across disposal sites. Holding profits and travel distance constant, routes with longer waiting times at sites are chosen less frequently, revealing collectors' value of time at sites.

8.4 Disposal sites costs

Given the estimated collector preference parameters $\hat{\boldsymbol{\nu}} = (\hat{\nu}_1, \hat{\nu}_2, \hat{\nu}_3)$ from Section 8.3, we now estimate the marginal cost parameters $\boldsymbol{\zeta} = (\zeta_j)_{j \in \mathcal{J}}$ for each disposal site. We employ a Simulated Method of Moments (SMM) approach that exploits the Bertrand-Nash pricing game. Intuitively, under candidate disposal cost parameters, we simulate collector route choices, and sites' disposal fees and market shares. We find the vector of costs such that the model outcomes most closely match the disposal sites prices and shares observed in the survey data.

Computing equilibrium pricing. Under Bertrand competition, each site's optimal price must satisfy the first-order condition in (18). Rearranging gives the best-response function

$$p_j^d = \zeta_j - \frac{\lambda_j(\mathbf{p}^d)}{\frac{\partial \lambda_j(\mathbf{p}^d)}{\partial p_j^d}} \tag{27}$$

where $\lambda_j(\mathbf{p}^d)$ depends on all prices $\mathbf{p}^d = (p_1^d, ..., p_J^d)$. The equilibrium prices form a system of J non-linear equations. We can solve numerically for equilibrium prices for any vector of marginal costs $\boldsymbol{\zeta}$ a using fixed-point iteration

$$\mathbf{p}^{d,k+1} = \mathbf{BR}(\mathbf{p}^{d,k}; \boldsymbol{\zeta}) \tag{28}$$

where $\mathbf{BR}(\cdot)$ is the vector of best-response functions. We can then iterate over candidate vectors $\boldsymbol{\zeta}$, matching the numerically simulated prices $\mathbf{p}^d$ and shares following the subsequent procedure.

SMM estimation procedure. For each candidate cost vector $\boldsymbol{\zeta}$, we solve for the Bertrand-Nash equilibrium prices $\mathbf{p}^d(\boldsymbol{\zeta})$ by iterating best responses, where each site j chooses its price to maximize profits given competitors' prices

$$p_j^{d,k+1} = \arg\max_{p_j} \left\{ (p_j - \zeta_j) \cdot \lambda_j(p_j, \mathbf{p}_{-j}^{d,k}) \right\}$$

We iterate until convergence: $||\mathbf{p}^{d,k+1} - \mathbf{p}^{d,k}|| < \epsilon$. Then, given equilibrium prices $\mathbf{p}^d(\boldsymbol{\zeta})$, we compute predicted market shares

$$s_j(\boldsymbol{\zeta}) = \frac{\lambda_j(\mathbf{p}^d(\boldsymbol{\zeta}))}{\sum_{j' \in \mathcal{J}} \lambda_{j'}(\mathbf{p}^d(\boldsymbol{\zeta}))}$$

Equipped with our simulated price and shares vectors, we select the vector of costs that satisfies the Bertrand-Nash equilibrium and solves

$$\hat{\boldsymbol{\zeta}} = \arg\min_{\boldsymbol{\zeta}} \left[\mathbf{m}(\boldsymbol{\zeta})\right]' W_d \left[\mathbf{m}(\boldsymbol{\zeta})\right] \tag{29}$$

where the moment vector is the following[31]

$$\mathbf{m}(\boldsymbol{\zeta}) = \begin{pmatrix} \mathbf{p}^d(\boldsymbol{\zeta}) - \mathbf{p}^{d,obs} \\ \mathbf{s}(\boldsymbol{\zeta}) - \mathbf{s}^{obs} \end{pmatrix}$$

In this procedure, the marginal costs are identified through the Bertrand pricing conditions. Intuitively, sites with higher observed prices relative to their market shares (controlling for location and competition) must have higher marginal costs to rationalize their pricing in equilibrium. The estimated collector preferences $\hat{\boldsymbol{\nu}}$ pin down the competitive interactions between sites. The estimated household demand parameters discipline collector routes. This identification strategy is valid under the assumption that disposal prices are set competitively given costs. The experimental variation in the first estimation stages do not affect site costs, hence justifying our sequential estimation.

The estimated costs, which we present in Table 5, range from 0.2 GHS to 1 GHS per bag for dumpsites and from 0.9 GHS to 2.4 GHS for transfer stations, reflecting the higher operational costs of formal waste processing. Across sites, our SMM algorithm achieves very good fit for model prices and market shares.

[31] And W_d is a positive definite weighting matrix.

Table 5: SMM estimation: Disposal costs, prices, and market shares

	Marginal Cost	Price (GHS)		Market Share	
Name	$\widehat{\zeta}_i$	Model	Data	Model	Counts
Agbogbloshie Sikkens	1	1.89	1.87	0.34	0.27
Mc Carthy	0.145	1.29	1.41	0.28	0.31
Mallam/Tetegu	0.197	1.06	1.17	0.095	0.10
Glefe	1	1.56	1.32	0.10	0.07
Ashaiaman Adjie-Kojo	0.9	4.08	4.69	0.07	0.11
Pantang	1.9	4.43	5.14	0.04	0.06
Korlebu (IRECOP)	2.357	3.02	3.30	0.06	0.06

Notes: The table reports SMM estimates for sites' marginal costs, and model-implied prices and market shares against their data counterparts. Market shares are calculated using the collector flows data at disposal sites. Prices are the average reported by collectors per number of daily customers.

8.5 Summary and model fit

Table 6 takes stock of all parameter estimates and calibrated values. Using these estimates, we solve the model for equilibrium prices and quantities in both collection and disposal using the conditions in Section 6. Figure 12 provides a first assessment of model fit by comparing model-implied collection and disposal routes to those observed in the Borla Taxi survey. Figure 13 extends the comparison between the data and model-implied values to the rest of our datasets and outcomes. The model matches the data well. First, the predicted collection flows on each *home location-collection area* pair in Panel B of Figure 12 mirror reasonable well those in the data (Panel A). The model captures the concentration of trips in the centre of the city, with differences in density driven by the difference between the number of collectors in the sample (400) and the model, which is adjusted to reflect the total population of collectors (2500). The model also predicts well the flows in the *collection area-disposal site* pairs. Importantly, it captures the higher market share of uncontrolled dumpsites, the longer trips made by collectors disposing of at this sites (in red), and in turn, the greater clustering of collection-disposal flows around transfer stations (in blue).

In Figure 13, we confirm that the model is able to replicate the remaining equilibrium outcomes. Panels A and B show the relationship between data and model-implied values for the targeted moments in our SMM estimation –disposal prices and shares–, which are

Table 6: Calibration

Parameter	Description	Value	Detail/Source
BDM, TIOLI, Stated Preference (DCE)			
κ_F	Formal truck utility cost	-0.260	DCE (Table 4)
κ_C	Container utility cost	-1.249	DCE (Table 4)
κ_{BD}	Burn/dump utility cost	-2.35	DCE (Table 4)
κ_1	Price elasticity	-0.0633	DCE, BDM, TIOLI (Figure 9)
κ_2	Frequency elasticity	-0.0265	DCE (Table 4)
κ_3	Waiting time elasticity	0.000111	DCE (Table 4)
μ_H	Gumbel shape (household disposal)	1	Normalisation
Field experiment & GMM			
ν_1	Route profit elasticity	0.069	
ν_2	Route commuting distance elasticity	0.293	
ν_3	Disposal site waiting time elasticity	0.0000	
μ_C	Gumbel shape (collector route)	1	Normalisation
SMM			
$(\zeta_1, ..., \zeta_7)$	Disposal sites costs	7×1	Collector counts & Collector survey
External calibration			
ϑ	Tricycle loading rate	0.15	Transaction data (Figure 6)
$\mathcal{A}$	Collection areas		Collector survey
$\mathcal{F}^{\mathcal{A}}$	Formal truck access/availability	$\mathcal{A} \times 1$	2021 Census
$\mathcal{C}^{\mathcal{A}}$	Communal container access/availability	$\mathcal{A} \times 1$	2021 Census
$\mathbf{P}$	Formal truck and container prices	$\mathcal{A} \times 2$	Household survey
$\mathbf{F}$	Disposal options frequencies	$\mathcal{A} \times 3$	Household survey
$\mathbf{T}$	Disposal options time costs	$\mathcal{A} \times 3$	Household survey
$\mathbf{N^H}$	Household population	$\mathcal{A} \times 1$	GHS data
$\mathbf{N_h^{BT}}$	Collector home population	$\mathcal{A} \times 1$	Collector survey
$\mathbf{T^d}$	Disposal sites waiting time	$\mathcal{J} \times 1$	Collector survey
$\mathbf{R^d}$	Disposal sites recycling prices	$\mathcal{J} \times 1$	Collector survey
ι	Local waste pollution costs	0.2	Waste pictures & survey (Table 2)
ϱ	Dumpsite costs	1.65	$\approx$ 200 \$/tonne (Literature)

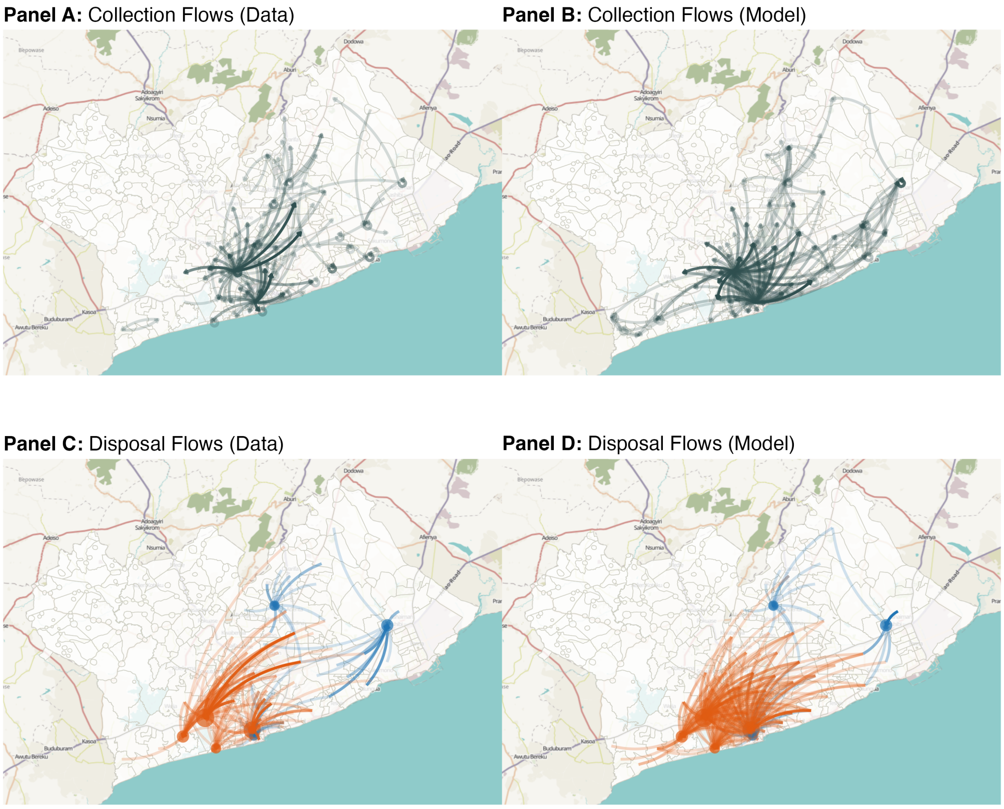
Notes: The table describes each model parameter/object, indicates the calibrated value, and provides a reference to the data source or empirical strategy used for estimation. We group parameters in three panels according to the estimation strategy. For the dumpsite social costs, we use the estimates in Jiang et al. 2024 & Rahim et al. 2013 for open dumps in Beijing and Makassar, Indonesia. They account for the external costs of air pollution, GHGs, and leachate using contingent valuation and life cycle assessments.

also detailed in Table 5. The estimated costs, lead to a good match between disposal prices in model and data, and are able to generate a market structure for disposal similar to that in the data, with two dumpsites dominating the market with around 30% shares, and transfer stations capturing between 5 and 10% of the market each only.

Panel C shows the relationship between the collection prices implied by the model and the data observed in the app, averaged at the locality level. Note that while we did not target or used transaction prices in the estimation, the model equilibrium prices correctly match the level in the data, and capture reasonably well the variation across localities. The linear fit (in blue) is close to the 45-degree line. Moreover, the variation observed in the app data can be driven by differences in bargaining, waste weight, or other factors we do not capture in the model. If the number of transactions registered in a locality is relatively low, those differences can explain the observed noise. The model however, struggles to generate some of the higher average prices –above 20 GHS– that we observe in the data. Panel D shows the distribution of customers in both the survey data (in red) and the model (blue). The model matches well the average but the distribution is less spread than in the data. Again, differences in the size of waste bag or the type of customer may drive part of this difference.

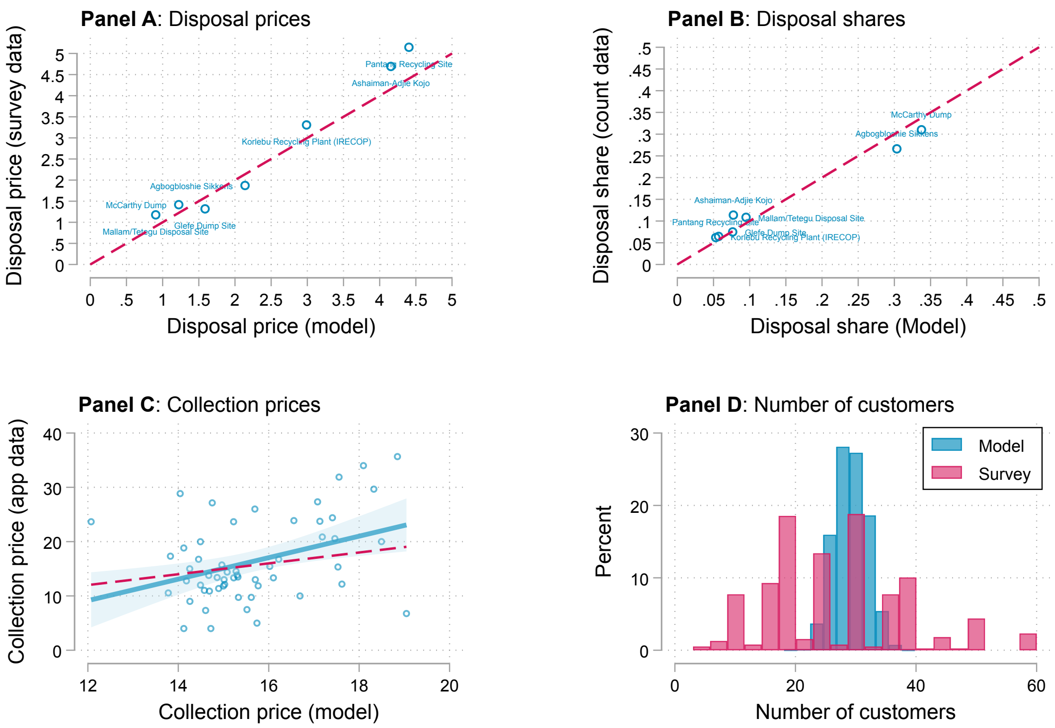
Finally, the full model, where collection and disposal prices are solved for in equilibrium, generates a very similar market share for collection to the one in Figure 11, with a household demand share of 60% for Borla Taxis and slightly lower than 20% predicted burning/dumping. This local waste pollution and the large market share of open dumpsites call for policy design evaluation. Counterfactuals will seek to internalise all external costs. Most importantly, the environmental damages associated with local waste pollution and waste volumes at illegal dumpsites. They will impose optimal pricing strategies, politically feasible transfer station subsidies, and assess the currently proposed construction of new waste management infrastructure. We will evaluate changes in collection and disposal outcomes relative to the model-implied baseline we have described in this section.

Figure 12: Collection and disposal flows (data and model)



Notes: The data flows are generated using survey data from 400 collectors. The model flows are generated based on our predictions using the estimated total number of collectors operating in the GAMA, which is 2500, hence the difference in density across the two flows. In Panels A and B, in dark gray, we represent the collection flows (from collector home location to collection area) in the data and model respectively. In Panels C and D we represent the flows from collection areas to disposal sites. The colour of the flow corresponds to the type of disposal site. Flows that end at an uncontrolled dumpsite are in red. Flows that end up a transfer station are in blue. We use red and blue circles to represent the location of dumpsites and transfer stations respectively.

Figure 13: Model fit for collection and disposal



Notes: We compare model predictions with survey data, app transaction data, and count data across key market outcomes. Panel A plots predicted disposal prices against survey-reported disposal fees by collectors for each site. The 45-degree line is the dashed red line. Panel B compares model-predicted market shares for disposal sites with observed shares from the count data. These two objects are targeted in the SMM estimation. Panel C shows collection prices from the model equilibrium, untargeted in the estimation, against prices from the mobile app data. The solid blue line shows the fitted relationship and the dashed red line is the 45-degree line. Panel D presents the distribution of the number of daily customers per collector for model (blue) and data (red).

9 Counterfactuals

9.1 Social planner optimum

As a benchmark, we solve the planning problem we characterised in Section 7 and implement the socially-optimal household disposal shares and collectors area-site routes using disposal prices of $\tilde{p}_j^d = \zeta_j + \varrho_j - \iota$, as in (21). The increase in prices at dumpsites driven by their social costs results in increases of disposal at transfer stations. Adjie-Kojo's market share increases to 12.3%, Pantang's to 8.6% and Korlebu's to 26.5%. Given its low cost and strategic position, the Mc Carthy dump maintains a high market share of 29.5%, even in the planner's allocation. Panels A and B of Figure 14 contrast the baseline equilibrium and social planner solution. The proposed decentralisation of the planner's allocation relies on setting prices at all sites, which in practice would involve taxing illegal dumpsites. As this is not feasible, we proceed to evaluate alternative pricing and infrastructure policies. The policy discourse so far has focused more on expanding infrastructure, so we now contrast pricing policies and the development of new facilities. We estimate how the market responds to subsidies at transfer stations and the construction of the infrastructure proposed by the city so far.

9.2 Transfer station subsidies

We implement final disposal price subsidies at transfer stations of 50% and 100% (i.e. free formal disposal). Both of these subsidies are higher than the one implicitly required to decentralise the planner's allocation, but are aimed to compensate for the lack of taxation to dumpsites. Notably, we allow dumpsites to change their prices endogenously, best responding to transfer stations' (and open dumps') new prices. The new equilibria emerge as a result of both the direct subsidy effect and the indirect competitive response. [In an extension, we will allow for dumpsite exit. How much dumpsites are able to lower their prices depends on their fixed costs. Dumpsite exit triggers a re-optimising response for other sites. We calibrate an upper bound of dumpsites fixed costs, assuming zero profits at current equilibrium prices. We report sensitivity of counterfactual results with respect to variation in fixed costs, noting that enforcement or policing may affect these. For now, we report results without exit.] A 50% subsidy achieves a split of formal an uncontrolled disposal very close to that in the planner allocation (Panel C in Figure 14). The planner relies more on low marginal cost dumpsites, but the split across transfer stations and across formal and illegal disposal coincides. This suggests that pricing policies downstream of waste flows, allows to internalise the social costs of waste upstream and downstream. Public delivery at no cost (i.e. free formal disposal) reduces illegal disposal share to 16%. (Panel D), from 56% with half the subsidy. Collection prices drop by 1.7% and 8.8% in these two scenarios, reducing slightly the share of waste burned or dumped by households too. In Figure A26 we illustrate how collector collection and disposal routes respond to transfer station subsidies.

9.3 Infrastructure expansion

The GAMA government has suggested the construction of disposal facilities, hoping to guarantee that waste haulage travel distances from major suburbs to nearest transfer stations don't exceed 17.9 km. A number of zonal transfer stations have been proposed to serve the waste transfer zones defined by the government. Figure A27 shows both the location of the stations and the boundaries of transfer zones. These are the Western zone (proposed station around Mallam Junction), the Southern Zone (undefined site placement) and the Northern Zone (proposed site around the Haatso/GAEC area). These sites were originally intended to complement the existing facilities at the Eastern Zone (Teshie) and Southern Zone (Achimota), which we identified are not currently in operation.[32] The Ministry of Sanitation and Water Resources (MSWR), through the World Bank GARID project, has already started the commissioning for the construction of the proposed transfer station at Haatso. And plans for the construction of the Mallam station have appeared recently in the news GBC 2024.

We evaluate the impact of the construction of the proposed transfer stations at GAEC/Haatso, and Mallam Junction separately. Panel E and F show market effects of the introduction of the two transfer stations at the planned locations and a subsidised rate of 1.5 GHS (current transfer station prices are between 3 and 5 GHS). Comparing Panels E (GAEC station) and F (Mallam station) with Panel C (50% subsidy), we conclude that the reduction in illegal disposal is considerably lower than that in the 50% subsidy scenario. It is also worth noting that the introduction of both the GAEC and Mallam transfer stations substantially reduce the market shares of the existing stations at current prices, potentially challenging their viability. 50% subsidies to existing stations

[32] The GARID report providing these details can be found at https://garid-accra.com/wp-content/uploads/2024/10/WTS-DED-Report-v7.0_010924.pdf.

compensates this effect (Panels G and H), however the total gain in reducing waste pollution at dumpsites is modest when compared to the scenario in Panel C, which does not require additional infrastructure. The construction of Mallam paired with 50% subsidies to existing stations reduces the market share of illegal disposal to 48% (versus 57% if the subsidy is given to existing sites with no new development). Figure 14 shows market shares by site and Figure 15 compares the aggregate share of illegal disposal under each counterfactual scenario. The overarching conclusions are that 50% price subsidies are enough to reduce the share of illegal disposal almost as much as in the planner allocation, that infrastructure investments crowd out formal disposal unless complemented with subsidies to existing sites, which bring modest gains, and that free formal disposal would almost eliminate open dumps.

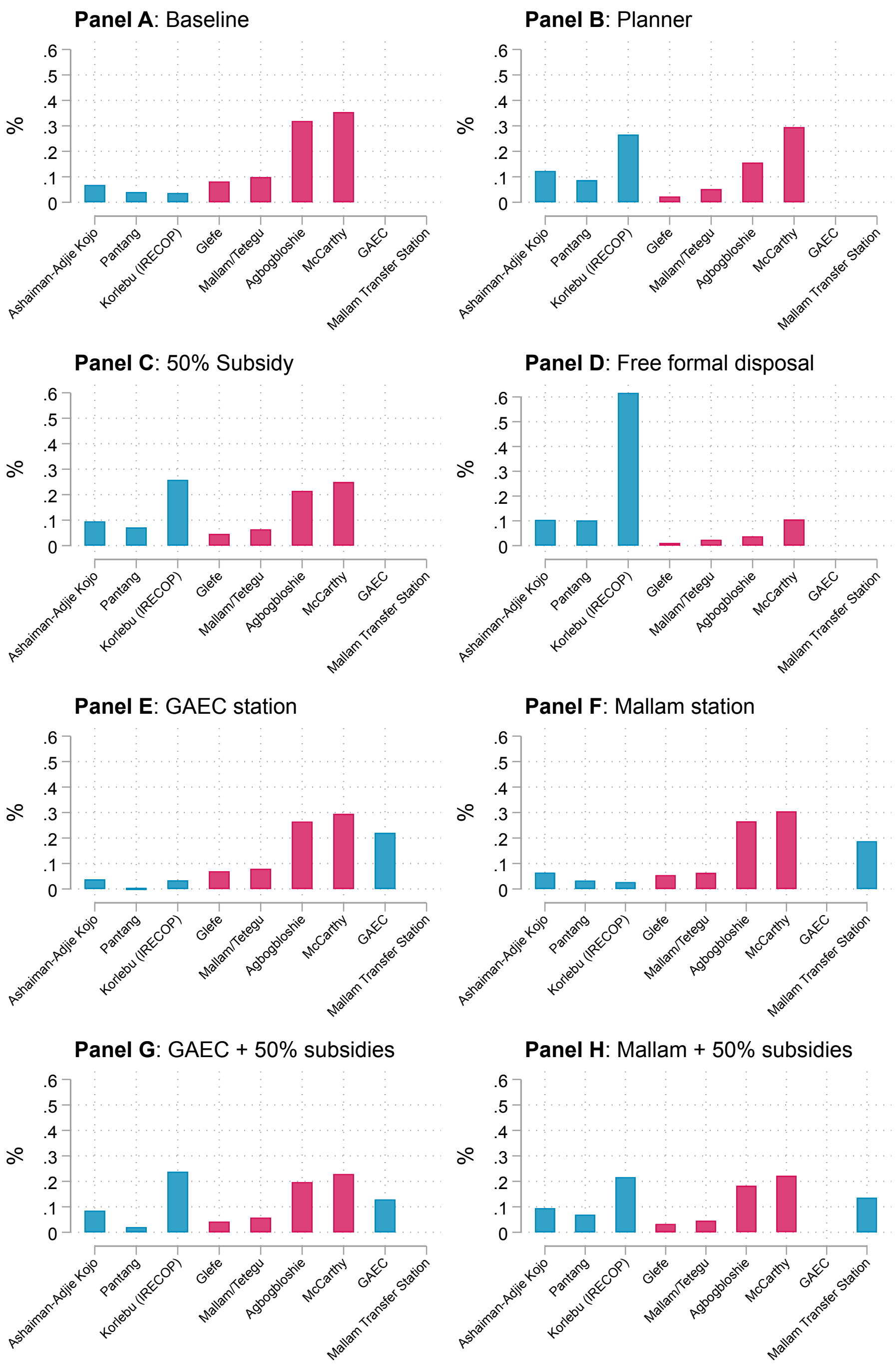
10 Conclusion

Limited fiscal capacity and rapid and uncontrolled urbanisation have led city governments to rely on markets for the provision or urban public goods and services. A clear example of this are sanitation and solid waste management, which despite their large environmental and health externalities, are provided via unregulated markets in cities across the developing world. This paper analyses Accra's market for solid waste collection and disposal. We use novel data collection via surveys, observations, images, and a self-developed smartphone app, to document the equilibrium and key characteristics or an understudied market. We use experimental variation from demand survey experiments, and a field experiment where we offer subsidies for disposal at transfer stations, to estimate a structural model of waste collection and disposal in the city.

We find that the collection side of the market operates competitively and delivers large surplus to households, but that disposal at illegal dumpsites leaves large social costs unaddressed. Price subsidies downstream, at transfer stations, are able to internalise damages, and achieve the socially optimal level of uncontrolled disposal. The construction of new public infrastructure achieves smaller gains than policies aimed at getting prices right, and risks reducing formal disposal unless deployed in a coordinated manner.

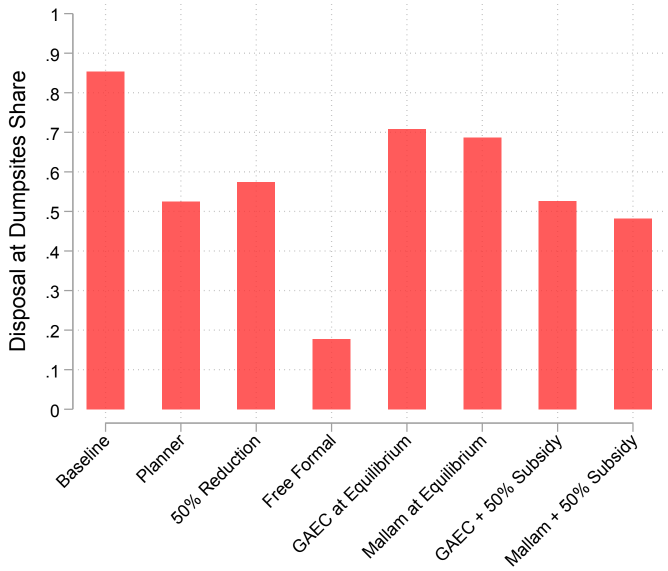
Quantifying these impacts, and how the market reacts to government policy is important. Our results illustrate how governments can leverage market forces when direct public provision is difficult. But also highlight the limitations of pushing a public goods problem onto private provision, as markets fail to price externalities without government intervention. In Accra, contracting only occurs over the value of removing waste from households. The effects of dumpsites on local communities, the city's air quality, and its water bodies, cannot be contracted upon and requires active government involvement. It is promising that limited downstream policies are successful in this setting, with governments and informal private actors working together in public service delivery.

Figure 14: Counterfactual disposal market shares



Notes: Disposal sites are indicated in the x-axis. Dumpsites in red, transfer stations in blue. Panel A is the baseline model, Panel B the planner allocation, Panel C a 50% to all transfer stations, Panel D free formal disposal, Panels E and F capture the impact of building two new stations with a disposal unit fee of 1.5 GHS, and Panels G and H add on top 50% subsidies to remaining stations.

Figure 15: Scenario comparison



Notes: The bars represent the share of illegal disposal (0-1) under each of the scenarios included in the x-axis.

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A Appendix

Contents

A.1 Background

A.1.1 Door-to-door collection

Formal collection trucks. Private contractors are hired by municipal assemblies, operate big trucks for collection, and a small set of communal containers in some neighbourhoods. They transport collected waste to transfer stations or directly to landfills generally outside of the GAMA. There is a very small number of companies that compete for these municipal contracts, with one dominating the market. Households need to register with these providers (82% of households in our sample relying on formal collectors are registered) and pay a registration fee that oscillates between 0 and 350 GHS (with an average of 17.74 GHS for the 100 households in our sample that report a registration fee). These providers often establish monthly payment arrangements with households (62% of respondents in our sample use monthly payment arrangements), even if occasionally resort to payments upon collection (24.4% of households).

Borla Taxis. There are around 2500 informal door-to-door waste collectors operating in our study area.[33] They travel the city using motorised tricycles, searching for customers and disposing of the collected waste at transfer stations or open dumpsites. Most of them (around 95% in our sample) work every weekday, with 37.28% and 44.84% working 6 and 7 days a week respectively. 57.7% of Borla Taxis in our sample own their tricycle. The remainder rent it. Borla Taxis don't have an explicit contractual relationship with their customers. Instead, they bargain with them and charge a price per bag each time they collect. 98% of households expressed being charged a collection fee every time they get their waste collected by a Borla Taxi, as opposed to an organised payment arrangement at certain frequency. Repeated interactions exist but are not the norm. 19.43% or households report always using the services of the same Borla Taxi (21.64 % report doing so most of the time). 42% state that most of the time they rely on a different Borla Taxi, and 16.9% report no repeated interactions. Similarly, only 21.16% of Borla Taxis report that all of their customers are regular customers. Otherwise, there is considerable variation in the percentage of daily customers that are regular or recurrent customers. The interactions between Borla Taxis and households always take the same form: Households wait and are present at home. In rare occasions they arrange collection over the phone (3.79% of households) or let Borla Taxis come in and collect waste when household members are not present (1.79% of households). Most collection transactions occur in the early morning. 14% of households in our sample get their waste collected between 4 and 6am, 70% do so between 6 and 8 am, and almost all respondents (over 97%) have their waste collected before or by 10 am.

A.1.2 Disposal

Borla Taxis transport collected waste to transfer stations or dumpsites for disposal. At both types of disposal sites collectors need to pay a disposal fee. Recycling is limited, run by intermediaries, informal pickers, scrap dealers, and processing companies. It takes place at both types of sites, offering collectors an additional small source of revenue.

[33] According to the 2021 report "Solid Waste Management Improvement Plan" conducted by the Greater Accra Resilient And Integrated Development (GARID) Project, coordinated by the World Bank and the Ministry of Sanitation And Water Resources. This report leverages what is to the best of our knowledge the only "census" of informal providers of waste management services done in the GAMA. The report can be found at https://garid-accra.com/wp-content/uploads/2024/05/SWM-Improvement.pdf.

Transfer stations. They are funded with assistance from the municipal governments, and operated by a private company. At these sites waste is compacted, occasionally recycled, and then sent to landfills for final disposal or processing. Transfer stations include leachate containment systems to prevent water pollution, covered storage to avoid air pollution, and paved surfaces to prevent soil pollution. Often located inside or close to the city, their objective is to be a clearly designated site for disposal, proximate enough to reduce the incentive for collectors to dump waste illegally in drains, vacant lots, illegal dumpsites, or open spaces. Over the years, the government has tried to build and maintain a network of transfer stations, but several are now closed, with remaining stations appealing for more funding to remain in operation (Al-Hassan 2025). We visited three transfer stations that were aimed to serve the main metropolitan area or had replaced old landfills. Two were no longer in operation, despite one of them being inaugurated in 2017. The other had been turned into a small recycling processing facility, no longer accepting general disposal. As of April 2025, there are three active transfer stations and one integrated disposal and recycling site that the government uses to control waste pollution.

Unregulated or illegal dumpsites. They are large pieces of cleared land with no infrastructure to control pollution. Waste is dumped indiscriminately. Some is separated by informal waste pickers; the rest is burned (Figure A1 shows an example of burning at these sites and exemplifies very clearly the difference between illegal sites and transfer stations). The city government has expressed concerns over the substantial risks to health and the environment posed by illegal dumpsites and has spent large resources in attempting to close them. It has succeeded at decommissioning several open dumpsites (in our disposal sites inventory exercise we identified a number of old dumpsites that are no longer operational) but new sites keep re-emerging and enforcement is faced with armed resistance (JoyOnline 2025) in some instances. As of April 2025, there are four operational dumpsites. Together they dominate final disposal, with around 70% of the waste collected by Borla Taxis ending up in illegal dumpsites according to our sites data.

Figure A1: Agbogbloshie Sikkens Dumpsite & Pantang Transfer Station

Notes: The pictures, taken during our data collection in March-April 20205, show the open dumpsite of Agbogbloshie Sikkens (figure on the left), and the Pantang Transfer Station (figure on the right). In the dumpsite, waste burning is clearly visible

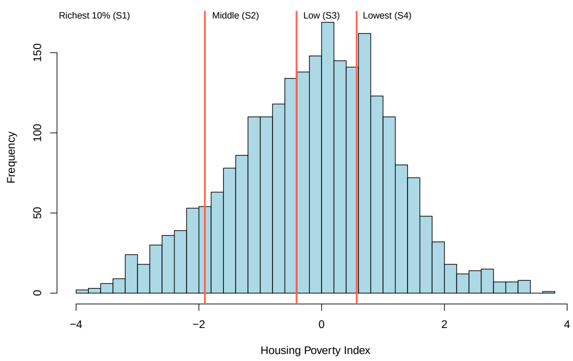
A.2 Data

A.2.1 Household survey

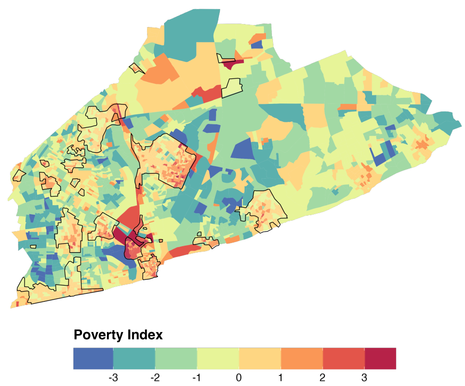
We limited the household demand data collection to the city of Accra due to logistical reasons and because it is the area where we observe the higher density of built-up area within the Greater Accra Metropolitan Area. We constructed a housing poverty index at the EA level based on the 2010 Population and Housing census. We dropped the top 10% (highest income category) EAs, as these are largely served by formal trucks, comprise a relatively small share of the total population, and the original focus of the project was on understanding how informal markets expanded access to waste management services. The remaining EAs form our population of interest. We created three income strata to construct our sample, each representing 30% of the population. The distribution of the index and the spatial distribution of the index are in Figure A2. We randomly selected 50 EAs within each stratum, and randomly surveyed 12 households within each EA via door-to-door interviews, to form a sample of 1800 households.

Figure A2: Housing poverty index

(a) Distribution



(b) Spatial variation



Notes: (a) Histogram of housing poverty index. The vertical lines represent the 10th, 40th, and 70th percentiles of the housing poverty index at the EA level using 2010 Census data. (b) The map represents the spatial variation of the housing poverty index. Officially designated slums are highlighted in black. Their location coincides with pockets of high housing poverty as measured by the index.

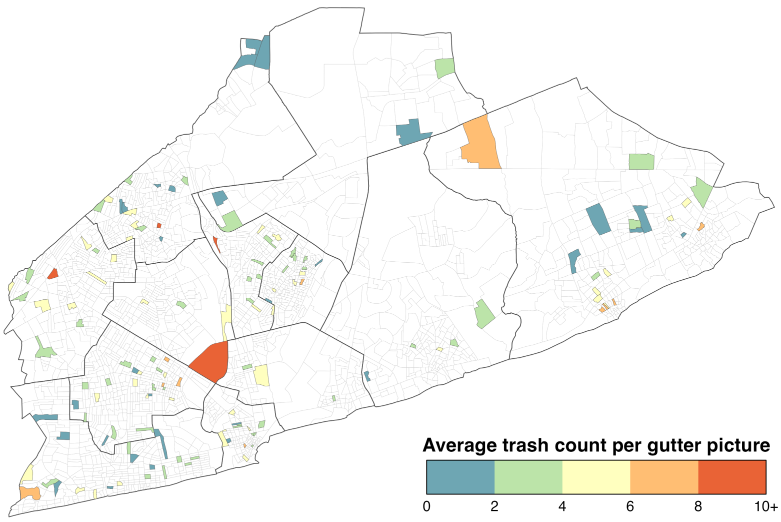
Figure A3: Waste pollution: Average trash count (1.09)

Notes: Subset of images from an EA where the average trash count is low (1.09). In this particular case, trash objects are only visible in the third and fourth images starting from the top left. All pictures are taken from a similar angle. The gutter is clearly visible.

Figure A4: Waste pollution: Average trash count (6.8)

Notes: Subset of images from an EA where the average trash count is high (6.8). In this particular case, trash objects are visible in all images. All pictures are taken from a similar angle. The gutter is clearly visible and full of turbid and stagnant water in most images. This figure illustrates the challenge in using deep-learning techniques to obtain an accurate number of trash objects.

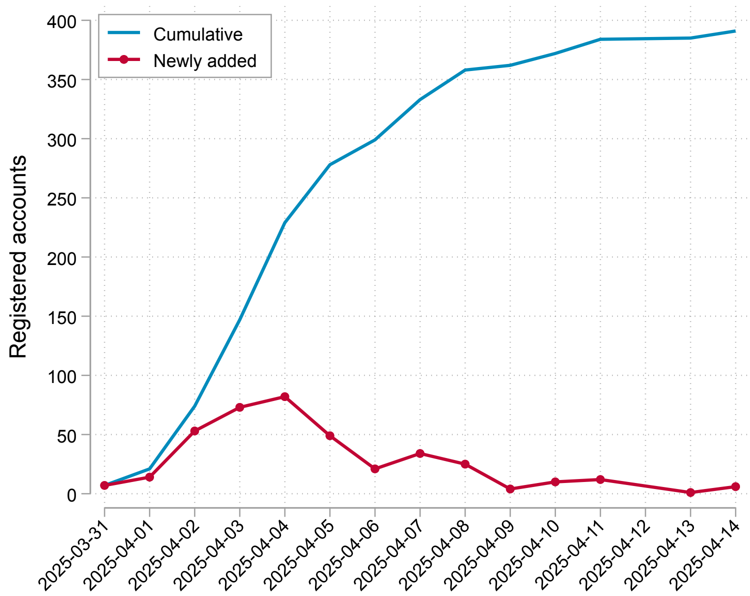
Figure A5: Average trash count in gutters



Notes: The map presents the average trash count for all 150 EAs in the household survey. Blue EAs have average counts of 0-2 trash objects. Green EAs have counts of 2-4. In yellow EAs we find an average of 4-6 trash objects across waste images. Orange EAs have between 6 and 8 trash objects on average. Red EAs have over 8 objects per image. The map shows substantial heterogeneity in waste pollution across EAs in our survey.

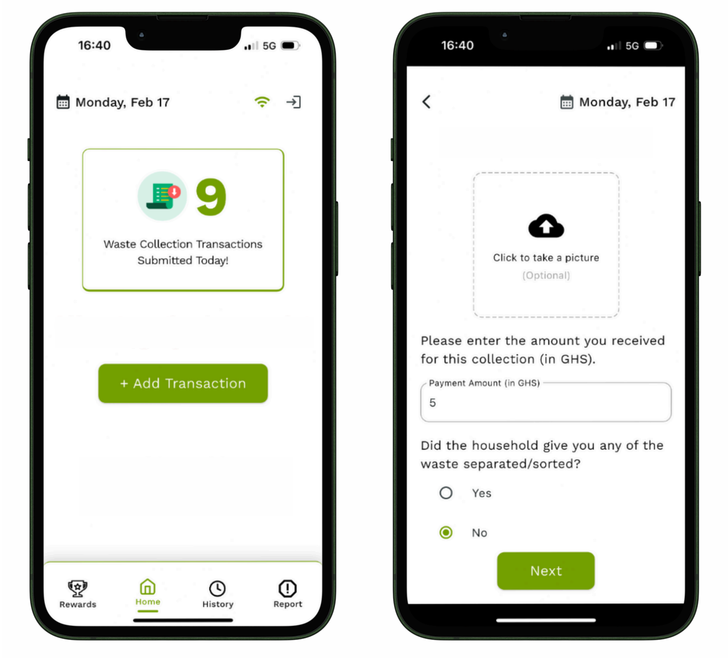
A.2.2 Borla Taxi survey and smartphone transaction data

Figure A6: Registration of smartphone app users



Notes: Survey participants were registered on the app at the time of the in-person interview or at a later date, in those cases were respondents owned a smartphone but had not brought brought it to the site at the time of the survey. In those instances, enumerators arranged the registration in the app with collectors at a later date. We show the time series for the first two weeks of April, when all registrations were completed.

Figure A7: Transaction registration in the smartphone app



Notes: The smartphone screens show the main steps required to register a transaction. In screen one, we display the number of transactions already submitted. The button "+ Add Transaction" leads to the second screen, where the user can write the price in GHS in a text box. The user can also indicate whether any of the waste they received was already separated for recycling, and optionally, upload a picture of the collected waste. The icons at the bottom of the main screen (screen one) allow users to access the system to redeem rewards for registering data, a list or history of their transactions, and an optional daily report where they can indicate whether they were able to register all of their transactions.

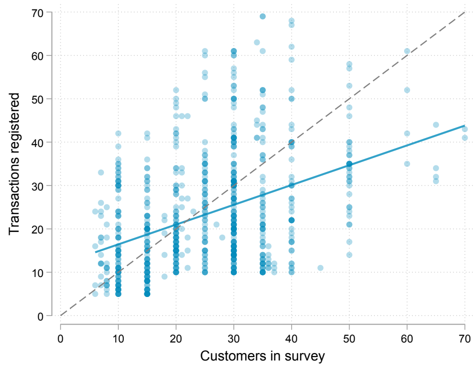
Table A1: Disposal sites inventory

Site	**Description**
	Sampling sites
1. Agbogbloshie Sikkens	Unregulated dumpsite with active flow of collectors.
2. Mc Carthy	Unregulated dumpsite with active flow of collectors.
3. Mallam/Tetegu	Unregulated dumpsite with active flow of collectors.
4. Glefe	Unregulated dumpsite with active flow of collectors.
5. Pantang	Transfer station with active flow of collectors.
5. Ashaiaman/Adjie-Kojo	Transfer station with active flow of collectors.
6. Korlebu (IRECOP)	Recycling site/transfer station with active flow.
7. Kokomleme Mini-Transfer Station	Small station with active and low flow of collectors.
	Not included in the sample
1. Kotoku/Amasaman/Pokuase Site	It is further away and has low Borla Taxi collector traffic (it's mostly used by big formal trucks).
2. Zoompak Teshie Transfer Station	It was not in operation in March–April 2025. According to the manager, it will re-open in June–July 2025.
3. ZoomPak Achimota Transfer Station	It had been closed for the past two years.
4. Mallam Old Landfill "Tidyup" Station	Used to be a landfill, then a transfer station, and now has been converted into a solely recycling centre, diverting collector traffic to McCarthy dumpsite.
5. Korle Lagoon (KLERP) Dump	Informal location, no longer in operation.
6. Tunga Dump	Very low collector traffic. Mostly used by households directly or pushcart/wheelbarrow collectors.
7. Old Pantang (Abokobi) Dumpsite	Decommissioned.
8. Oblogo/Weija Dumpsite	Decommissioned.
9. Mallam Market Dump	Decommissioned.
10. Madina Open Dump	Decommissioned.
11. Bawaleshie "Mpraeso" Dumpsite	Decommissioned.
12. Okponglo Dump	It is used only by households and some scrap dealers.
13. Kpone and Kpone II Landfills	We did not include them in our sampling list as these are far from the main metropolitan area and used mostly by formal trucks or collectors operating solely east of the Tema area.
14. Adipa Waste Management Centre	This is a newly engineered landfill. It is outside the Greater Accra Metropolitan Area and, like Kpone, is mostly used by formal trucks or a small number of collectors from the vicinity.

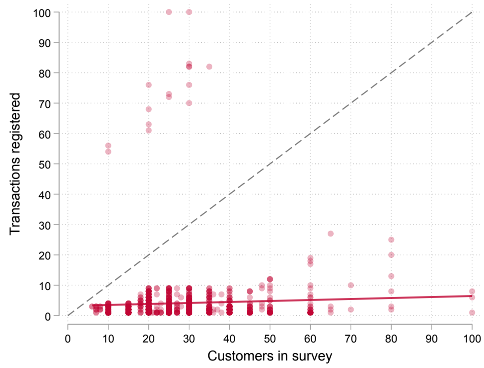
Notes: The table provides details on our disposal sites inventory; for both the sites included in the sample and those we discarded. The descriptions are based on field visits conducted during March 2025.

Figure A8: Transactions and number of customers in survey

(a) *Normal usage*



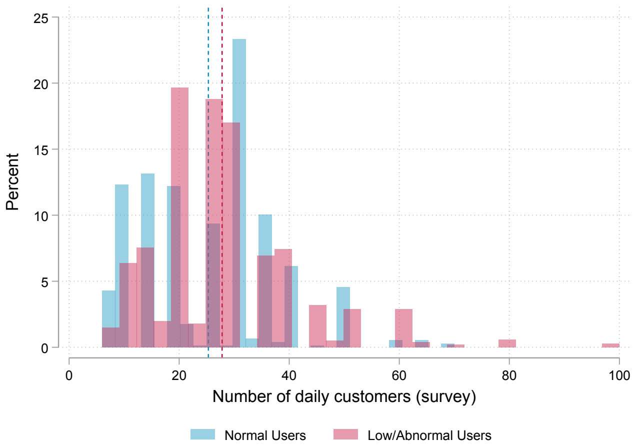
(b) *Abnormal/low-usage*



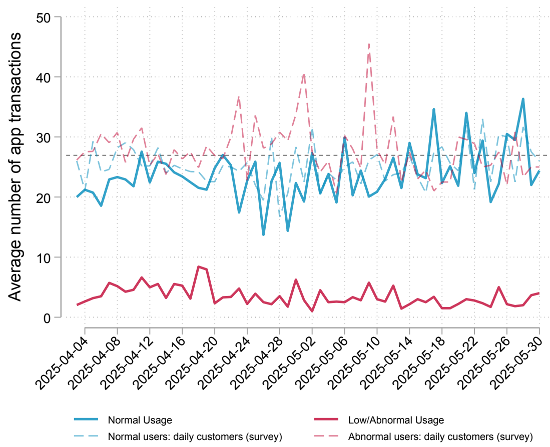
Notes: Panel A shows, in blue the scatter plot of daily registered transactions against the number of customers reported in the survey. Each dot is a collector-day level, where we have aggregated all transactions each collector registers in a day. Variation within the same number of customers in survey (x-axis) therefore contains both cross-sectional variation across collectors and time variation in registered transactions for different dates. The dotted black line corresponds to the 45-degree line. In solid blue we include the line of best fit through the raw data. Panel B represents the same relationship for the collectors we classify as having abnormal/low-usage. The observations and line of best fit are now in red. Collectors in Panel B either report too many transactions –the small cloud above 50 registered transactions on the upper left of the plot–, or report too little transactions, creating a flat relationship between transactions and number of customers –at the bottom of the plot.

Figure A9: Number of customers for both types of users

(a) *Distribution of customers*



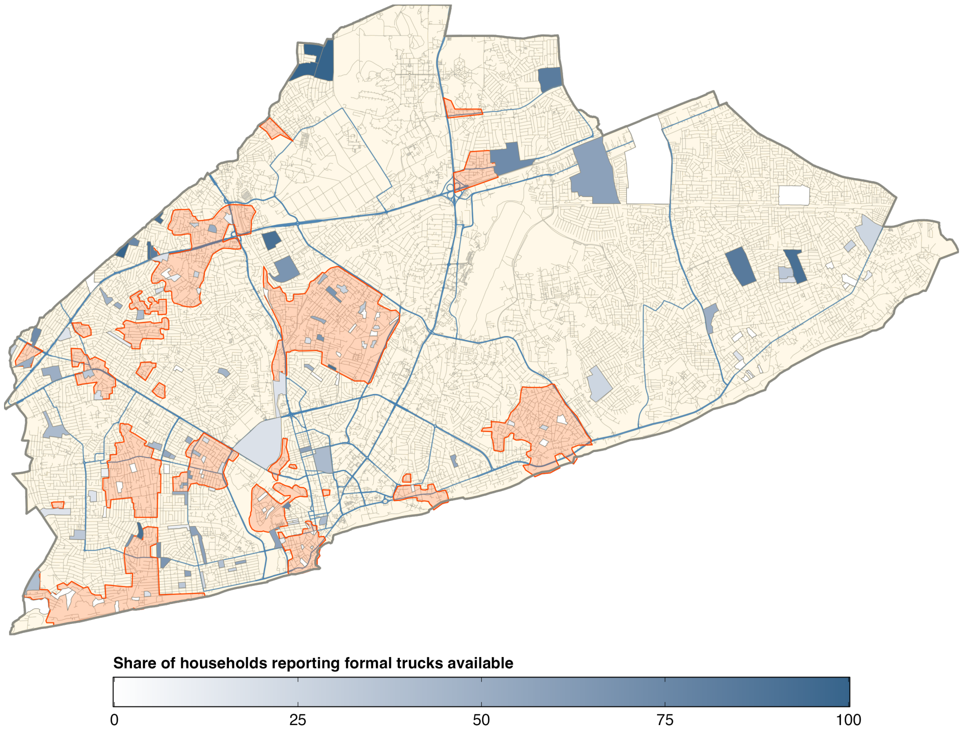
(b) *Daily classification*



Notes: In Panel A, we include the histogram of number of customers as measured in the survey data. Our observations are at the collector-day level, where each collector-day is classified as *Normal User* or *Low/Abnormal User*. The distribution for those that show normal usage is in blue, and for those classified as low/abnormally-high usage in red. We include as a vertical dotted line in blue (25.3) and red (27.8) the average number of customers for both groups. In Panel B, we present four time series: (1) average number of transactions for those with normal usage (solid blue line), (2) average number of customers in survey for those with normal usage (dotted blue line), (3) average number of transactions for those with low/abnormal usage (solid red line), (4) average number of customers in survey for those with low/abnormal usage (dotted red line). We compute the averages for each given day. Because the classification is at the collector-day level, there is variation in the sample of collectors that falls within each classification in each date. Hence, the variation in the survey-based values.

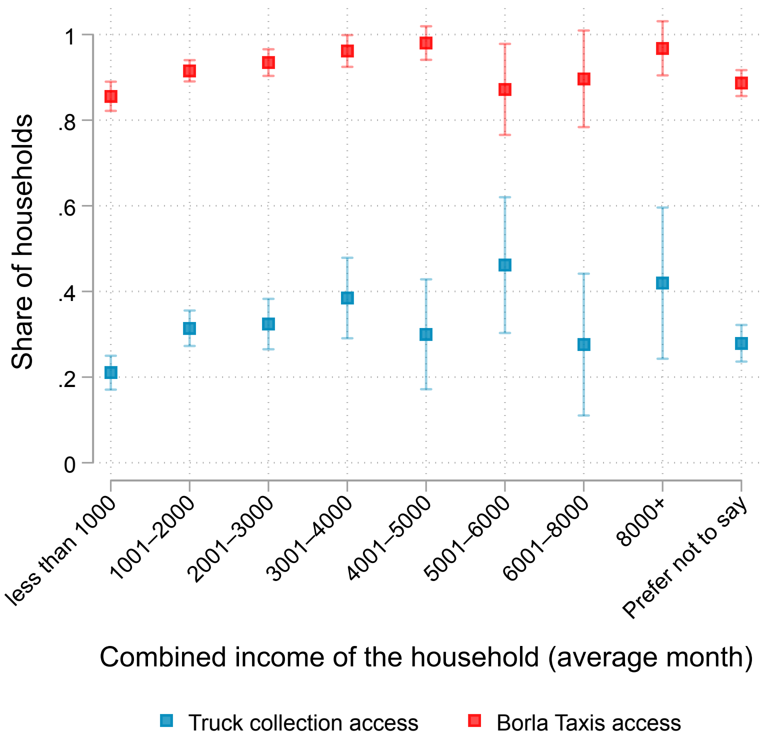
A.3 Descriptive facts

Figure A10: Formal truck collection availability



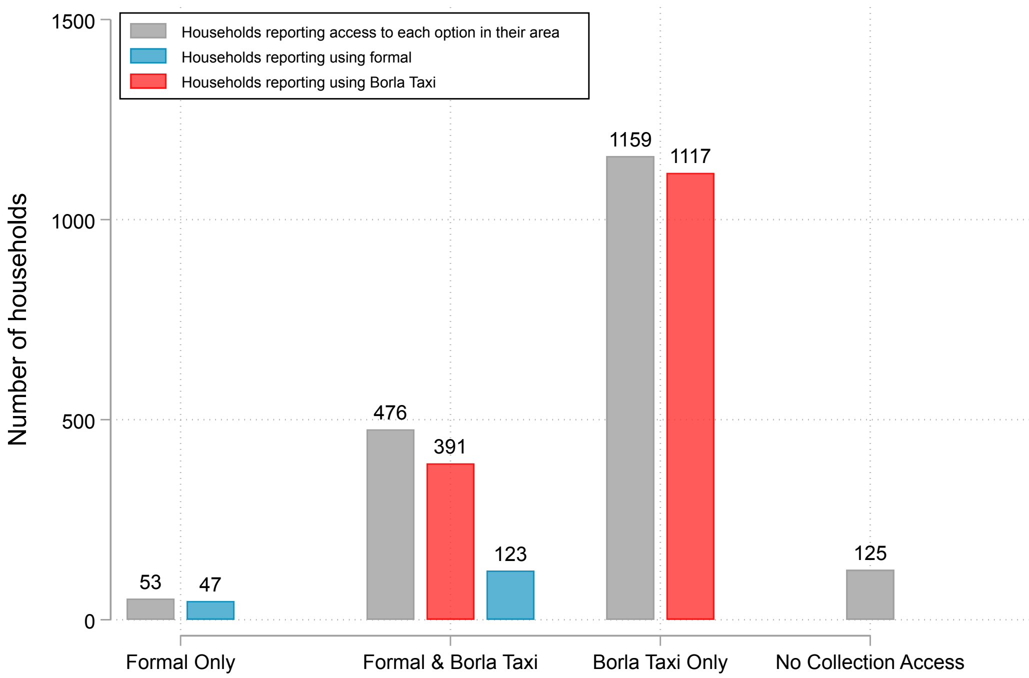
Notes: We represent data from our household survey at the EA level on the share of respondents that report that formal trucks operate in their neighbourhood. This information is represented with the blue gradient (from 0 in white to 100 in dark blue). We also include in blue part of Accra's road network. We represent the highways/motorways (trunk), the major arterial roads (primary), and regional district-level medium-capacity roads (secondary). These are meant to capture the main arterials that would be suitable for heavy collection trucks. We include the full road network in light grey. In red we depict the areas that the city formally classified as slums.

Figure A11: Collection availability by income



Notes: The figure represents the share of households within each income bracket that report access to truck collection (blue) and Borla taxi collection (red). The data is from our household survey. Income is self-reported, combined at the household level, for a representative month, and in GHS. We report raw shares of households reporting access to each option in their neighbourhood by income categories as squares and 95% confidence intervals in the same colour.

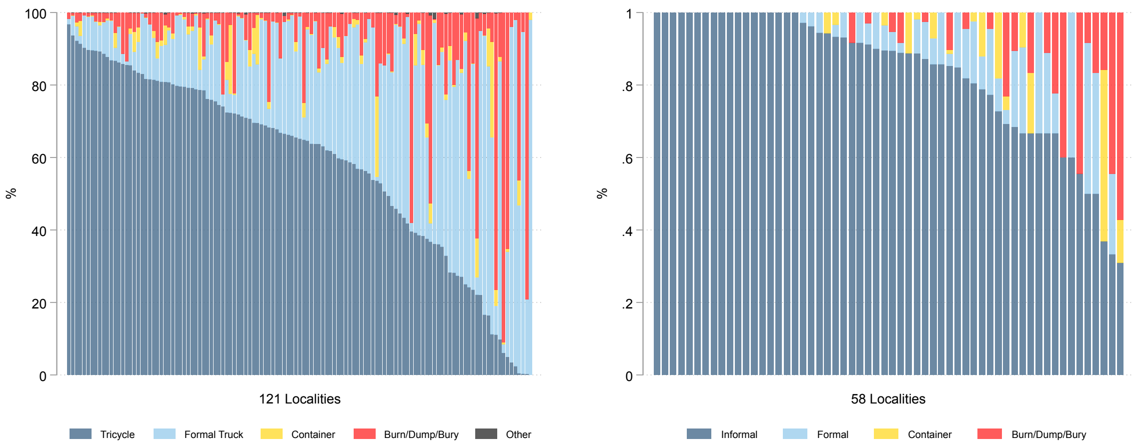
Figure A12: Waste collection access and usage



Notes: We show raw counts of households belonging to each access and choice group. The data comes from our household survey. In gray we show the number of households that report access to each category: formal only, formal and Borla Taxi, Borla Taxi only, or no door-to-door collection access. The blue bars indicate the number of households that report using formal. We report this both within those that report access to formal only and within those that report access to both formal and Borla Taxi collection services. The red bars, analogously, represent those households that report using Borla Taxi services within the two categories corresponding to Borla Taxi access. 125 households in the sample report no access to door-to-door collection services whatsoever.

Figure A13: Household collection/disposal choices (main)

(a) 2021 Census (Locality) (b) Survey (Locality)



Notes: Panel B shows survey responses to the question on main waste disposal option. There is a total of 1813 households participating in the survey. We calculate shares at the locality level. The figure plots the shares for each disposal option stacked, at the locality level. Localities have been sorted based on the share of Tricycle/Borla Taxi collection share. In dark blue, we present tricycle collection shares, in light blue, formal truck collection shares, in yellow, the share of households using containers as their main option, and in red the share using burning/dumping/burying trash. In Panel A we represent the same variable –we used the same question on main disposal choice in our survey –but using locality-level 2021 census data we obtained from the Ghana Statistical Service.

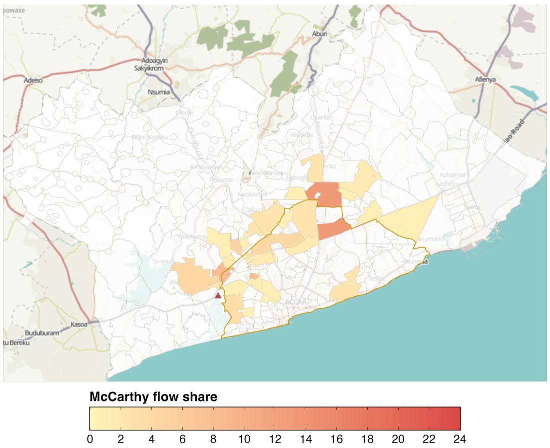
Table A2: Collection and accounting

	(1) Unofficial	(2) Formal	(3) Δ	(4) Ha: $\Delta < 0$	(5) Ha: $\Delta \neq 0$	(6) Ha: $\Delta > 0$
Collection						
Price charged for small bag (main locality)	5.31	5.12	0.19	0.791	0.418	0.209
	(N= 283)	(N= 95)				
Price charged for big bag (main locality)	13.51	12.48	1.03	0.928	0.145	0.072
	(N= 283)	(N= 95)				
Price charged for small dustbin (main locality)	17.57	17.58	-0.01	0.495	0.990	0.505
	(N= 282)	(N= 96)				
Price charged for big dustbin (main locality)	37.19	35.88	1.32	0.808	0.384	0.192
	(N= 284)	(N= 97)				
Number of household customers in main locality	23.83	22.22	1.61	0.876	0.249	0.124
	(N= 287)	(N= 97)				
Daily waste collection revenue	343.30	357.32	-14.02	0.218	0.437	0.782
	(N= 286)	(N= 97)				
Average daily collection revenue (app)	365.15	355.83	9.32	0.587	0.826	0.413
	(N= 69)	(N= 23)				
Costs & Profits						
Daily total costs from being a waste collector	132.79	177.37	-44.58***	0.000	0.000	1.000
	(N= 286)	(N= 97)				
Fuel costs in a typical week	364.90	267.22	97.68***	1.000	0.000	0.000
	(N= 287)	(N= 97)				
Daily profits (inputed)	234.43	228.80	5.63	0.627	0.745	0.373
	(N= 286)	(N= 97)				

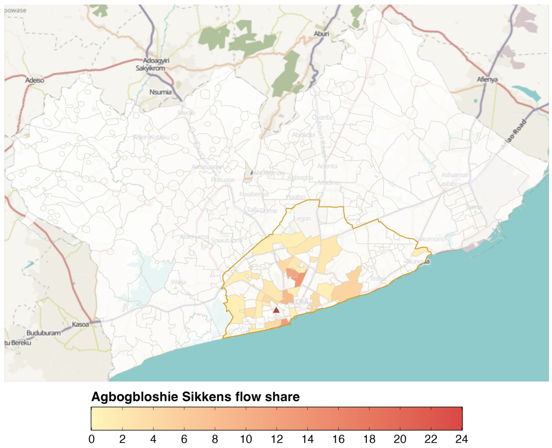
Notes: The table reports mean outcomes for waste collectors at Unofficial (col. (1)) and Formal (col. (2)) disposal sites. Δ (col. (3)) is the difference in means for collectors disposing at unofficial and formal sites. Sample sizes (N) for each group appear in parentheses below the means. Stars on Δ denote significance from two-sided Welch t-tests: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Columns (4)–(6) give one-sided p-values for the hypotheses $H_a : \Delta < 0$, $H_a : \Delta \neq 0$, and $H_a : \Delta > 0$, respectively. Formal sites are the Ashaiman-Adjie Kojo transfer station, the Pantang transfer station, the Korlebu Recycling Plant (IRECOP), the Kotoku Trash Site/Amasaman, and the Kokomlemle Mini Transfer Station. Unofficial or illegal sites are the Mallam/Tetegu dumpsite, the Glefe dumpsite, the Agbogbloshie Sikkens dumpsite, and the McCarthy dumpsite. All variables in the table are winsorised (1st and 99th percentiles).

Figure A14: Main collection locality share (dumpsites)

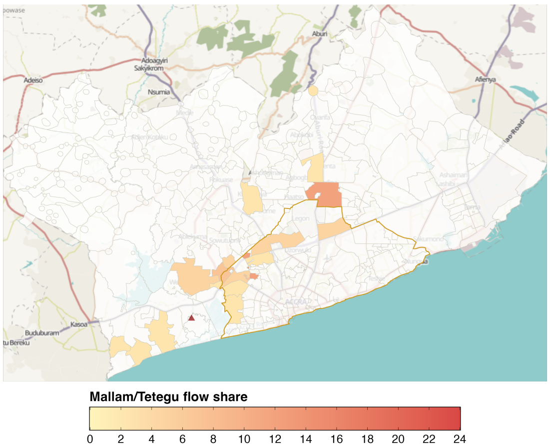
(a) Mc Carthy



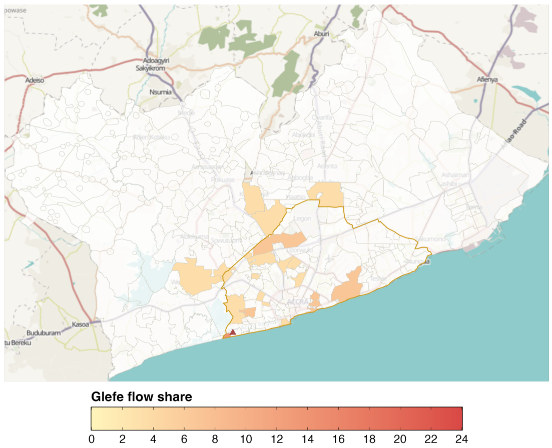
(b) Agbogbloshie Sikkens



(c) Mallam-Tetegu



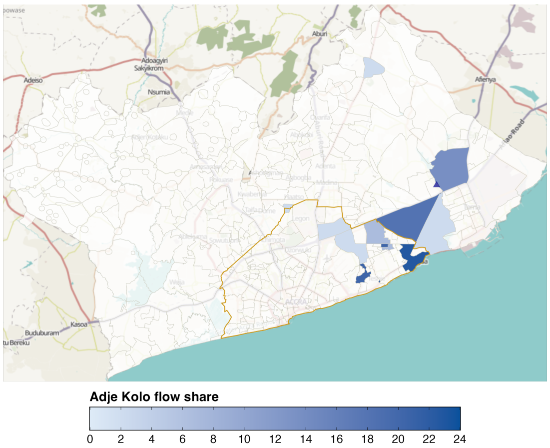
(d) Glefe



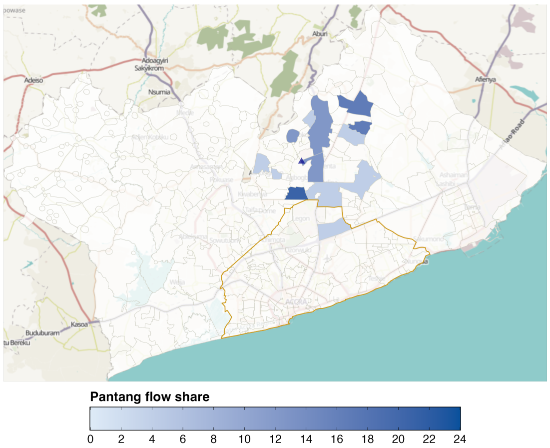
Notes: The maps use survey data from 400 collectors. Each locality in the GAMA gets a value that corresponds to the share of collectors that dispose in the corresponding site, who identify that locality as their main collection area. Areas with darker shades of orange correspond to areas where more collectors operate in, of the ones that dispose of the waste they collect in the particular disposal site. The location of the site is indicated using a small red triangle. In panel A we represent the collection locality shares for Mc Carhty, in B for Agbogbloshie, in C for Mallam-Tetegu and in D for Glefe. The maps show the catchment areas for each. Localities in white are those in which collectors disposing at the site do not collect waste in.

Figure A15: Main collection locality share (formal sites)

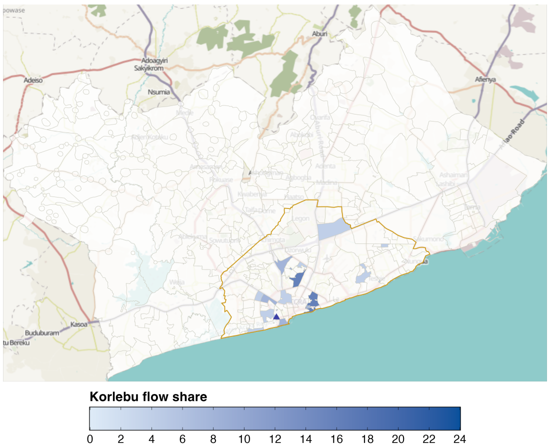
(a) Adjie-Kojo transfer station



(b) Pantang transfer station



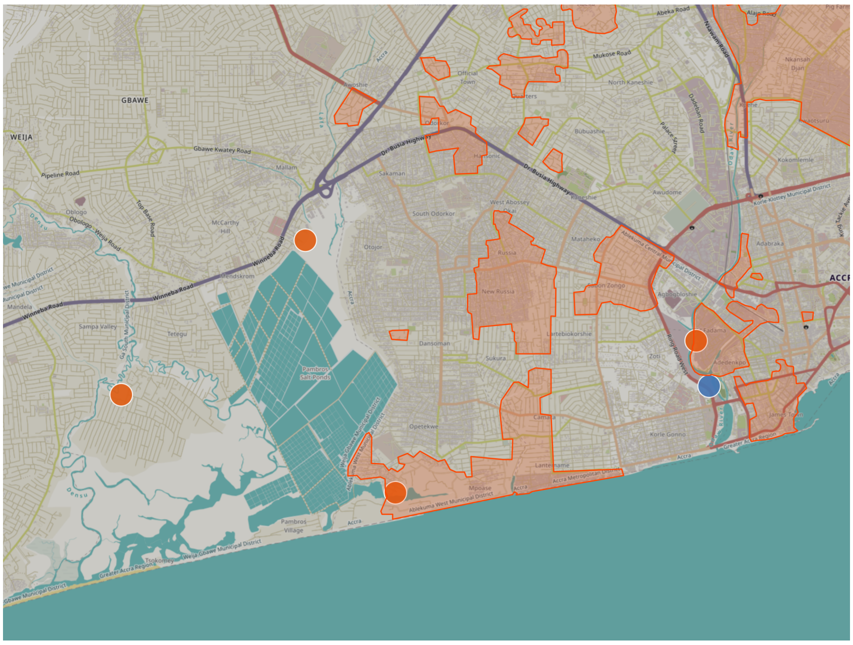
(c) Korlebu recycling and disposal site



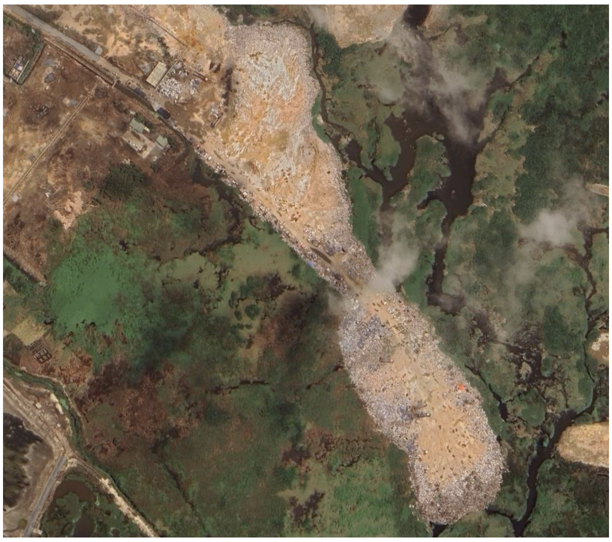
Notes: The maps use survey data from 400 collectors. Each locality in the GAMA gets a value that corresponds to the share of collectors that dispose in the corresponding site, who identify that locality as their main collection area. Areas with darker shades of blue correspond to areas where more collectors operate in, of the ones that dispose of the waste they collect in the particular transfer station. The location of the site is indicated using a small blue triangle. In panel A we represent the collection locality shares fort the Adjie Kojo transfer station, in B for Pantang, and in C for Korlebu. The maps show the catchment areas for each, which are highly concentrated. Localities in white are those in which collectors disposing at the site do not collect waste in.

Figure A16: Detail on the location of dumpsites)

(a) Dumpsites location



(b) Mc Carthy (Google Maps)



Notes: (a) Detail of Open Street Map with the location of the Agbogbloshie Sikkens, Mc Carthy, Glefe, and Mallam-Tetegu dumpsite. Water bodies are in blue. The red boundaries correspond to the officially- designated slum areas. Dumpsites are shown as red dots. The Korlebu transfer station appears as a blue dot. (b) Satellite image from Google Maps of the area covered by one of the main dumpsites in Accra. Waste burning from the site appears to be visible in the image.

A.3.1 Randomised response exercise

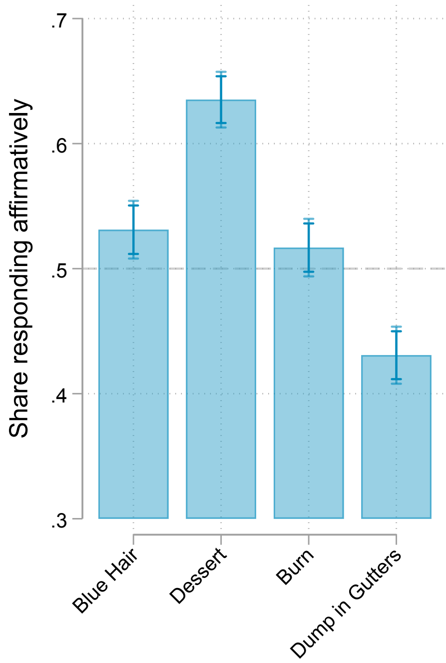
The randomised response method (Warner 1965) seeks to reduce potential biases due to non-response or social desirability, and elicit honest answers to questions on beliefs or sensitive behaviours (e.g. e.g. drug use, illegal dumping, tax evasion), while preserving respondent's privacy. The key idea behind this technique is to introduce random noise into the individual responses such that the interviewer cannot determine with certainty the respondent's true answer, but aggregate statistics (e.g. aggregate share of waste dumping) can be estimated accurately.

We asked four survey questions: one placebo to test comprehension (*"Do you have blue hair?"*), one non-sensitive question (*"Do you sometimes eat dessert after dinner?"*), and two potentially sensitive questions (*"Do you sometimes burn waste?"* and *"Do you sometimes dump waste in gutters/drains"*). Answering "Yes" to waste burning and dumping may be incriminating or embarrassing. Instead, we introduced random noise by asking respondents to flip a coin. If *heads*, they had to answer "Yes" regardless of the truth. If it landed *tails* they had to answer truthfully. With probability 50%, the respondent gives a true answer, limiting our ability to infer if a "Yes" to the sensitive questions is truly an indication of the behaviour or due to the 50% chance of the coin landing *heads*.

This method can reduce social desirability bias by giving respondents "the benefit of the doubt". A "No" fully reflects a truthful "No", as only *tails* gives a chance to answer something other than "Yes". Nonetheless, ex-ante we expect at least 50% of affirmative responses to the sensitive questions. Thus, respondents may be more willing to report affirmatively about sensitive behaviours if they engage in them. We ask the four questions using four independent coin flips.

We include the raw shares responding "Yes" to each question in Figure A17. Respondents appear to have understood the exercise. The placebo "blue hair" should be close to 50% by chance. And likely there are no truly positive cases. The share of respondents answering "Yes" to this question is slightly over 50 %. The share that respond "Yes" to a non-sensitive behaviour like *"having dessert after dinner"* is well above 50%, with around an estimated 30% engaging in this behaviour. More strikingly the share of households answering "Yes" to dumping waste in gutters is below 50%. This indicates that even when households *had to answer "Yes"* due to the coin flip result, they refused doing so. This points to some social stigma, and social desirability bias, perhaps due to fear of judgement. The suggestive results from this exercise point towards the need for model-based approaches to estimate sensitive behaviours and complement potentially biased aggregate statistics based on survey data.

Figure A17: Randomised response results



Notes: Each bar represents the share of households that responded "Yes" to the following questions: *"Do you have blue hair?"*, *"Do you sometimes eat dessert after dinner?"*, and two potentially sensitive questions *"Do you sometimes burn waste?"* and *"Do you sometimes dump waste in gutters/drains"*. We plot 90 and 95% confidence intervals.

A.4 Survey experiments

Figure A18: Scales used to measure bags' weight

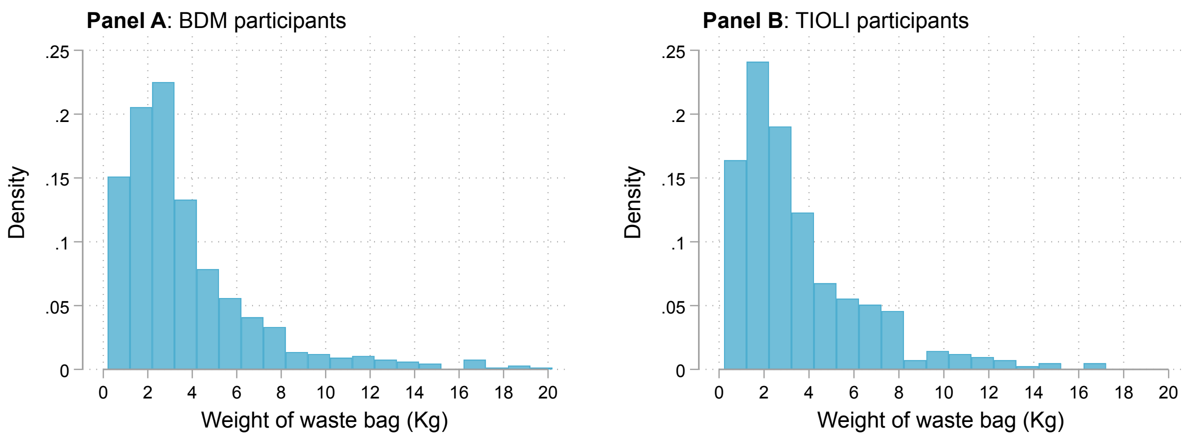
Notes: The picture illustrates the procedure followed to weight all waste bags of households participating in the survey. Enumerators used sanitary gear, and all carried individual scales to measure waste bags in the BDM and TIOLI demand elicitation exercises. The bags were measured at the start of each survey experiment.

Figure A19: Examples of waste bags that enumerators could not weigh

(a) *Example 1* (b) *Example 2* (c) *Example 3*

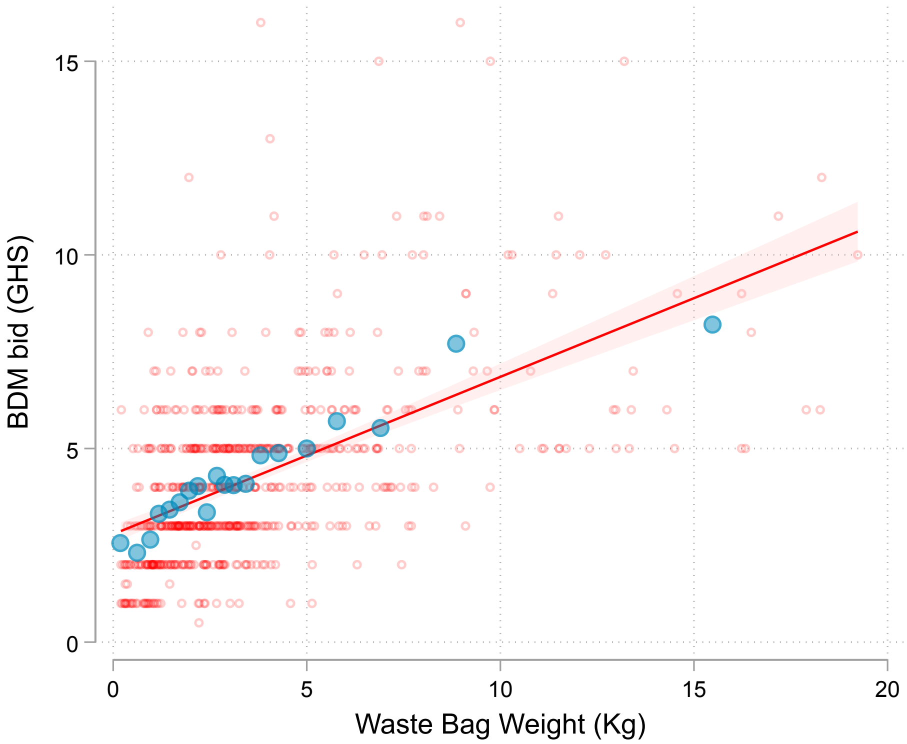
Notes: We include illustrative examples of cases where enumerators were unable to obtain weight measurements using the scales. Most commonly the issue arises not from differences in quantity accumulated, but from the arrangement of waste in sacks, directly in bins with no bag, or in a small pile.

Figure A20: Distribution of bags' weight



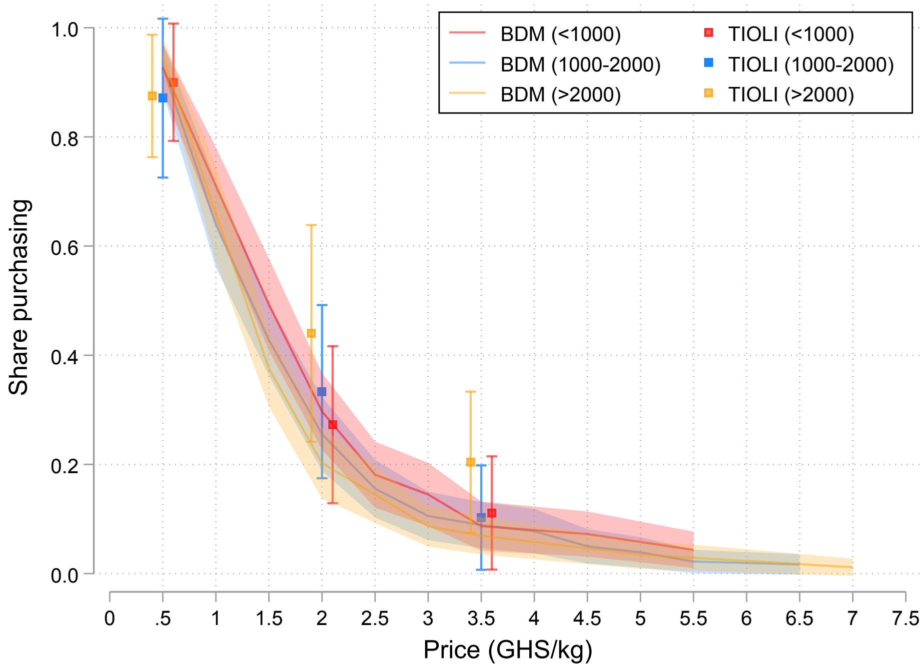
Notes: Histograms of weight of waste bags, measured using identical scales for survey participants. The data used for the distributions is for all income groups. In Panel A, we include the histogram of bag's weight for BDM survey participants, after removing extreme values (observations greater than 20 kg, which are likely an error in the scale used for measurement) (662 observations). In Panel B, we include the histogram of bag's weight for TIOLI survey participants, after removing extreme values using the same criterion (415 observations). As expected, the randomisation of participation across demand elicitation mechanisms yields very similar distribution of waste bag's weights.

Figure A21: BDM bids against waste bag weight



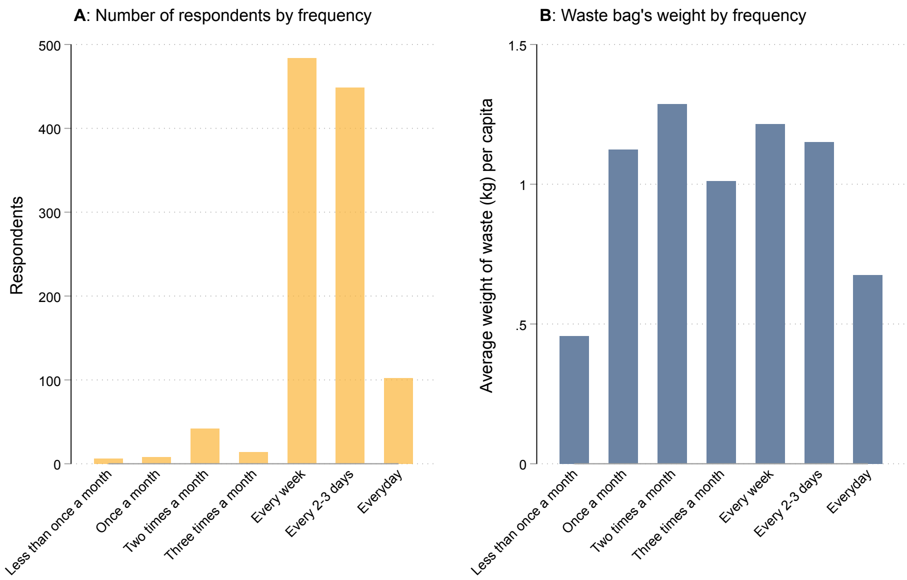
Notes: The scatter plot in red is constructed using raw bids and weight data for the households participating in the BDM elicitation exercise. The linear fit and 95% confidence intervals for it are represented in the red line and shaded area. Using bigger dots in blue, we represent a binned scatter plot for the same data.

Figure A22: Heterogeneity in BDM and TIOLI demand estimates



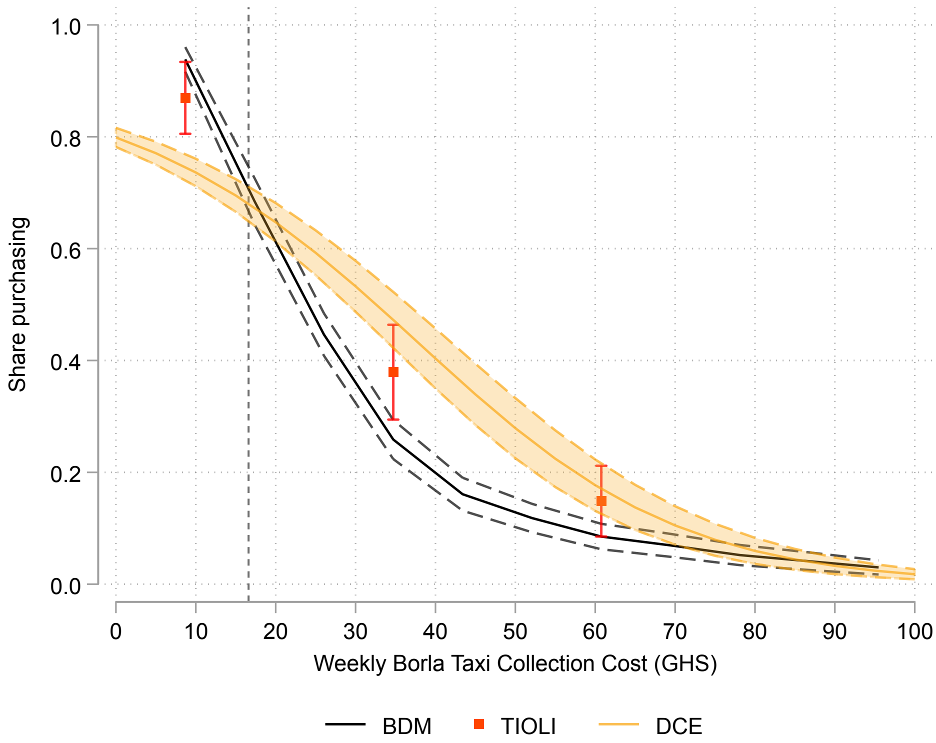
Notes: We represent BDM and TIOLI estimates for three monthly household income groups: 1) below 1000 GHS in red, 2) Between 1000 and 2000 GHS in blue, and 3) Over 2000 GHS in gold. BDM demand curves, with 95% confidence areas and standard errors clustered at the survey enumeration area level, run for each group separately. TIOLI demand at three price points (GHS/kg) –0,5, 2, and 3.5, with 95% confidence intervals and EA-level clustering of standard errors. Run for each group/sample separately. The BDM demand curve reflects the share of households that bid higher or equal than the indicated price in GHS/kg. The TIOLI point estimates reflect the share of households that accepted the price (i.e. purchased the collection service) at each of the random price points. We use point-wise inference from logit regressions for each sample at prices/kg going from 0.5 to 7.5 with 0.5 increments. There are a total of 685 clean BDM final bids, and 394 TIOLI accept/reject observations (115 at 0.5 GHS/kg, 124 at 2 GHS/kg, and 155 at 3.5 GHS/kg). In the whole household survey sample, 409 households report incomes lower than 1000 GHS, 484 report earnings between 1001 and 2000 GHS, 244 report earnings in the 2001-3000 bracket, 104 do so in the 3001-4000 bracket, and a combined total of 149 report earnings in the remaining higher-income brackets. 423 preferred not to reveal their income.

Figure A23: Daily waste generation per capita



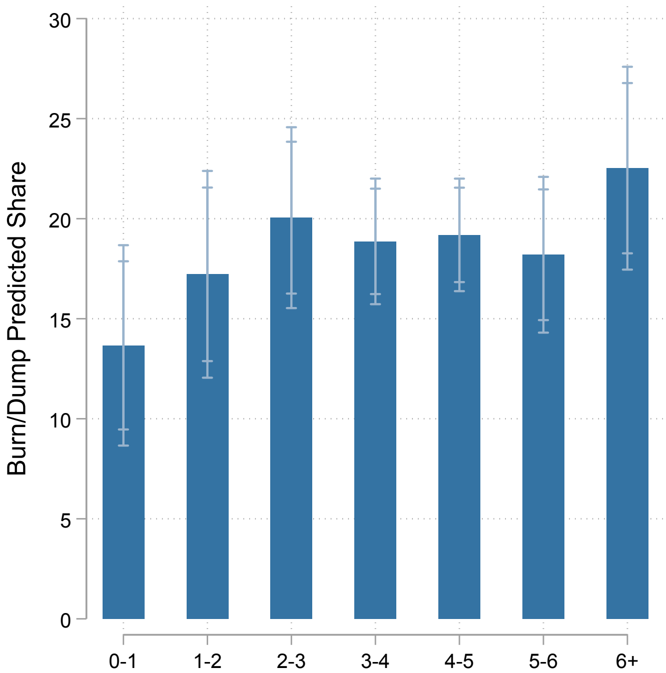
Notes: We use a total of 1105 weight measurements for survey participants in both the BDM and TIOLI elicitation exercises. For 706 households across both exercises, the available waste was too heavy or arranged in a way that it was difficult to weigh (e.g. already in a bin or sack that made the measurement challenging). Enumerators took pictures in all of these cases. We include illustrative examples in Figure A19. In panel A we plot the number of respondents, for which we have weight measurements that fall within each collection frequency category. The majority express getting their waste collected once a week (45.55%) or every 2-3 days (37.27%). Followed by those that get their waste collected every day (8.17%). In Panel B we represent the average weight of bags per capita in kg by each collection frequency category. We calculate kg per capita values by dividing waste measurements over the household size, as reported in our survey. Those that get their waste collected every day have lower kg per capita. Respondents in the the rest of relevant categories (every week and every 2-3 days) report very similar waste per capita at the time of the interview.

Figure A24: BDM, TIOLI, and stated preference estimates



Notes: BDM demand curve, with a 95% confidence band and standard errors clustered at the survey enumeration area level. TIOLI demand at three price points (GHS/kg) –0,5, 2, and 3.5, with 95% confidence intervals and EA-level clustering of standard errors. The BDM demand curve reflects the share of households that bid higher or equal than the indicated price in GHS/kg. The TIOLI point estimates reflect the share of households that accepted the price (i.e. purchased the collection service) at each of the random price points. We use point-wise inference from logit regressions at prices/kg going from 0.5 to 7.5 with 0.5 increments. There are a total of 685 clean BDM final bids, and 394 TIOLI accept/reject observations (115 at 0.5 GHS/kg, 124 at 2 GHS/kg, and 155 at 3.5 GHS/kg). The orange line represents the demand curve we obtain using our stated preference estimates and attribute values. The shaded area corresponds to 95% confidence intervals. In the vertical dotted line we indicate the equilibrium weekly price of 17 that we measure in the household survey.

Figure A25: Predictions and trash counts



Notes: The figure uses the EA level data on both predicted market shares and waste pollution, measured as average number of trash objects across all households and pictures in an EA. We construct bins based on the trash count (0-1), (1-2), (2-3), (3-4), (4-5), (5-6), and 6+. For each bin we compute the mean burn/dump choice probability across EAs (the blue bars in the figure), and 95 and 90% confidence intervals (indicated in lighter blue in the figure).

A.5 The environmental costs of open dumpsites

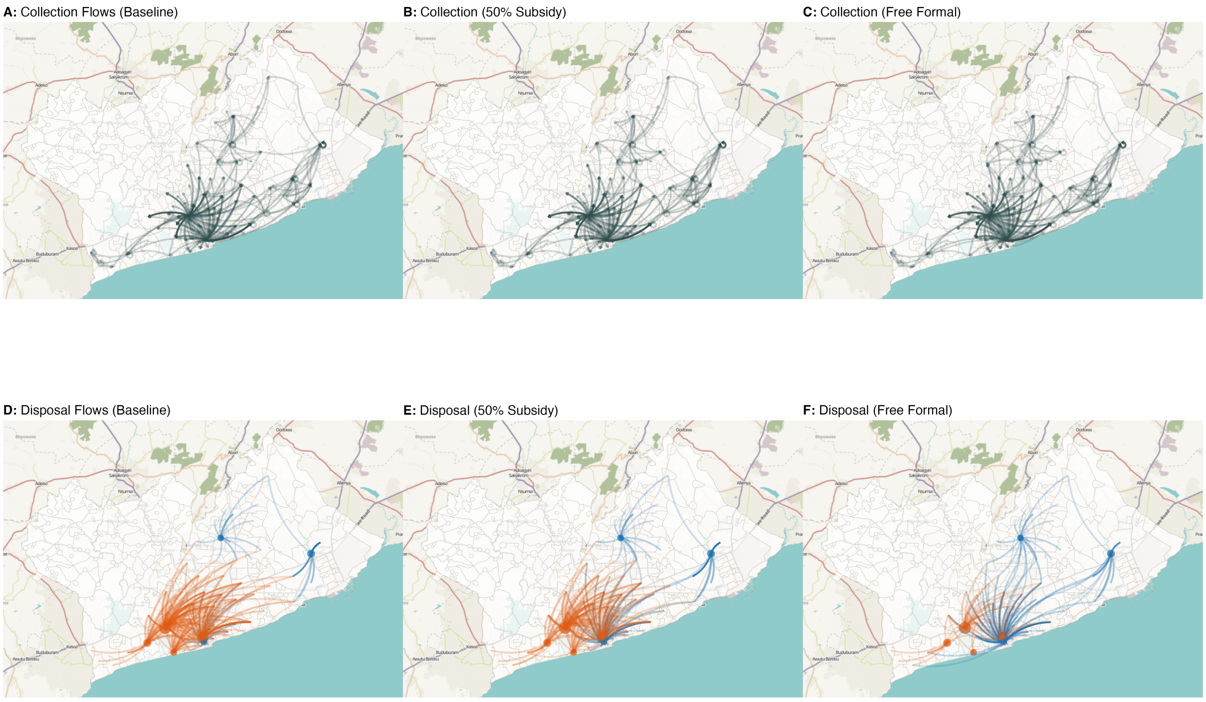
This section reviews the literature on the environmental and health costs of municipal open dumpsites, with the goal of providing an estimate for the external costs per tonne of waste they create. Uncontrolled solid waste disposal at open dumpsites generates large environmental and health consequences through GHG emissions, air pollution, groundwater and soil contamination, and the spread of infectious diseases.

Emissions of Greenhouse Gases: At disposal sites, bacteria decompose the degradable organic carbon contained in solid waste under anaerobic conditions into methane (CH_4) and additional compounds. Open dumps don't have the infrastructure required for gas capture, and as a result emit methane et high rates (100-200 m^3CH_4/t of municipal solid waste, according to the emissions model in U. E. P. A. EPA 2005), being an important contributor to global anthropogenic methane emissions. Estimates for the social cost of methane range from 880–8100 USD/tCH4 in 2020, with a base case estimate of 4000 USD/tCH4, in Azar et al. 2023, 933 USD/tCH4 in Errickson et al. 2021, 470-2900 USD/tCH4 in 2020 in EPA 2023, or between 2400/tCH4 and 3600/tCH4, in Shindell et al. 2017, depending on the discount rates used. Accounting for these emissions alone implies external costs that range between 34 USD/t MSW to 1,163 USD/t MSW, depending on the assumed methane generation rate and social cost of methane, with a base-case estimate of around 287–573 USD/t MSW. This is substantially higher than the cost implied by controlled engineered landfills with gas capture.

Air pollution: The open burning of waste, whether at neighbourhoods or dumpsites, is a major source of air pollution. Open burning is very common at dumpsites, producing PM2.5, dioxins, and black carbon.

A.6 Counterfactuals

Figure A26: Counterfactual collector flows



Notes: Panels A, B, and C display collector *home-collection area* flows for the baseline scenario, 50% and free formal disposal respectively. Flows are represented in black. Panels D, E, and F display *collection area-disposal site* flows for the three same scenarios. In red, flows to dumpsites. In blue, flows to transfer stations.

Figure A27: Candidate disposal sites and transfer zones

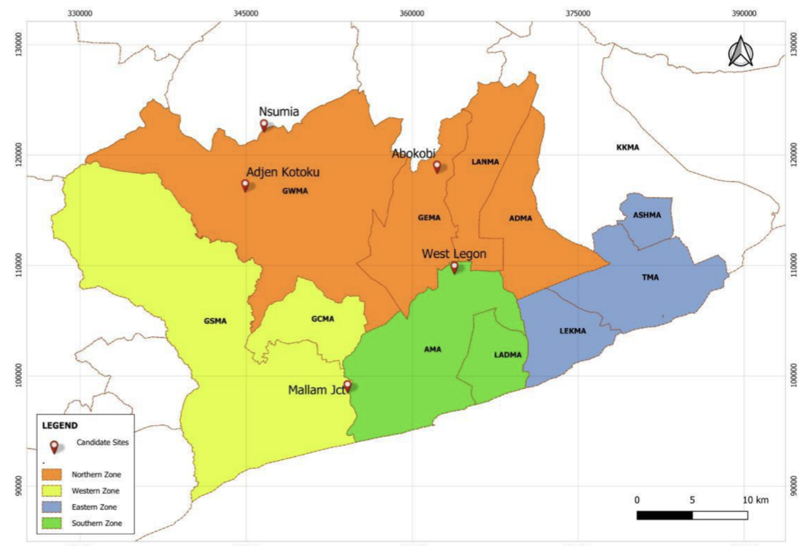


Fig 2: Solid waste transfer zones for GAMA (Source: IUESMP 2020, MSWR)

Notes: The map shows the waste transfer zones and candidate disposal sites, proposed by the government, as illustrated in the GARID report https://garid-accra.com/wp-content/uploads/2024/10/WTS-DED-Report-v7.0_010924.pdf. The report mentions as source of information the The Ministry of Sanitation and Water Resources (MSWR).

A.7 Theoretical Appendix

A.7.1 Expected utility of households and Borla Taxis

This section details the derivation of the expected utility (3) of a household living in area a. To simplify notation, we expresse utility (1) as $U_{io} = \mathbf{x}_o\boldsymbol{\kappa} + \epsilon_{io}$, surpressing the area subscript. The expected utility can be stated as

$$\begin{aligned}
\mathbb{E}\left[\max_w \mathbf{x}_w\boldsymbol{\kappa} + \epsilon_{iw}\right] &= \mu_H\Gamma + \mu_H \cdot \ln\left(\sum_h \exp\left(\frac{\mathbf{x}_h\boldsymbol{\kappa}}{\mu_H}\right)\right) \\
&= \sum_o \pi_o \left(\mu_H\Gamma + \mu_H \cdot \ln\left(\sum_h \exp\left(\frac{\mathbf{x}_h\boldsymbol{\kappa}}{\mu_H}\right)\right)\right) \\
&= \sum_o \pi_o \left(\mu_H\Gamma + \mathbf{x}_o\boldsymbol{\kappa} + \mu_H \cdot \ln\left(\frac{\sum_h \exp\left(\frac{\mathbf{x}_h\boldsymbol{\kappa}}{\mu_H}\right)}{\exp\left(\frac{\mathbf{x}_o\boldsymbol{\kappa}}{\mu_H}\right)}\right)\right) \\
&= \mu_H\Gamma + \sum_o \pi_o \left(\mathbf{x}_o\boldsymbol{\kappa} - \mu_H \cdot \ln\left(\pi_o\right)\right)
\end{aligned}$$

Where the first line applies the well know result on the expected utility under a Gumbel distribution. The second line multiplies by one and the expression is rewritten in line three and four. The derivation of the expected utility (8) of a Borla Taxis with home location h follows analogous steps.

A.7.2 Social optimum

This section formally states the social planners problem and details the derivation of prices $\tilde{\mathbf{p}}$ that implement the socially optimal allocations, as stated in Proposition 1 in Section 7.

Social planner's problem

The social planner chooses the allocations $\{\boldsymbol{\pi}, \boldsymbol{\phi}, \mathbf{q}, \boldsymbol{\lambda}, \mathcal{J}\}$ to maximise welfare Ω, subject to collection and disposal market clearing, as well as all shares being non-negative and summing up to one at the relevant levels of aggregation

$$
\begin{aligned}
\max_{\boldsymbol{\pi},\boldsymbol{\phi},\mathbf{q},\boldsymbol{\lambda},\mathcal{J}} \quad & \Omega \\
\text{st.} \quad \pi_{l,BT} N_l^H &= \sum_k \sum_m \phi_{klm} N_k^{BT} q_{lm}, \quad \forall\, l \in \mathcal{A} && \text{(A.1)} \\
\pi_{l,o} N_l^H &= Q_{l,o}, \quad \forall\, l \in \mathcal{A} \text{ and } o \in \{F, C\} && \text{(A.2)} \\
\lambda_m &= \sum_k \sum_l \phi_{klm} N_k^{BT} q_{lm}, \quad \forall\, m \in \mathcal{J} && \text{(A.3)} \\
\sum_o \pi_{lo} &= 1, \quad \forall\, l \in \mathcal{A} && \text{(A.4)} \\
\sum_l \sum_m \phi_{klm} &= 1, \quad \forall\, k \in \mathcal{H} && \text{(A.5)} \\
\pi_{lo} &\geq 0, \quad \forall\, l \in \mathcal{A} \text{ and } \forall\, o \in \mathcal{O} && \text{(A.6)} \\
\phi_{klm} &\geq 0, \quad \forall\, k \in \mathcal{H}\,, \forall\, l \in \mathcal{A} \text{ and } \forall\, j \in \mathcal{J} && \text{(A.7)}
\end{aligned}
$$

By using the notation $\{\tilde{\boldsymbol{\kappa}}, \tilde{\mu}_H, \tilde{\boldsymbol{\nu}}, \tilde{\mu}_C\} = \left\{\frac{\boldsymbol{\kappa}}{|\kappa_1|}, \frac{\mu_H}{|\kappa_1|}, \frac{\boldsymbol{\nu}}{\nu_1}, \frac{\mu_C}{\nu_1}\right\}$ considering that $\kappa_1 < 0$ and substituting in the constrains (A.1), (A.2), (A.3), and (A.4), the welfare expression can be rewritten as

$$
\begin{aligned}
\hat{\Omega} = &\tilde{\mu}_H \Gamma \sum_l N_l^H + \tilde{\mu}_C \Gamma \sum_k N_k^{BT} \\
&+ \sum_l \sum_k \sum_m \phi_{klm} N_k^{BT} q_{lm} \left(\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{l,BT} + \tilde{\kappa}_3 w_{l,BT} + \tilde{\kappa}_4 s_{l,BT} - \tilde{\mu}_H \ln \left(\frac{\sum_s \sum_t \phi_{slt} N_s^{BT} q_{lt}}{N_l^H} \right) \right) \\
&+ \sum_l N_l^H \pi_{l,F} \left(\tilde{\kappa}_F + \tilde{\kappa}_2 f_{l,F} + \tilde{\kappa}_3 w_{l,F} + \tilde{\kappa}_4 s_{l,F} - \tilde{\mu}_H \ln \left(\pi_{l,F} \right) \right) \\
&+ \sum_l N_l^H \pi_{l,C} \left(\tilde{\kappa}_C + \tilde{\kappa}_2 f_{l,C} + \tilde{\kappa}_3 w_{l,C} + \tilde{\kappa}_4 s_{l,C} - \tilde{\mu}_H \ln \left(\pi_{l,C} \right) \right) \\
&+ \sum_l N_l^H \left(1 - \frac{\sum_s \sum_t \phi_{slt} N_s^{BT} q_{lt}}{N_l^H} - \pi_{l,F} - \pi_{l,C} \right) \Bigg(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{l,BD} + \tilde{\kappa}_3 w_{l,BD} + \tilde{\kappa}_4 s_{l,BD} \\
&\qquad - \tilde{\mu}_H \ln \left(1 - \frac{\sum_s \sum_t \phi_{slt} N_s^{BT} q_{lt}}{N_l^H} - \pi_{l,F} - \pi_{l,C} \right) - \iota \Bigg) \\
&- \sum_k N_k^{BT} \sum_l \sum_m \phi_{klm} \left[\frac{\delta}{2} \left(\frac{q_{lm}}{\vartheta} \right)^2 + \tilde{\nu}_2 \tau_{klmk} + \tilde{\nu}_3 T_m + \tilde{\mu}_C \ln \left(\phi_{klm} \right) \right] \Bigg] \\
&- \sum_m \left[\left(\zeta_m + \varrho_m - r_m \right) \sum_k \sum_l \phi_{klm} N_k^{BT} q_{lm} + F_m \right] \\
&- \sum_l \left[mc_{l,F} \, N_l^H \pi_{l,F} + F_{l,F} \right] - \sum_l \left[mc_{l,C} \, N_l^H \pi_{l,C} + F_{l,C} \right]
\end{aligned}
$$

Note that the all prices have cancelled out from this expression, due to market clearing. Intuitively, monetary transfers between agents do not affect societal welfare, only changes in allocations do. Using this rewritten version of the welfare expression, the social planner's problem reduces to maximising $\hat{\Omega}$ by choosing the allocations $\{\boldsymbol{\pi}_F, \boldsymbol{\pi}_C, \boldsymbol{\phi}, \mathbf{q}, \mathcal{J}\}$ taking into account constraints (A.5), (A.6), (A.7).

The social planner's problem can be solved in two steps. In the first step the allocations $\{\boldsymbol{\pi}_F, \boldsymbol{\pi}_C, \boldsymbol{\phi}, \mathbf{q}\}$ are chosen for a given set of actives sites $\mathcal{J}$. In the second step, the planner then selects the set of actives sites $\mathcal{J}$ that yields the highest welfare.

First order conditions

Formal collection and communal container. We obtain the following first order conditions

$$\frac{\partial\hat{\Omega}}{\partial\pi_{a,F}} = N_a^H \left(\tilde{\kappa}_F + \tilde{\kappa}_2 f_{a,F} + \tilde{\kappa}_3 w_{a,F} + \tilde{\kappa}_4 s_{a,F} - \tilde{\mu}_H \ln\left(\pi_{a,F}\right) - \tilde{\mu}_H - mc_{a,F}\right) \\ - N_a^H \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \tilde{\mu}_H \ln\left(\pi_{a,BD}\right) - \iota - \tilde{\mu}_H\right) = 0 \tag{A.8}$$

$$\frac{\partial\hat{\Omega}}{\partial\pi_{a,C}} = N_a^H \left(\tilde{\kappa}_C + \tilde{\kappa}_2 f_{a,C} + \tilde{\kappa}_3 w_{a,C} + \tilde{\kappa}_4 s_{a,C} - \tilde{\mu}_H \ln\left(\pi_{a,C}\right) - \tilde{\mu}_H - mc_{a,C}\right) \\ - N_a^H \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \tilde{\mu}_h \ln\left(\pi_{a,BD}\right) - \iota - \tilde{\mu}_H\right) = 0 \tag{A.9}$$

Routes. In deriving the first order conditions for the collection routes, constraint (A.5) needs to be considered. For a given home location h, we thus denote the share choosing route $ha'j'$ as function of all other shares $\phi_{ha'j'} = 1 - \sum_{l \neq a'} \sum_{m \neq j'} \phi_{hlm}$. Taking this into account, the first order conditions for collection routes are

$$
\begin{aligned}
\frac{\partial\hat{\Omega}}{\partial\phi_{haj}} =& N_h^{BT} q_{aj} \left(\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a,BT} + \tilde{\kappa}_3 w_{a,BT} + \tilde{\kappa}_4 s_{a,BT} - \tilde{\mu}_H \ln\left(\pi_{a,BT}\right)\right) \\
& - \sum_k \sum_m \phi_{kam} N_k^{BT} q_{am} \left(\tilde{\mu}_H \frac{N_a^H}{\sum_s \sum_t \phi_{sat} N_s^{BT} q_{at}} \frac{N_h^{BT} q_{aj}}{N_a^H}\right) \\
& - N_a^H \frac{N_h^{BT} q_{aj}}{N_a^H} \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \tilde{\mu}_H \ln\left(\pi_{a,BD}\right) - \iota\right) \\
& + \pi_{a,BD} \frac{\tilde{\mu}_H N_h^{BT} q_{aj}}{\pi_{a,BD}} \\
& - N_h^{BT} \left(\frac{\delta}{2}\left(\frac{q_{aj}}{\vartheta}\right)^2 + \tilde{\nu}_2 \tau_{hajh} + \tilde{\nu}_3 T_j + \tilde{\mu}_C \ln\left(\phi_{haj}\right) + \tilde{\mu}_C\right) \\
& - \left(\zeta_j + \varrho_j - r_j\right) N_h^{BT} q_{aj} \\
& - \Bigg[N_h^{BT} q_{a'j'} \left(\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a',BT} + \tilde{\kappa}_3 w_{a',BT} + \tilde{\kappa}_4 s_{a',BT} - \tilde{\mu}_H \ln\left(\pi_{a',BT}\right)\right) \\
& - \sum_k \sum_m \phi_{ka'm} N_k^{BT} q_{a'm} \left(\tilde{\mu}_H \frac{N_{a'}^H}{\sum_s \sum_t \phi_{sa't} N_s^{BT} q_{a't}} \frac{N_h^{BT} q_{a'j}}{N_{a'}^H}\right) \\
& - N_{a'}^H \frac{N_h^{BT} q_{a'j'}}{N_{a'}^H} \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a',BD} + \tilde{\kappa}_3 w_{a',BD} + \tilde{\kappa}_4 s_{a',BD} - \tilde{\mu}_H \ln\left(\pi_{a',BD}\right) - \iota\right) \\
& + \pi_{a',BD} \frac{\tilde{\mu}_H N_h^{BT} q_{a'j'}}{\pi_{a',BD}} \\
& - N_h^{BT} \left(\frac{\delta}{2}\left(\frac{q_{a'j'}}{\vartheta}\right)^2 + \tilde{\nu}_2 \tau_{ha'j'h} + \tilde{\nu}_3 T_{j'} + \tilde{\mu}_C \ln\left(\phi_{ha'j'}\right) + \tilde{\mu}_C\right) \\
& - \left(\zeta_{j'} + \varrho_{j'} - r_{j'}\right) N_h^{BT} q_{a'j'} \Bigg] = 0
\end{aligned}
$$

which can be further simplified to

$$\begin{aligned}
\frac{\partial \hat{\Omega}}{\partial \phi_{haj}} =& q_{aj}\Bigg[\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a,BT} + \tilde{\kappa}_3 w_{a,BT} + \tilde{\kappa}_4 s_{a,BT} - \tilde{\mu}_H \ln\left(\pi_{a,BT}\right) \\
& - \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \tilde{\mu}_H \ln\left(\pi_{a,BD}\right) - \iota\right) \\
& - \left(\zeta_j + \varrho_j + \frac{\frac{\delta}{2}\left(\frac{q_{aj}}{\vartheta}\right)^2 + \tilde{\nu}_2 \tau_{hajh} + \tilde{\nu}_3 T_j + \tilde{\mu}_C \ln\left(\phi_{haj}\right)}{q_{aj}} - r_j\right)\Bigg] \\
& - q_{a'j'}\Bigg[\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a',BT} + \tilde{\kappa}_3 w_{a',BT} + \tilde{\kappa}_4 s_{a',BT} - \tilde{\mu}_H \ln\left(\pi_{a',BT}\right) \\
& - \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a',BD} + \tilde{\kappa}_3 w_{a',BD} + \tilde{\kappa}_4 s_{a',BD} - \tilde{\mu}_H \ln\left(\pi_{a',BD}\right) - \iota\right) \\
& - \left(\zeta_{j'} + \varrho_{j'} + \frac{\frac{\delta}{2}\left(\frac{q_{a'j'}}{\vartheta}\right)^2 + \tilde{\nu}_2 \tau_{ha'j'h} + \tilde{\nu}_3 T_{j'} + \tilde{\mu}_C \ln\left(\phi_{ha'j'}\right)}{q_{a'j'}} - r_{j'}\right)\Bigg] = 0 \qquad \text{(A.10)}
\end{aligned}$$

Quantity. The first order conditions for the collection quantity are

$$\begin{aligned}
\frac{\partial \hat{\Omega}}{\partial q_{aj}} =& \sum_k N_k^{BT} \phi_{kaj} \left(\tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a,BT} + \tilde{\kappa}_3 w_{a,BT} + \tilde{\kappa}_4 s_{a,BT} - \tilde{\mu}_H \ln\left(\frac{\sum_s \sum_t \phi_{sat} N_s^{BT} q_{at}}{N_a^H}\right)\right) \\
& + \sum_l \sum_m \phi_{kam} N_k^{BT} q_{am} \left(-\tilde{\mu}_H \frac{N_a^H}{\sum_s \sum_t \phi_{sat} N_s^{BT} q_{at}} \frac{\sum_s N_s^{BT} \phi_{saj}}{N_a^H}\right) \\
& - N_a^H \frac{\sum_s N_s^{BT} \phi_{saj}}{N_a^H} \Bigg(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} \\
& \quad - \tilde{\mu}_H \ln\left(1 - \frac{\sum_k \sum_l \phi_{kal} N_k^{BT} q_{al}}{N_a^H} - \pi_{a,F} - \pi_{a,C}\right) - \iota\Bigg) \\
& + \left(1 - \frac{\sum_k \sum_l \phi_{kal} N_k^{BT} q_{al}}{N_a^H} - \pi_{a,F} - \pi_{a,C}\right) \left(\frac{\tilde{\mu}_H \sum_k N_k^{BT} \phi_{kaj}}{1 - \frac{\sum_k \sum_l \phi_{kal} N_k^{BT} q_{al}}{N_a^H} - \pi_{a,F} - \pi_{a,C}}\right) \\
& - \sum_k N_k^{BT} \phi_{kaj} \delta \frac{q_{aj}}{\vartheta^2} \\
& - \left(\zeta_j + \varrho_j - r_j\right) \sum_k N_k^{BT} \phi_{kaj} = 0
\end{aligned}$$

which further simplifies to

$$
\begin{aligned}
\frac{\partial \hat{\Omega}}{\partial q_{aj}} =& \tilde{\kappa}_{BT} + \tilde{\kappa}_2 f_{a,BT} + \tilde{\kappa}_3 w_{a,BT} + \tilde{\kappa}_4 s_{a,BT} - \tilde{\mu}_H \ln\left(\pi_{a,BT}\right) \\
& - \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \tilde{\mu}_H \ln\left(\pi_{a,BD}\right) - \iota\right) \\
& - \delta \frac{q_{aj}}{\vartheta^2} - \left(\zeta_j + \varrho_j - r_j\right) = 0
\end{aligned} \tag{A.11}
$$

Decentralising the social optimum

In the following we denote the welfare maximising allocations as $\left\{\tilde{\boldsymbol{\pi}}, \tilde{\boldsymbol{\phi}}, \tilde{\mathbf{q}}\right\}$, which need to satisfy the first order conditions (A.8), (A.9), (A.10), and (A.11). We define $\tilde{\mathbf{p}} = \left\{\tilde{\mathbf{p}}_{BT}, \tilde{\mathbf{p}}_F, \tilde{\mathbf{p}}_C, \tilde{\mathbf{p}}^d\right\}$ as the set of prices that the planner needs to impose to decentralise the social optimum, that is to achieve $\left\{\boldsymbol{\pi}\left(\tilde{\mathbf{p}}\right), \boldsymbol{\phi}\left(\tilde{\mathbf{p}}\right), \mathbf{q}\left(\tilde{\mathbf{p}}\right)\right\} = \left\{\tilde{\boldsymbol{\pi}}, \tilde{\boldsymbol{\phi}}, \tilde{\mathbf{q}}\right\}$, given a set of disposal sites $\mathcal{J}$. Under these prices $\tilde{\mathbf{p}}$, the households choice probabilities follow (2) and are given by

$$
\pi_{ao}\left(\tilde{\mathbf{p}}\right) = \frac{\exp\left(\kappa_o + \kappa_1 \tilde{p}_{ao} + \kappa_2 f_{ao} + \kappa_3 w_{ao} + \kappa_4 s_{ao}\right)^{\frac{1}{\mu_H}}}{\sum_{h \in \mathcal{O}_a} \exp\left(\kappa_h + \kappa_1 \tilde{p}_{ah} + \kappa_2 f_{ah} + \kappa_3 w_{ah} + \kappa_4 s_{ah}\right)^{\frac{1}{\mu_H}}} \tag{A.12}
$$

The route choices of Borla Taxis are governed by (7) and can be expressed as

$$
\phi_{haj}\left(\tilde{\mathbf{p}}\right) = \frac{\exp\left(\nu_1\left(\tilde{p}_{a,BT} - \tilde{p}_j^d + r_j\right) q_{aj}\left(\tilde{\mathbf{p}}\right) - C\left(q_{aj}\left(\tilde{\mathbf{p}}\right)\right) + \nu_2 \tau_{hajh} + \nu_3 T_j\right)^{\frac{1}{\mu_C}}}{\sum\limits_{(b,k) \in \mathcal{C}} \exp\left(\nu_1\left(\tilde{p}_{a,BT} - \tilde{p}_j^d + r_j\right) q_{aj}\left(\tilde{\mathbf{p}}\right) - C\left(q_{aj}\left(\tilde{\mathbf{p}}\right)\right) + \nu_2 \tau_{hajh} + \nu_3 T_j\right)^{\frac{1}{\mu_C}}} \tag{A.13}
$$

And the quantity choice is analogous to (12) and given by

$$
q_{aj}\left(\tilde{\mathbf{p}}\right) = \frac{\left(\tilde{p}_a - \tilde{p}_j^d + r_j\right)\vartheta^2}{\delta} \tag{A.14}
$$

In the decentralised social optimum, prices $\tilde{\mathbf{p}}$ further adjusts to satisfy market clearing analogously to (13)

$$
\pi_{a,BT}\left(\tilde{\mathbf{p}}\right) N_a = \sum_k \sum_m \phi_{kam}\left(\tilde{\mathbf{p}}\right) N_k \, q_{am}\left(\tilde{\mathbf{p}}\right) \tag{A.15}
$$

Note that in deriving the decentralised optimum, we considered constraints (A.1), (A.2), (A.3), (A.4), (A.5) in deriving the first order conditions and the remaining constraints (A.6) (A.7) are satisfied due to the Gumbel-type form of the choice probabilities.

Formal collection and communal container prices $\{\tilde{\mathbf{p}}_{\mathbf{F}}, \tilde{\mathbf{p}}_{\mathbf{C}}\}$. Rearranging the first order conditions (A.8) and (A.9) leads that

$$\begin{aligned}
\ln\left(\frac{\tilde{\pi}_{a,F}}{\tilde{\pi}_{a,BD}}\right) =& \frac{1}{\tilde{\mu}_h}\left[\tilde{\kappa}_F + \tilde{\kappa}_2 f_{a,F} + \tilde{\kappa}_3 w_{a,F} + \tilde{\kappa}_4 s_{a,F} - mc_{a,F}\right. \\
&\left. - \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \iota\right)\right] \\
\ln\left(\frac{\tilde{\pi}_{a,C}}{\tilde{\pi}_{a,BD}}\right) =& \frac{1}{\tilde{\mu}_h}\left[\tilde{\kappa}_C + \tilde{\kappa}_2 f_{a,C} + \tilde{\kappa}_3 w_{a,C} + \tilde{\kappa}_4 s_{a,C} - mc_{a,C}\right. \\
&\left. - \left(\tilde{\kappa}_{BD} + \tilde{\kappa}_2 f_{a,BD} + \tilde{\kappa}_3 w_{a,BD} + \tilde{\kappa}_4 s_{a,BD} - \iota\right)\right]
\end{aligned}$$

Comparing these expressions with (A.12) leads that they coincide if

$$\begin{aligned}
\tilde{p}_{a,F} &= mc_{a,F} - \iota \\
\tilde{p}_{a,C} &= mc_{a,C} - \iota
\end{aligned}$$

Disposal prices $\{\tilde{\mathbf{p}}^{\mathbf{d}}\}$. Using that in the decentralised optimum $\tilde{\pi}_{ao} = \pi_{ao}(\tilde{p})$, the first order condition for the collectors route choice (A.10) can be expressed as

$$\begin{aligned}
0 =& \tilde{q}_{aj}\left[\tilde{p}_{a,BT} + \iota - \left(\zeta_j + \varrho_j + \frac{\frac{\delta}{2}\left(\frac{\tilde{q}_{aj}}{\vartheta}\right)^2 + \tilde{\nu}_2\tau_{hajh} + \tilde{\nu}_3 T_j + \tilde{\mu}_C \ln\left(\tilde{\phi}_{haj}\right)}{\tilde{q}_{aj}} - r_j\right)\right] \\
&- \tilde{q}_{a'j'}\left[\tilde{p}_{a',BT} + \iota - \left(\zeta_{j'} + \varrho_{j'} + \frac{\frac{\delta}{2}\left(\frac{\tilde{q}_{a'j'}}{\vartheta}\right)^2 + \tilde{\nu}_2\tau_{ha'j'h} + \tilde{\nu}_3 T_{j'} + \tilde{\mu}_C \ln\left(\tilde{\phi}_{ha'j'}\right)}{\tilde{q}_{a'j'}} - r_{j'}\right)\right]
\end{aligned}$$

where we substituted out $\pi_{ao}(\tilde{p})$ using their definitions given in (A.12). Rearranging leads that

$$\begin{aligned}
\ln\left(\frac{\tilde{\phi}_{haj}}{\tilde{\phi}_{ha'j'}}\right) =& \frac{1}{\tilde{\mu}_C}\left[\tilde{q}_{aj}\left(\tilde{p}_{a,BT} - \zeta_j - \varrho_j + \iota + r_j\right) - \frac{\delta}{2}\left(\frac{\tilde{q}_{aj}}{\vartheta}\right)^2 - \tilde{\nu}_2\tau_{hajh} - \tilde{\nu}_3 T_j\right] \\
&- \frac{1}{\tilde{\mu}_C}\left[\tilde{q}_{a'j'}\left(\tilde{p}_{a',BT} - \zeta_{j'} - \varrho_{j'} + \iota + r_{j'}\right) - \frac{\delta}{2}\left(\frac{\tilde{q}_{a'j'}}{\vartheta}\right)^2 - \tilde{\nu}_2\tau_{ha'j'h} - \tilde{\nu}_3 T_{j'}\right]
\end{aligned}$$

Comparing this expression with the one based on (A.13), it follows that they coincide if

$$\tilde{p}^d_j = \zeta_j + \varrho_j - \iota \tag{A.16}$$

Optimal quantity. Using that in the decentralised optimum $\tilde{\pi}_{ao} = \pi_{ao}(\tilde{p})$, the first order condition for quantities (A.11) can be expressed as

$$\tilde{p}_{a,BT} + \iota - \delta\frac{\tilde{q}_{aj}}{\vartheta^2} - (\zeta_j + \varrho_j - r_j) = 0$$

here we substituted out $\pi_{ao}(\tilde{p})$ using their definitions given in (A.12). Rearranging leads that

$$\tilde{q}_{aj} = \frac{\vartheta^2}{\delta}\left[\tilde{p}_{a,BT} - \zeta_j - \varrho_j + \iota + r_j\right]$$

Comparing this expression with (A.14), it follows that they coincide if the disposal prices are given by (A.16) indeed.

Borla Taxi prices $\{\tilde{\mathbf{p}}_{BT}\}$. A closed form solution for $\tilde{\mathbf{p}}_{BT}$ does not exist. Therefore, $\tilde{\mathbf{p}}_{BT}$ needs to be solved for numerically, as the vector of prices satisfying market clearing (A.15) given the disposal prices (21), formal collection and communal container prices (22), and choices being governed by (A.12), (A.13), and (A.14).

A.7.3 Extension: Endogenous loading rate

We denote the matches between collectors and households at any point in time t and location a as $\mathcal{M}_{at}$, and assume they take a Cobb-Douglas functional form, the most common specification in the matching function estimation literature (Petrongolo and Pissarides, 2001; Elsby et al., 2015; Brancaccio et al., 2020)

$$\mathcal{M}_{at} = \xi_a h_{at}^{\alpha} S_{at}^{\beta} \tag{A.17}$$

h_{at} is the mass of waiting households at a point in time, S_{at} the mass of searching collectors at a point in time, ξ_a captures the matching efficiency in each region, and α_a and β_a the elasticities of matches with respect to the number of households and Borla Taxis, respectively. The loading rate ϑ_{at}, that is, how quickly collectors fill their tricycle in a location, is the ratio between the number of transactions and the number of active collectors; $\vartheta_{at} = \frac{\mathcal{M}_{at}}{S_{at}} = \xi_a h_{at}^{\alpha} S_{at}^{\beta-1}$. In the data, during the period at which most transactions are done, and most waste collectors are searching for customers, loading rates are relatively constant. In our medium to long-term analysis, we therefore assume a constant loading rate and in what follows we denote

$$\vartheta_a = \xi_a H_a^{\alpha} S_a^{\beta-1}\,, \tag{A.18}$$

where H_a is the number of households who demand Borla Taxi collection services in a and S_a is the number of collectors commuting to a. We therefore abstract from within-day variation in these objects, as our goal, in a static framework, is to capture medium to long-run behaviour across space.

Given a loading rate ϑ_a, collecting waste from q customers requires a total time $T(q) = \frac{q}{\vartheta_a}$. Note that all demand is eventually met, as markets clear. Here we allow for the time cost of meeting such demand to vary across areas and such time to be determined by the number of active collectors in each area.

Estimation: We use our geolocated and timestamped transaction data to estimate the parameters governing the matching process via which collectors find customers. Taking logs of the matching process in Equation A.17, we rewrite it as an estimating equation we can take to the data.

$$\log(\mathcal{M}_{at}) = (\beta)\log(S_{at}) + \underbrace{\log(\xi_a) + \alpha\log(h_{at})}_{\varepsilon_{at}} \tag{A.19}$$

We do not observe the number of households waiting for their waste to be collected in every minute, but we do observe the number of active collectors and completed transactions at each time period in every area. We further assume constant returns in matching ($\alpha + \beta = 1$) to recover the match elasticity with respect to searching households. Using an instrument for $\log(S_{at})$ we can estimate β directly. As an instrument for the number of active collectors in each location and time bin, we use the sum of the distances from a locality to all collectors' home localities. Our instrument strongly predicts collector presence (Columns (3)-(6) in Table A3). Collectors minimise commute times when choosing where to search for customers. Therefore, areas closer to where collectors live should see more numerous and earlier collector activity.

We argue that the instrument also satisfies the exclusion restriction. Areas might differ in matching efficiency due to geographic factors, such as road layout, area dimensions, ruggedness, slope, etc. These physical characteristics of area a are plausibly orthogonal to where waste collectors happen to live. Collectors' residential choices are primarily driven by affordability (many live close or near slums), religion, or family ties. And it is unlikely they are determined by the matching efficiency of potential collection areas. Nonetheless, we control for the total surface of collection areas to account for the main way geography may impact matching efficiency. It is also reasonable to believe that collectors do not strategically choose to live near high-demand areas. The number of households demanding collection services at time t in area a is driven by waste generation rates (household size, income), alternative disposal options available to households, preferred/available disposal frequency, household members' work schedules and commuting patterns. It is plausible that these demand-side factors are uncorrelated with collectors' residential locations.

Table A3 gathers the results. Columns (1) and (2) report OLS results. Column (2) includes population, area, and 20 min time-bin fixed effects. In columns (3) to (6) we report IV estimates. The full specification, including population, area, and time-bin fixed effects is in Column (6). The large estimate of the match elasticity with respect to the number of active collectors, ranging from $\hat{\beta} = 0.85$ to $\hat{\beta} = 0.91$, makes sense, as one collector can serve multiple customers in an area. In our survey, we observe that collectors spread geographically, with each area being served by 5 to 20 collectors in most cases, meaning that a relatively small number of collectors can serve many households. Furthermore, if collectors don't travel to a particular neighbourhood in one day, waiting households can postpone collection until the next day, muting the household demand elasticity. The sum of coefficients in rows one and two (for active collectors and population) in Columns (5) and (6) are very close to 1, providing suggestive evidence for our constant returns to scale assumption.

A.7.4 Extension: Borla Taxi entry

This section presents a model extension where the number of collectors N_h^{BT} living in each home location h is determined endogenously. This allows for both adjustments of the distribution of collector across home locations and the total number of collectors operating in the city.

Different from Section 5.2, collector i maximizes utility by now also choosing where to live h, in addition to where to work a and where to dispose of waste j. The indirect utility function is given by

$$U_{ihaj} = u_{haj} + \theta_h + \epsilon_{ihaj} \tag{A.20}$$

Table A3: Matching estimates

	Dependent variable: Log (Transactions)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	IV	IV	IV
Log (Active collectors)	1.376***	1.353***	1.056***	0.970***	0.852*	0.910*
	(0.112)	(0.122)	(0.383)	(0.375)	(0.505)	(0.490)
Log (Population)		0.0578*			0.137**	0.107*
		(0.033)			(0.062)	(0.065)
Log (Area)		0.0228			-0.0329	-0.0114
		(0.033)			(0.054)	(0.053)
Observations	984	984	984	984	984	984
First-stage F-stat			24.10	23.43	11.29	11.10
Time-bin FE		✓		✓		✓

Notes: * 0.1 ** 0.05 *** 0.01. Robust standard errors in parentheses, clustered at the locality level. We use data at the locality time-bin level. Time-bins are of 20 minutes. We aggregate the raw app transaction data at the time-bin and locality level. We compute the number of active collectors in each locality. A collector is active if he is registering transactions spaced by less than 3 hours in the same place. The sample is restricted to areas with active collectors. And we pull across different dates for each time bin. Columns 1–2 present OLS estimates of the matching equation in A.19. Column (2) uses time-bin fixed effects and population and area regressors. We use Global Human Settlements Data to compute population at the locality level. We calculate the area of each locality based on the 2010 EA level polygons, aggregating geometries to construct locality polygons. Columns (3) to (6) present results from our IV regressions. We instrument the number of active collectors in a location at a time-bin using the distance between their home location, as reported in the survey, and the area where transactions are registered in the app. In Columns (3) to (6), we include specifications with different combinations of time-bin fixed effects, and population and area regressors.

where $u_{haj} = \nu_1 \Pi_{aj} + \nu_2 \tau_{hajh} + \nu_3 T_j$ captures the utility of travelling on route $hajh$ to collect and dispose of waste. The term θ_h captures any remaining aspects influencing the utility of living in location h, such as amenities, or the availability of housing and consumption goods. As the population of collectors is arguably too small to impact these aspects, we assume θ_h to be exogenous.

We model the idiosyncratic utility component ϵ_{ihaj} to now also vary by home location, leading that the probability that a collector chooses combination haj is given by

$$\pi_{haj} = \frac{\exp\left[u_{haj} + \theta_h\right]^{\frac{1}{\mu_C}}}{\sum_{k,l,m} \exp\left[u_{klm} + \theta_k\right]^{\frac{1}{\mu_C}}} \tag{A.21}$$

It follows that the choice probability (7) for the case where the number of collectors is exogenously determined can be understood as the conditional probability of choosing route aj given that a collector lives in h.

Using expression (A.21), the number of Borla Taxis in h can be expressed as

$$N_h^{BT} = \sum_{l,m} \pi_{hlm} \, N^{BT} \tag{A.22}$$

and the expected utility of working as a collector in the city is given by

$$\mathcal{U}\left(N^{BT}\right) = \mu_C \, \Gamma + \mu_C \, \ln\Big[\sum_{k,l,m} \exp\left[u_{klm} + \theta_k\right]^{\frac{1}{\mu_C}}\Big] \tag{A.23}$$

Denoting the outside option of waste collectors as $\bar{\mathcal{U}}$, new Borla Taxis will enter or exit the market until

$$\mathcal{U}\left(N^{BT}\right) = \bar{\mathcal{U}} \tag{A.24}$$

Given that the observed market is in equilibrium, one can solve (A.22) for $\boldsymbol{\theta}$ and to obtain $\bar{\mathcal{U}}$ from (A.23).