# Efficient Market Structure of the Portuguese Municipal Solid Waste Sector

Estimating economies of scale and scope in collection, disposal, and recycling for Portuguese municipal solid waste management operators

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*Estimating economies of scale and scope in collection, disposal, and recycling for Portuguese municipal solid waste management operators*

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**Abstract.** The purpose of this study is to analyze the cost and production structure of the Portuguese municipal solid waste management sector in light of the expected sustainability transformation. Cobb-Douglas and Translog production functions are estimated using a panel data set covering the full set of on average 250 downstream operators over the period 2016-2020. Results hint at increasing returns to scale in waste collection. Subsample regressions suggest that in particular rural operators do not operate at optimal scale.

For a panel of 11 upstream operators over the period 2013-2020, a Cobb-Douglas cost function is specified that takes into account the multi-output structure of upstream services. Estimation results hint at cost savings arising from the joint provision of mixed and separate waste management services.[1]

**Keywords.** Solid Waste Management - Regulation - Market Structure - Circular Economy
**JEL Codes.** Q38 - H44 - L99

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# 1 Introduction

Municipal solid waste (MSW) - that is, household waste and waste from other sources, that is similar in its nature - accounted for roughly 10% of total waste generated in the European Union in 2018 (Eurostat 2021). Despite its relatively small quantity, MSW and its management is a highly political and complex topic that requires more attention from research and policymakers for several reasons. Firstly, landfilling, one of the most frequent disposal methods of MSW, has adverse effects on the environment and human health due to the emission of methane and other gases (Lee et al. 2017). Secondly, on EU average the amount of MSW generated has increased in the last 20 years by about 8% between 2019 and 1995 (Eurostat 2021). Thirdly, as often local public authorities are in charge of managing MSW in EU member states it requires huge public investment (Salvetti 2021). Lastly, the management of MSW is particularly complex, as it consists of different materials, and is strongly linked to household consumption behavior (Eurostat 2021). In recent years, several national and EU level targets aiming at fostering sustainability and resource efficiency in waste generation and management have been introduced (see e.g. Council of European Union (2018)). Next to putting great emphasis on the prevention of waste, these targets see an important role for the waste management sector in the transition towards a more circular economy. More precisely, the EU- and national frameworks point at the need for a shift away from landfilling towards increased recycling, and re-use of waste (Lee et al. 2017). These objectives are expected to require restructuring and high financial investments for the sector. The question of how to most efficiently organize the MSW-management market is thus as relevant as ever in the light of the aspired sustainability transformation.

This article investigates the cost and production structure of MSW operators for the EU-member state of Portugal. It will explore the efficiency of the Portuguese MSW-market structure by posing two main questions. Firstly, it will ask whether economies of scale and density exist in different phases of MSW-management. Studying scale and density economies is needed to give advice on the optimal operator number and size. Secondly, this study will investigate if economies of scope from jointly managing different streams of waste exist. Knowing whether operators experience cost savings from offering different waste management services is key for a cost-efficient market design of the sector.

The case of Portugal is of particular interest, as it is one of the few EU-member states in which the MSW-sector is regulated by an independent regulation authority. Furthermore, the current organization of the Portuguese market offers several avenues for efficiency analysis. The sector is divided into *downstream* and *upstream* services. Downstream operators are responsible for mixed and partly separate collection only, whereas upstream service providers treat and dispose mixed and separate waste, and are in part responsible for separate collection. While the Portuguese downstream sector can be characterized as fairly fragmented with more than 230 active operators in 2020, there are only 23 upstream operators in continental Portugal.

To take into account the differences in production processes and technologies, I specify two separate models for upstream and downstream MSW-management. For collection providers, a Cobb-Douglas and a Translog production function are specified that allow testing for the existence of returns to density and scale in the downstream sector. Then, a Cobb-Douglas cost function of upstream waste management is introduced that takes into account the multi-product nature of the services. The set-up allows testing for the existence of cost-complementarities between managing mixed and separate waste.

Production functions for downstream operators are estimated using panel data covering the full set of on average 250 operators over the period 2016-2020. This data was made available by the regulation authority *ERSAR*. Estimation results using the pooled OLS estimator hint at the existence of returns to scale in waste collection, while returns to density have most likely already been fully exploited. Further subsample regressions help to divide the operators into different efficiency clusters by type of intervention area. I find efficiency incentives for adjacent rural operators to merge. The estimation of the cost function of upstream operators is based on a sample of 11 operators for the period 2013-2020. Results sugguest that operators experience economies of scope between managing mixed and separate streams of waste. Moreover, evidence for economies of scale in the upstream sector is found. Since the sample size for the upstream estimation is small and because endogeneity bias cannot be ruled out, results have to be treated with care. Nevertheless, the estimation can give valuable guidelines for regulation authorities. They provide intervals for economies of scale and identify clusters of operator groups where distinct efficiency patterns seem to exist.

The rest of the article is structured as follows: Section 2 will give an overview of the economic literature on MSW-management and highlight the contributions of this article. Section 3 will describe in more detail the context of Portuguese MSW-management - ranging from a general description of MSW-management and its different phases to a detailed summary of the Portuguese sector. In section 4, I specify and discuss the production and cost functions of waste management. Section 5 will outline in more detail the data sets that were gathered for the estimation. Section 6 proceeds by describing and discussing the result of downstream and upstream estimations. After highlighting that the results are robust to two main robustness checks (section 7), I will discuss the meaning and the limits of the estimation results in section 8.

## 2 Related Literature

This article contributes to the empirical economic literature on MSW waste management. Research can be divided into two main strands mirroring the two main actors involved in the waste management process: i) households and firms that *generate* different types of waste (demand side) and ii) operators that are responsible for *managing*, that is collecting, transporting, sorting, disposing, and/or recycling waste (supply-side).

## 2.1 Demand Side Literature:

Economic research that investigates the demand side is mainly interested in understanding waste generation behavior often in the light of political reforms to the waste management system in place. Most authors have hereby focused on estimating the short-term impacts of different reforms in a given local setting (often at the municipality level).

A seminal paper by Fullerton and Kinnaman (1996) evaluates the impact of the introduction of a unit-based pricing system in the US, that charges households per amount of waste collected. More recent studies have extended this analysis not only by expanding its geographical scope but also by the set of policies and outcome variables investigated. Both Ferrara and Missios (2005) and Dijkgraaf and Gradus (2017), for example, assess the impact of waste user fees on the recycling rates for different waste materials in Canada, and the Netherlands, respectively. In a related study, Yang and Innes (2007) examine the differential impact of unit-based pricing systems, national mandatory recycling programs, and nationwide pricing of plastic bags on household waste generation in Taiwan. Three more recent studies exploit natural variation in the waste management systems and identify the impacts on household waste generation. While Bueno and Valente (2019) mainly rely on a synthetic control approach to assess the effect of the introduction of a unit-base-pricing mechanism in Italy, Pfister and Mathys (2022) apply a difference-in-difference estimation to evaluate the impact of a tax raise on unsorted waste on household waste production and recycling rates in Switzerland. Set in Sweden, Alacevich, Bonev, and Söderberg (2021) look at the effect of policies meant to encourage home-based waste sorting and find that such policies not only affect household sorting behavior but will also reduce the quantities of waste *generated* by households.

## 2.2 Supply-Side Literature:

Whereas both strands are surely interlinked, this article contributes primarily to the literature dealing with the *supply side* of waste management. Economic research on the supply-side has been concentrating mostly on detecting efficiency and cost drivers of the various phases of waste management. Scholars have hereby highlighted the role of the overall market structure (operator size, (un)bundling of services, and ownership structure) as well as the impact of specific policies and technologies affecting the efficiency of waste management in different settings.

*Market Structure:* Building on traditional studies by Dubin and Navarro (1988) and Tickner and McDavid (1986), Antonioli and Filippini (2002) investigate the optimal size of the Italian collection service. Using panel data on costs and output of 30 Italian waste collection operators they specify and estimate a translog-cost function using the seemingly-unrelated-regression approach.[2] The authors find both evidence for economies of density and scale in the sector. From these results, they conclude that a market structure with few operators and relatively large intervention areas is more efficient than having side-by-side competition of many small firms.[3] Two more recent studies apply a similar

[2] See Zellner (1962) for more details on this estimation specification.
[3] See e.g. Bel and Fageda (2010) for a study that finds qualitatively similar results for the waste collection services

methodology to estimate the costs of recycling, another phase of waste management. Bohm et al. (2010) find evidence for the existence of economies of scale at higher levels of quantity in the US recycling sector, while Carvalho and Marques (2014) estimate the costs of Portuguese utilities responsible for separate waste collection and treatment. Using a sample of 37 recycling utilities from the years between 2006 and 2010, they estimate a Translog cost function of sorted waste treatment and find evidence for economies of density and scale to exist, in particular for small to medium-sized utilities. Moving beyond size and density effects, economic literature has also been focusing on the potential efficiency differential between private and public provision of MSW services. Ohlsson (2003), for example, estimates the effect of ownership structure on the costs of Swedish collection services. Using a two-step regression framework he takes into account the potential self-selection of operators into their ownership type.

*Parametric vs. non-parametric:* From a methodological perspective, the non-parametric *data envelope analysis* (DEA), has become increasingly popular to analyze the efficiency of various economic sectors, including waste management (Hjalmarsson, Kumbhakar, and Heshmati 1996).[4] Unlike parametric approaches the DEA technique does not require the specification a functional form for the production or cost structure of operators in the waste sector.[5]

*Effects of vertical and horizontal (dis)integration*: Despite the growing number of studies estimating the efficiency of single phases of waste management, there is relatively little research that takes into account its multi-product nature and tests for the existence of potential cost savings for offering several services at the same time. Callan and Thomas (2001) investigate the cost structure of municipal solid waste management in Massachusetts using cost and output data at the municipality level. They use a Cobb-Douglas cost function of upstream waste management but distinguish between waste being disposed and waste being recycled. They find evidence for cost-complementarities and hence economies of scope between recycling and disposal of waste. In a related study, Abrate et al. (2014) use a panel of 529 Italian municipalities between 2004-2006 to estimate economies of scope between waste disposal and recycling. In line with Callan and Thomas (2001), their results indicate cost savings from the joint provision of these two services.

*Policies and other cost drivers:* Two more recent studies link policies and seasonality to efficiency in the Dutch and the Italian MSW system. Dijkgraaf and Gradus (2015) investigate how the introduction of a unit-based pricing system affects the efficiency of service suppliers. They thereby distinguish between different types of pricing systems introduced in the Dutch municipalities. Moreover, the authors differentiate whether the introduction of a pricing system alters the quantities of waste entering into management and whether the price per unit of waste being managed changes. Caponi (2022) takes a more detailed look at the relationship between seasonal tourism and the efficiency of waste collection operators in Tuscany. Applying a DEA estimation, he finds a negative

in Galicia, Spain.

[4] See e.g. Fried, Lovell, and Schmidt (2008) and Daraio and Simar (2007) for a more detailed discussion on the DEA methodology.

[5] See e.g. Rogge and De Jaeger (2013) for an application of the DEA technique for the cost-efficiency estimation of waste collection services in Flanders. Belgium.

effect of seasonality. This is explained mostly by the fact that seasonality hinders service providers from operating at their optimal scale over a whole year - with very high scales during peak seasons and relatively low scales in off-peak seasons.

This study contributes to the literature in three main ways: Firstly, it is to the best of my knowledge the first study that tests for the existence of cost complementarities between the management of sorted and mixed waste. Given that the type of collection (sorted or mixed) will largely determine *how* it will be processed further, a waste management model that investigates the interaction between mixed and separate waste services seems most meaningful.[6]

Secondly, it is to my knowledge the first study that considers all waste management phases for a given country at the same time. Hence, it will give a complete picture of the efficiency of the waste management system of a given country. This is important since different phases of waste management are interdependent (i.e. a higher quality of collection will affect the recycling rates, or a higher rate of recycling will mean less disposal of waste on landfills). Moreover, it delivers a framework that will eventually allow testing for spillovers between different phases of management. Such spillovers can occur after the introduction of a new policy (e.g. pricing systems or new regulatory guidelines) but also in the light of economic shocks.

The last main contribution of this article is that it investigates the efficiency of waste collection for different clusters of operators. In particular, it highlights differences between rural, medium urban, and urban operators, and thereby takes into account that these types of operators differ in both operation scale and density. This exercise is relevant as it can hint at the need for more regionally refined regulation frameworks.

# 3 Context: The Portuguese Municipal Waste Sector

## 3.1 Phases of MSW-management

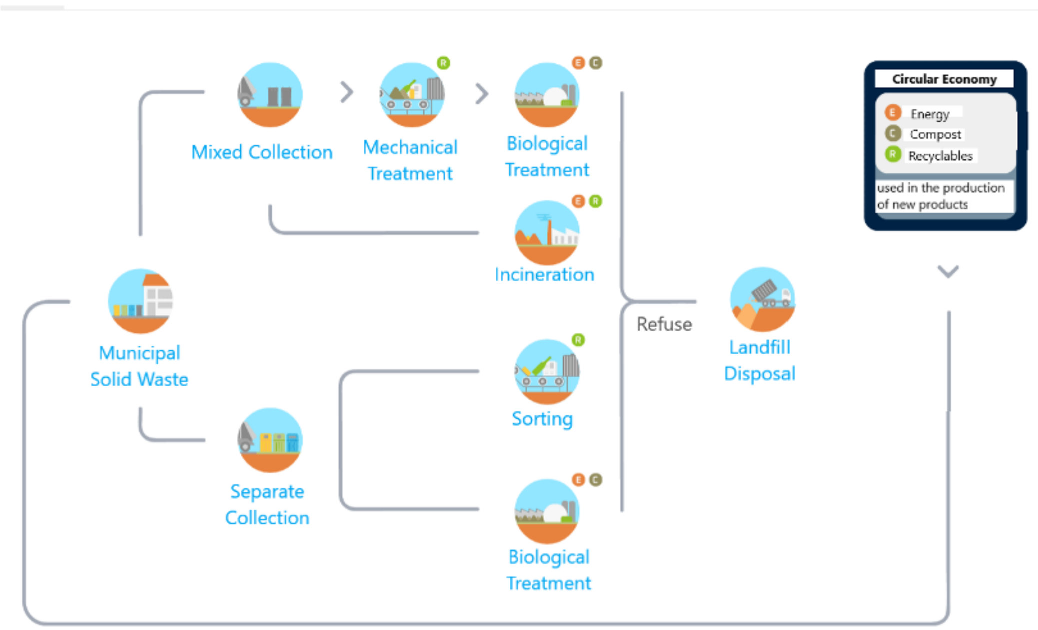
According to the definition of the EU waste framework directive (Directive 851/2018), the term *municipal solid waste* refers to waste of different material composition[7], that is being collected from households either mixed or separately, and all other types of waste collected from other sources, that is "[...] similar in nature and composition to waste from households". (Council of European Union 2018). Managing municipal solid waste involves different stages. Even though their exact design can differ between countries, one can typically distinguish between three main *phases* of MSW management (Dri et al. 2018). As illustrated in figure 1, depicting the MSW management system in Portugal, waste is first being *collected*. Collection of waste will typically differ w.r.t. to its timing (frequency of pick-up, time of the day), its point of collection (communal containers,

[6] This is also reflected in the regulatory framework that has been put in place in Portugal, that largely distinguishes flows of mixed from separate waste. See e.g. https://www.ersar.pt/pt/setor/caracterizacao/residuos-urbanos

[7] More precisely, the directive lists "[...] paper and cardboard, glass, metals, plastics, bio-waste, wood, textiles, packaging, waste electrical and electronic equipment, waste batteries and accumulators, and bulky waste, including mattresses and furniture." (Council of European Union 2018)

kerbside, or door-to-door collection), and its methods of loading and transporting waste (Coffey and Coad 2010). The material composition of the collected waste determines the type of treatment materials that will enter. We can distinguish between *streams of mixed waste*, that is different materials are collected together, and *separate waste*, i.e. waste is collected separately depending on its composition. Separately collected waste streams can either be sent to sorting plants where they are prepared for recycling or - for separately collected bio-waste - enter into composting and anaerobic digestion plants. The final output will thus be either energy, compost, recyclables, or disposed waste (for the refuse/rejects that are typically generated during recycling). Mixed waste, on the other side, can either be sent directly to incineration or landfill disposal or can enter into mechanical or biological treatment to be prepared for energy recovery or composting (Dri et al. 2018). Looking at the current country-level waste generation and treatment statistics in table 1

Figure 1: Phases of MSW-Management Portugal




Adopted from ERSAR (2022c)

reveals, that generation in Portugal has risen from about 460 kg in 2015 to 513 kg per capita in 2020 to lie just above EU average (Eurostat 2021). From 2013 to 2020 the amount of waste being landfilled has contrary to the EU average increased, and landfills remain by far the largest final waste destination. Conversely, recycling rates for both biowaste and other streams of separate waste remain on average fairly low. In the light of the most recent EU legislation that aims at fostering the transition towards a circular economy in EU member states, the Portuguese waste management sector is thus expected to experience significant transformation. This is in particular needed to achieve the MSW related targets from EU waste legislation that see a sharp decrease in the share of MSW landfilled and in return a significant increase in the amount of waste being recycled and reused by 2035.[8]

Table 1: Yearly MSW quantities generated and treated (in kg/capita)

| | Landfill | Incineration/ Energy Recovery | Composting | Material Recycling | Other | Total Waste Treated | Total Waste Generated |
|---|---|---|---|---|---|---|---|
| **2020** | | | | | | | |
| EU 27 | 115 | 137 | 90 | 151 | 11 | 495 | 505 |
| Portugal | 263 | 93 | 70 | 65 | 22 | 492 | 513 |
| **2013** | | | | | | | |
| EU 27 | 142 | 127 | 71 | 128 | 2 | 468 | 470 |
| Portugal | 222 | 104 | 57 | 57 | 0 | 440 | 440 |

Source: Eurostat (2022b)

## 3.2 Portuguese Market Structure:

Portugal is one of the few EU member countries where an economic regulation entity has been established, as opposed to relying on the self-regulation of the MSW sector (Salvetti 2021). The Entity for Regulation of Water and Waste Services, *ERSAR*, was created in 1997 and has become an independent administrative unit in 2014. ERSAR is responsible for the structural regulation, as well as, the behavioral regulation and supervision of the entities operating in water-, wastewater-, and waste management. In the latter sector, the regulation authority is involved in the implementation of the *Strategic Plan for Municipal Solid Waste 2014-2020*, (PERSU 2020), which aims among other things, at a shift from landfill disposal to recycling of waste, and at establishing new pricing methods for waste producers (ERSAR 2022b).

The Portuguese MSW-management system is vertically disintegrated and divided into a *downstream* (*baixa*) and *upstream* (*alta*) sector. Operators in the *downstream* service, on the one hand, are responsible for the collection of waste only. Some entities are solely responsible for the collection of mixed waste while others collect separate waste in addition. *Upstream* operators, on the other hand, are responsible for the treatment and disposal of mixed waste as well as the collection, sorting, and treatment of separate waste. Operators in both systems are either publicly or privately managed. As illustrated in figure 2, we can distinguish between direct municipal waste management services - either managing single or multiple municipalities (referred to as municipal associations, (inter-) municipalized, or municipal service in figure 2)[9] and delegated/concessioned management.

[8] See e.g. Salvetti (2021) for a more detailed overview of the European MSW legislation and future challenges for MSW-management systems.

[9] Municipal services differ from municipalized services by having less financial and administrative autonomy. See ERSAR (2022b) for more details on the exact distinction. For this project, a more broad distinction between private and public service will suffice.

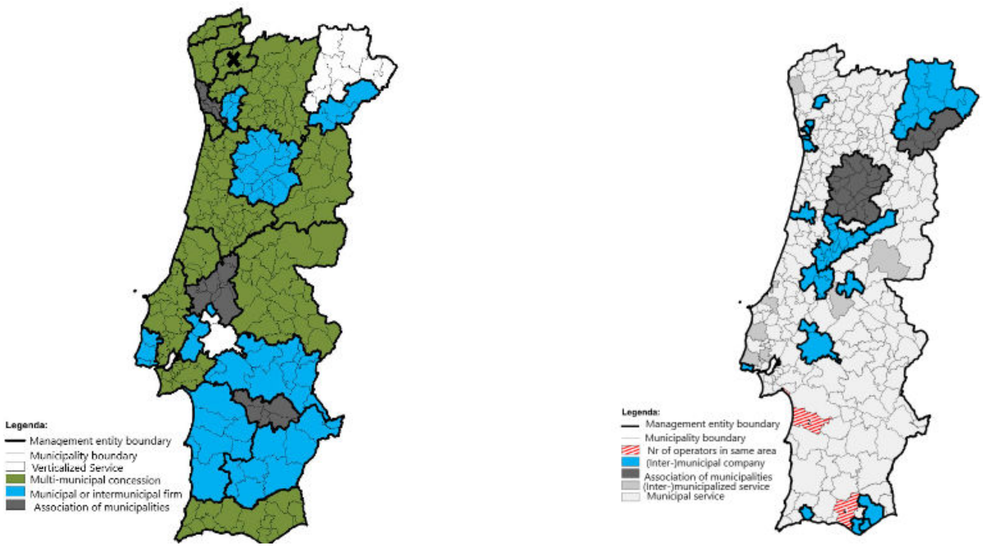
In the latter case, a private company is managing waste, typically in more than one municipality.[10] 23 upstream operators managing the MSW-system in Portugal and this number has been stable since 2010. Private - either delegated or concessioned - is the dominating management type. 11 out of these 23 operators are operated by companies that belong to the same holding group called *Environmental Global Facilities* (EGF). These operators are marked in the figure 2 in green.[11] EGF operators cover about 54% of the area and about 60% of the population in continental Portugal (ERSAR 2022b).[12]

Compared to the upstream sector, the downstream service market is much more fragmented. There are 237 active entities in 2020 - out of which 207 are municipal services that are responsible for the waste collection in one single municipality. The remaining part is administered by municipal associations or private companies. The number of entities remained fairly stable from 2016 to 2020, where only 2020 saw the entry of 3 new operators that aggregated several direct municipal services into one delegated service (ERSAR 2022b).

To sum up, the Portuguese MSW-sector is characterized by vertical disintegration of mixed collection and all other stages of waste management. The upstream sector consists of relatively few and large operators that are responsible for different phases and streams of waste management (i.e. *collection* and *treatment*, as well as, treatment of *mixed and separate waste*). The downstream operators, in contrast, are numerous and accountable for relatively small areas. They are typically in charge of *one phase* and *one stream* of waste management, namely mixed collection.

[10] Again, see ERSAR (2022b) for a more detailed distinction between delegated and concessioned management.
[11] There is one multi-municipal concession that does not belong to EGF, which is marked on the map.
[12] Shares are based on the population and territory data from the *Portuguese National Institute for Statistic*, INE. See INE (2022b) and INE (2022a)

Figure 2: Upstream (left) and downstream (right) operators in Portugal 2020




Maps are adopted from ERSAR (2022b)

# 4 Theoretical Model and Estimation Methodology

In this section, I will outline the theory and estimation strategy used to model MSW-management systems. To take into account the different production processes between upstream and downstream management they are modeled separately. This is needed most notably since both service sectors will differ in the types and shares of inputs used. Furthermore, one would expect external factors (such as density of the area size) to affect collection differently than the treatment of waste. In the following, two production functions of downstream waste services, and a cost function of upstream waste services are specified. Because of missing data on input prices, and frequency of waste collection in the downstream sector, the specification of a production function, linking input to output quantities is most appropriate for estimating economies of scale. To take into account potential cost savings from the joint provision of mixed and separate in modeling upstream waste management sector, a multi-output cost function was chosen.

## 4.1 Efficiency in the downstream sector: Waste collection

### 4.1.1 Cobb-Douglas production function:

I specify and estimate a three-input Cobb-Douglas production function of waste collection services.

$$\begin{aligned} ln(Y_{it}) \quad &= \quad \beta_0 + \beta_L ln(L_{it}) + \beta_K ln(K_{it}) + \beta_E ln(E_{it}) + \beta_N ln(N_{it}) + \\ &\quad\quad SEP_{it} + PRIV_{it} + AREATYPE_{it} + \gamma_t + \epsilon_{it} \end{aligned} \tag{1}$$

- $Y_{it}$ denotes the output quantity, measured by the amount of waste [in t] collected by firm $i$ in period $t$.
- The firm's input quantities (labor, $L_{it}$, capital $K_{it}$, and energy, $E_{it}$) are measured by the total equivalent number of full-time employees assigned to the MSW-service[13], the number of vehicles used for collection, and the amount of fuel [toe] consumed by the collection vehicles of firm $i$ in year $t$.
- $N_{it}$ denotes the network size that firm $i$ is operating in. It is measured by the number of accommodations with mixed or separate collection services in the intervention area.[14]
- Further categorical control variables are included. $SEP_{it}$ is a dummy indicating whether the operator is responsible for separate collection, $PRIV_{it}$ takes on the value 1 if the operator is a private company, and 0 if the service is provided through public service. $AREATYPE_{it}$ is a categorical variable that classifies an operator's area of intervention into rural, medium urban, and urban (with the latter as the reference category).
- $\gamma_t$ are period-fixed effects capturing all unobserved factors that vary across time (but not between operators), e.g. macroeconomic shocks (reference period 2016). $\epsilon_{it}$ captures all unobserved factors that are driving a firm's output.

Following the definition given by D. W. Caves, Christensen, and Tretheway (1984) we can define *returns to density*, $RD_Y$, as the proportional increase in output after a proportional increase in inputs holding the network size fixed. As argued by Antonioli and Filippini (2002), who estimate economies of density[15] in the Italian waste collection services, the measure gives insights on the optimal number of firms within a given network size. More precisely, it can be used to decide whether, in a given intervention area, it is more efficient to have a monopoly or side-by-side competition of multiple MSW operators. Returns to density exist if $RD_Y > 1$, i.e. if doubling all input quantities but leaving the network size constant, is associated with more than doubling the amount of waste being

[13] The measure will count both internal and external employees. Hence, the number of workers involved in the waste management activity that the operator has outsourced to an external service is accounted for.

[14] Alternatively, following Morikawa (2011) one can include a direct measure of density, i.e. by dividing the number of pick-up points over the area size. I differentiate between size and density in the robustness checks of this article.

[15] See Gelles and Mitchell (1996) for a more detailed distinction between returns to and economies of scale. Under the assumption that input prices are constant in input quantities returns to scale/density are a necessary condition for economies of scale/density to exist.

collected.

$$
\begin{aligned}
RD_Y &= \sum_i^I \varepsilon_{X_i} && (2)\\
\text{where} \quad & \varepsilon_{X_i} \text{ denote output elasticity w.r.t to input } X_i \\
& \varepsilon_{X_i} = \frac{\delta Y}{\delta X_i}\frac{X_i}{Y} \\
& \text{For the Cobb-Douglas production function we get} \\
RD_Y &= \beta_L + \beta_K + \beta_E && (3)
\end{aligned}
$$

*Returns to scale*, $RS_Y$, again referring to D. W. Caves, Christensen, and Tretheway (1984) and Antonioli and Filippini (2002), will then measure the proportional increase in outputs after a proportional increase in inputs *and* network size. Increasing returns to scale exist if $RS_Y > 1$, and indicate whether it is more efficient to merge adjacent operators in different intervention areas, as e.g. doubling inputs and network size will more than double the output quantities.[16]

$$
\begin{aligned}
RS_Y &= \sum_i^I \varepsilon_{X_i} + \varepsilon_N \\
\text{where} \quad & \varepsilon_N \text{ denotes the output elasticity w.r.t. network size } N \\
& \varepsilon_N = \frac{\delta Y}{\delta N}\frac{N}{Y} \\
& \text{In the Cobb-Douglas production function we get} \\
RS_Y &= \beta_L + \beta_K + \beta_E + \beta_N && (4)
\end{aligned}
$$

### 4.1.2 Translog production function:

While the Cobb-Douglas function is often preferred for its simplicity, it is also a restrictive functional form, as it assumes that scale and density economies are the same for all levels of inputs. To allow for variable returns to scale and to test the robustness of the results w.r.t. the functional specification, I follow Kim (1992) and specify and estimate a three-input Translog production function that is

[16] Of course, there may well be other, non-output-efficiency-related reasons, why merging two intervention areas is not desirable.

non-homothetic and imposes no restrictions on the production technology.[17][18]

$$\begin{aligned} ln(Y_{it}) &= \beta_0 + \beta_L ln(L_{it}) + \beta_K ln(K_{it}) + \beta_E ln(E_{it}) + \beta_N ln(N_{it}) + \\ & \frac{1}{2}\beta_{LL} ln(L_{it})^2 + \frac{1}{2}\beta_{KK} ln(K_{it})^2 + \frac{1}{2}\beta_{EE} ln(E_{it})^2 + \frac{1}{2}\beta_{NN} ln(N_{it})^2 + \\ & \beta_{LK} ln(K_{it})\ ln(L_{it}) + \beta_{LE} ln(L_{it})\ ln(E_{it}) + \beta_{LN} ln(L_{it})\ ln(N_{it}) + \\ & \beta_{KE} ln(K_{it})\ ln(E_{it}) + \beta_{KN} ln(K_{it})\ ln(N_{it}) + \beta_{EN} ln(E_{it})\ ln(N_{it}) + \\ & SEP_{it} + PRIV_{it} + AREATYPE_{it} + \gamma_t + \epsilon_{it} \end{aligned} \tag{5}$$

All variables are measured as indicated before. Returns to scale and density are now, however, not constant in input quantities but will differ in the point of evaluation. They are identified by $RD_Y^T$ and $RS_Y^T$:

$$\begin{aligned} RD_Y^T &= \beta_L + \beta_K + \beta_E + \\ & (\beta_{LL} + \beta_{LK} + \beta_{LE})\ ln(L) + \\ & (\beta_{KK} + \beta_{LK} + \beta_{KE})\ ln(K) + \\ & (\beta_{EE} + \beta_{LE} + \beta_{KE})\ ln(E) \end{aligned} \tag{6}$$

$$\begin{aligned} RS_Y^T &= \beta_L + \beta_K + \beta_E + \beta_N + \\ & (\beta_{LL} + \beta_{LK} + \beta_{LE} + \beta_{LN})\ ln(L) + \\ & (\beta_{KK} + \beta_{LK} + \beta_{KE} + \beta_{KN})\ ln(K) + \\ & (\beta_{EE} + \beta_{LE} + \beta_{KE} + \beta_{EN})\ ln(E) + \\ & (\beta_{NN} + \beta_{LN} + \beta_{KN} + \beta_{EN})\ ln(N) \end{aligned} \tag{7}$$

## 4.2 Efficiency in the upstream sector: Managing Separate and Mixed Waste Streams

### 4.2.1 Cost function specification

A multi-product Cobb-Douglas variable cost function of upstream waste management is specified. The functional form allows to test for both economies of scale and scope of joint management of mixed and separate waste streams. The specification is based on Callan and Thomas (2001), but adjusted to differentiate outputs by *stream* (mixed and separate) of waste rather than *final destination* (disposal and recycling) of waste. Given the design of the Portuguese MSW-system, it appears to be most relevant to differentiate the output along the dimension of collection type. The cost function assumes that treating, disposing, and collecting separate waste and the upstream

[17]In contrast to Kim (1992) I assume Hicks neutral technical change - i.e. technical change that does not affect the balance of inputs used to collect waste. This is plausible since I am looking at a rather short time frame of 5 years.
[18]The translog function was first specified by Christensen, Jorgenson, and Lau (1973).

management of mixed waste are two distinct activities. Nevertheless, both will use similar common inputs. Hence, the total cost an upstream operator will face can be modeled as the sum of separate and mixed waste management. For both services, a given operator will use labor, electricity, fuel, and repair services, as the main inputs, where each input price is included in the cost function.[19] Note, that a variable short-run cost function is estimated, that uses a quasi-fixed capital input $K_{it}$. The short-run specification seems more plausible than a long-run cost function since operators are typically not able to adjust capital input directly to its equilibrium level.[20]

$$ln(C_{it}^{TOT}) = ln(C_{it}^{SEP}) + ln(C_{it}^{MIX}) \tag{8}$$

The total costs that operator $i$ faces in period $t$ is the sum of the costs associated with the collection, treatment, and disposal of *separate* waste streams and the costs associated with the disposal and treatment of *mixed* waste streams. The costs for the two products (mixed and separate waste management) can be specified as follows:

$$\begin{aligned} ln(C_{it}^{TOT}) \quad = \quad & \alpha_0 + \alpha_{mix} ln(Y_{it}^{MIX}) + \alpha_{sep} ln(Y_{it}^{SEP}) + \alpha_{cc} ln(Y_{it}^{MIX}) \times ln(Y_{it}^{SEP}) + \\ & \alpha_{p_l} ln(PL_{it}) + \alpha_{p_f} ln(PF_{it}) + \alpha_{p_e} ln(PE_{it}) + \alpha_{p_s} ln(PS_{it}) + \alpha_K ln(K_{it}) + \\ & + ln(density_{it}) + LSHARE_{it} + SSHARE_{it} + \gamma_t + \epsilon_{it} \end{aligned} \tag{9}$$

- $C_{it}^{Tot}$ denotes the variable total costs [in EUR] of upstream MSW-management. They are equated to the sum of labor costs, and expenditures on external supplies & services (including fuel, electricity, and repair services) for both management of mixed and separate waste.[21] Costs are deflated using the national CPI (reference year 2012).

- $Y^{MIX}$ denotes the output quantities of mixed waste management - proxied by the amount of mixed waste [t] that the upstream entity received for further treatment or disposal.

- $Y^{SEP}$ denotes the output quantities of separate waste management as measured by the amount of waste collected [in t] by the managing entity that entered into separate waste treatment. For this sample of EGF operators, this amounts to the separate waste an operator collected.

- $PL_{it}$, $PF_{it}$, $PE_{it}$, and $PS_{it}$ are the prices of labor, fuel, electricity, and equipment and other services that an operator faces in a given period $t$. Labor price is recovered by dividing the total labor expenditure by the total equivalent number of full-time employees in a given firm. Electricity prices are obtained by dividing the total expenditure on electricity by the amount of electricity [in 1000 KWh] consumed by each operator. Since remaining supplies and services

[19] Note, that fuel is an important input in upstream service of *mixed* waste even though, the operators are not responsible for collection. Fuel is among other things needed to transfer waste between treatment and disposal plants.

[20] See e.g. Antonioli and Filippini (2002), Ivaldi and Mc Cullough (2001), and Gagnepain and Ivaldi (2002) who estimate short-run cost function in the waste, urban transport, and railroad sector, respectively.

[21] That means, direct expenditures associated with the energy recovery of waste are not included, since it is not captured by the output measure.

mainly reflect equipment supply and repair services, I divide the residual supply and service costs by the total number of plants of a given operator to recover the average price of *residual services*. To account for the fact, that material use and repair service may differ by the load factor of each plant, each plant is weighted by the amount of waste that had entered into further treatment.[22] I cannot recover the fuel price due to missing data. Instead, an index of the average national fuel price is used, that alters between periods and is expressed in EUR per liter of fuel. Hence, I assume that all operators face the same fuel price.

- The capital input $K_{it}$ is proxied by the total number of plants for separate treatment (sorting stations and biological treatment plants), and mixed treatment and disposal (mechanical, and mechanical-biological treatment plants, landfills, and incineration plants).
- Further control variables include a measure of $density_{it}$. It is computed by dividing the number of accommodations in the intervention area by the area size of the intervention area (in $km^2$). As before a dummy variable indicating the $AREATYPE_i$ is included. The variable $LSHARE_{it}$, ($SSHARE_{it}$) denotes the share of waste entering into landfills (sorting) out of all mixed (separate) waste the operators have received.
- $\gamma_t$ denotes period dummies (reference period 2013) and $\epsilon_{it}$ stands for the error term, capturing all unobserved factors that drive costs of operator $i$ in period $t$.

### 4.2.2 Economies of Scale and Scope in the upstream sector

Economies of scale in the upstream sector are defined in accordance to Baumol, Panzar, and Willig (1982) by:

$$ES_Y = \frac{1}{\sum_i \varepsilon^C_{Y_i}} \tag{10}$$

where $\varepsilon^C_{Y_i}$ denote the cost elasticity w.r.t to output $Y_i$

$$\varepsilon^C_{Y_i} = \frac{\delta C}{\delta Y_i}\frac{Y_i}{C}$$

For the Cobb-Douglas cost function we get

$$ES_Y = \frac{1}{\alpha_{mix} + \alpha_{sep} + \alpha_{cc}[ln(Y^{MIX}) + ln(Y^{SEP})]} \tag{11}$$

Economies of Scale exist, i.e. $ES_Y > 1$, if doubling both output quantities will less than double the total costs of upstream waste management.

In addition, this article wants to test for the existence of economies of scope. That is if cost savings exist that are associated with the joint management of mixed and separate waste. Following Baumol, Panzar, and Willig (1982) such cost savings can arise if mixed and separate MSW-management can jointly use or share its inputs. Even though mixed and separate MSW-management will involve the

[22] See more details on the computation of the residual service price in the appendix, section 10.

use of different treatment plants, both services are expected to require the use of similar equipment, labor skills (e.g. driving and handling of machinery), as well as repair and maintenance activities. Multi-product synergies may also exist w.r.t. advertising, schooling of personnel, or management activities in the MSW-management sector (Farsi, Fetz, and Filippini 2007). Formally, economies of scope exist if the joint costs of separate and mixed waste management are lower than the sum of costs for only managing mixed and only managing separate waste.[23]

$$C^{Tot}(Y^{MIX}, Y^{SEP}) < C^{SEP}(Y^{SEP}, 0) + C^{MIX}(0, Y^{MIX}) \tag{12}$$

where the degree of economies of scope is denoted by

$$SE = \frac{[C^{SEP}(Y^{SEP}, 0) + C^{MIX}(0, Y^{MIX}] - C^{Tot}}{C^{Tot}} \tag{13}$$

There are three caveats to the estimation of economies of scope in this article.

Firstly, since the Cobb-Douglas specification uses output in logs, it is not possible to evaluate the function at zero output quantities and therefore estimate the degree of economies of scope. Instead, the functional specification will only allow testing for the existence of cost-complementarities between managing different streams of waste. Cost-complementarities exist if an increase in the quantity of output $j$ will decrease the marginal cost of output $i$ (Abrate et al. 2014). This is, however, no serious shortcoming, as the existence of cost-complementarities between two outputs is a sufficient condition for economies of scope to exist (Baumol, Panzar, and Willig 1982). More formally, cost complementarities exist if:

$$\frac{\delta^2 C_{it}^{Tot}}{\delta Y_{it}^i \, \delta Y_{it}^j} < 0 \text{ where } i \neq j \tag{14}$$

For the two output Cobb-Douglas function we obtain:

$$\alpha_{cc} < 0 \tag{15}$$

An $\alpha_{cc}$ coefficient that is smaller than zero, therefore means providing mixed waste management alongside separate waste management is decreasing the marginal costs of mixed waste management (and analogously for separate management).

Secondly, the sample contains only upstream operators that provide both mixed and separate waste management. Hence, cost-complementarities and economies of scope are assessed in a regime where the separate and mixed waste management is integrated. As there exists no control group of single product operators to which the cost structure of multi-product firms can be compared, any extrapolation to markets where both single and multi-product operators are active has to be treated with care.[24] Nevertheless, given that joint management of mixed and separate waste is quite

[23] I follow Baumol, Panzar, and Willig (1982) and Callan and Thomas (2001) for the formal definition and its application to MSW-management.

[24] This remark is referring to how total costs are defined (see equation 8). The equation assumes that total costs are the sum of mixed waste and separate waste costs, where their only interaction is through the output quantities. If one is to argue, however, that $C^i(Y^i)$ in the multi-product firm differs from $C^i(Y_i)$ in the single output firm (other than

common, the assessment of cost-complementarities in this article can give important insights as to whether or not joint management should be further expanded. Thirdly, since only data on variable costs of upstream service providers is available, the estimation can only investigate operating cost complementarities. Whether or not further cost complementarities w.r.t. capital expenditures exist, cannot be addressed here. If one is to assume that operators face (if anything) savings in capital costs from offering both separate and mixed waste services, the presented estimates are lower bounds for the total economies of scope in the MSW-upstream sector.

# 5 Data and Summary Statistics:

## 5.1 Data

I gather data on annual input and output quantities, number of pick-up points, management type, the classification of the intervention area, and further controls, for the full set of downstream service entities of continental Portugal. These publicly available data sets come from ERSAR and are published together with an annual report characterizing the current status quo of the MSW-sector. To match the intervention area of a given operator to municipalities, I use the information on Portuguese municipality characteristics made available by the *Portuguese National Institute of Statistics*, INE.[25] Overall, I obtain an unbalanced panel of on average 250 operators for the period 2016 to 2020 with a total of $1,254$ observations.[26][27]

To estimate the cost of upstream management I use the information on the costs and quantities of 11 EGF operators from 2013-2020 disaggregated by phase and stream of waste management. This data is not publicly available and was provided by ERSAR. The data contains detailed information on total costs and cost shares for treatment of mixed, and separate waste, as well as separate waste collection. Furthermore, it includes measures of the quantities of mixed and separate waste that have been collected and entered into treatment and disposal (broken down by the exact type of final destination).[28] The EGF data is matched with the public ERSAR data to link cost and outputs to the inputs used by the operators and to other control variables, such as the type of intervention area. Moreover, I gather additional information on capital input from public annual reports on the Portuguese MSW system from the Portuguese Environment Agency (APA).[29] Due to missing information on fuel consumption, I use the average yearly fuel price index for continental Portugal

through output $j$), e.g. because prices for a single product operator differ from prices that a multi-product operator faces, evidence of cost-complementarities for multi-product firms do not necessarily imply the existence of economies of scope between mixed and separate waste management.

[25] See ERSAR (2022a) and INE (2022b) to access the data sources.

[26] Note, that due to a missing outcome variable, one operator was dropped from the total sample.

[27] Note, that the ERSAR data sets are available from 2011 on. Since, however, output quantities were only recorded at the operator level from 2016 on, I cannot use prior periods to estimate the production functions of waste collection.

[28] For waste treatment the measure will therefore not include the amount of final output obtained from the waste that entered into the treatment. For example, there is no measure available on the number of recyclables that were recovered as the final output, but only on how much separate waste entered into sorting stations.

[29] See APA (2022) to access the sources.

from the *General directorate of energy and geology* (DGEG 2022b). All costs are deflated using the aggregate Consumer Price Index for continental Portugal (base year 2012) (INE 2022c). Overall, I obtain a balanced sample covering 11 upstream operators for 8 years (88 observations).

### 5.2 Summary statistics: downstream sector

A look at the summary statistics of Portuguese downstream operators in table 2 reveals a large variation in both output and input quantities in the sample. Downstream services have on average 40 full-time employees, and use about 8 vehicles and 86 toe of fuel for the yearly waste collection. Note, that for some observations, zero input quantities are recorded. Because both production functions use the logarithm of the input variables, however, these observations are discarded for the estimation.[30] Downstream operators also vary strongly in their network size (as measured in the number of dwellings with separate and mixed collection services), and the density of the intervention area. Values range from intervention areas with only roughly 2 to 7026 pick-up points per $km^2$. As

Table 2: Summary statistics of downstream operators, numeric variables

| Variable | N | Mean | Sd | Min | Median | Max |
|---|---|---|---|---|---|---|
| Amount of waste collected [1000 t] | 1254 | 17.51 | 31.03 | 0.56 | 6.52 | 327.14 |
| Nr of Employees | 1254 | 40.11 | 94.89 | 1.10 | 14.90 | 1375.60 |
| Nr of Vehicles | 1254 | 8.57 | 14.91 | 1.00 | 5.00 | 231.00 |
| Amount of fuel consumed [toe] | 1254 | 86.62 | 158.41 | 2.00 | 36.40 | 2045.50 |
| Nr of Pickup-points | 1254 | 31882.54 | 57578.61 | 511.00 | 12992.00 | 596113.00 |
| Density [pick-up points per $km^2$] | 1254 | 262.50 | 783.35 | 2.25 | 56.71 | 7026.37 |
| Population | 1254 | 39100.63 | 64003.49 | 1623.00 | 15965.00 | 509614.00 |

[1]Density, population and number of pickup-point estimates refer to the intervention area an operator is responsible for.

depicted in table 3, only 10% of operators in the sample collect waste separately, in contrast to only mixed. As already mentioned above, the majority of operators are direct municipal services, while there are only about 7% of private companies in the downstream management. Most intervention areas are rural, with only 8% of observations of operators active in an urban area.

Looking at the yearly summary statistics in table 4, we see a slight decrease in the number of operators in 2020 while the number remained fairly stable before. Trends in the quantities of waste collected by year reveal that 2020 saw the end of an upward trend in the downstream waste collection that had started in 2016.

[30]Since the number of zero inputs is fairly low this should not affect the results of the estimation strongly. Moreover, since operators who do not use all or one of their main inputs are fairly uncommon, excluding these observations will ensure that outliers are not driving the results.

Table 3: Summary statistics downstream services, categorical variables

| Variable | N | Nr of categories | Shares |
|---|---|---|---|
| Separate Collection | 1254 | 2 | No: 90, Yes: 10 |
| Type of Intervention area | 1254 | 3 | rur: 65.2, med: 26, urb: 8.8 |
| Management Type | 1254 | 2 | Mun: 92.7, Pri: 7.3 |

[1]Mun = Municipal management, Pri = Private management
[2]rur = rural, med = medium urban, urb = urban
[3]Row one of the table can be interpreted as follows: 90% of all observed observations are not responsible for separate collection

Table 4: Number of downstream operators and output per year

| Year | Number of operators | Quantities of waste collected |
|---|---|---|
| 2016 | 256 | 4193.01 |
| 2017 | 255 | 4309.54 |
| 2018 | 254 | 4471.06 |
| 2019 | 253 | 4510.43 |
| 2020 | 236 | 4479.72 |

[1]Quantities in [1000 t]

### 5.3 Summary statistics upstream operators

Summary statistics of the Portuguese EGF upstream operators (see table 5) show great fluctuations in costs and outputs over the sample period. While the observation with the lowest cost spends about 700,000 EUR on upstream waste management, the highest operating expenditures go up to 42 million EUR. On average, operators face higher costs for mixed than for separate waste management. This is in line with the output quantities observed in the sample period. On average upstream services manage a much higher amount of mixed waste (261,000 t) as compared to separate waste (30,000 t). When further differentiating between the final destination of mixed and separate waste, it is important to note that the share of waste entering for landfilling among all mixed waste varies strongly within the sample. As landfilling is arguably the cheapest management option this has to be kept in mind when estimating the cost function. Of all separate waste, a quite large fraction of on average 89 percent is being sent to sorting stations where waste is prepared for further recycling. Variation in the type of treatment/disposal exists but is smaller than for mixed waste management.

As explained above prices were recovered from the expenditure shares and the input quantities. The observed annual labor prices (EUR per full-time equivalent employee) range from roughly $13,300$ to $40,000$ with an average of $18,600$. To put these values into context I compare them to the average labor costs statistics in Portugal by Eurostat (2022c). Using the statistics on average hourly labor

Table 5: Summary statistics of upstream EGF operators

| Variable | N | Mean | Sd | Min | Median | Max |
|---|---|---|---|---|---|---|
| Total costs [in $10^6$ EUR] | 88 | 9.89 | 8.76 | 0.71 | 6.24 | 42.44 |
| Separate Waste Costs [in $10^6$ EUR] | 88 | 3.79 | 3.47 | 0.35 | 2.65 | 19.62 |
| Mixed Waste Costs [in $10^6$ EUR] | 88 | 6.11 | 5.57 | 0.35 | 3.69 | 23.94 |
| Share of labor expenditures | 88 | 0.37 | 0.06 | 0.23 | 0.37 | 0.50 |
| Share of electricity expenditures | 88 | 0.05 | 0.02 | 0.02 | 0.05 | 0.12 |
| Share of fuel expenditures | 88 | 0.10 | 0.03 | 0.03 | 0.10 | 0.17 |
| Share of residual services | 88 | 0.48 | 0.06 | 0.36 | 0.49 | 0.63 |
| $Y^{Mix}$ [1000 t] | 88 | 260.98 | 209.30 | 32.06 | 172.03 | 821.90 |
| $Y^{Sep}$ [1000 t] | 88 | 30.13 | 30.54 | 3.09 | 19.10 | 136.36 |
| Landfilling Share | 88 | 52.96 | 33.75 | 1.40 | 52.21 | 100.00 |
| Sorting Share | 88 | 89.42 | 12.08 | 55.56 | 95.50 | 100.00 |
| Labor price [$10^3$EUR per full-time employee] | 88 | 18.56 | 5.80 | 13.32 | 16.93 | 40.60 |
| Electricity price [EUR per 1000KWh] | 88 | 115.58 | 16.35 | 79.55 | 113.56 | 201.10 |
| Fuel price [EUR per liter] | 88 | 1.31 | 0.08 | 1.18 | 1.30 | 1.41 |
| Residual Service price [$10^3$EUR per weighted plant] | 88 | 2,452.40 | 3,383.98 | 165.61 | 1,435.76 | 15,693.77 |
| Nr of Plants | 88 | 5.06 | 2.61 | 2.00 | 4.00 | 11.00 |
| Density [inhabitants per $km^2$] | 88 | 310.81 | 568.52 | 20.21 | 138.01 | 4,677.15 |

[1]Density statistics refer to the intervention area an operator is responsible for.

costs per employee expressed in full-time units, annual labor costs for upstream waste management are below the national average of roughly EUR $30,000$ for 2020.[31] Overall, the observed Portuguese labor costs for waste management appear to be quite low compared to other European countries.[32]

The sample statistics on the electricity price indicate that operators pay on average 115 EUR per 1000 KWh across all periods. The observed price ranges are in line with national indexes for electricity prices in Portugal (DGEG 2022a). Prices are expected to decrease in the quantities of electricity consumed.

Fuel prices show less variation as no operator-specific fuel prices could be recovered. The range of observed values is fairly small with a difference of 0.2 EUR per liter of gasoline between the

[31]See Eurostat (2022a) for the data source. I convert the average hourly labor costs per full-time employee into the yearly labor costs per full time employee by multiplying its value by 2080 (assuming 40h per 52 workweeks a year). Using the Eurostat estimate for hourly labor costs for 2020, this yields an average of EUR 32,656 yearly labor expenditures per full-time employee in Portugal. Unfortunately, no data on the labor cost distribution within Portugal is available to make further plausibility checks.

[32]See e.g. Abrate et al. (2014) who obtain an average of 36,607 EUR per full-time employee. Again this result is in line with Eurostat (2022a) who estimate hourly labor costs in Italy to be nearly twice as high as in Portugal.

minimum and maximum value.

The price for other services and materials is expressed per number of plants weighted by the quantities of waste processed. This is because residual services and supplies mainly include the repair and maintenance of vehicles and machinery in plants. Operators face a large price range. This can be due to the fact that different plant and machine types may create different a priori costs. Since operators differ in plant and machine type composition they may face a different service prices. Other than that, operators might be using equipment of different ages - which can explain varying repair and maintenance prices. Unfortunately, no information on the machine types and ages of plants and machines are available to better explain the variation in residual service prices.[33]

EGF companies operate on average in areas with about 300 inhabitants per $km^2$. Again, heterogeneity in the intervention areas between rural (low population density) and urban areas (high population density) can be found.

Table 6: Upstream operators: Average Output and Costs by Year

| Year | #Operators | #Mix. Waste | #Sep. waste | Tot. Costs | Sep. Treat. Cost | Sep. Col. Cost | Mix. Treat./ Disp Cost |
|---|---|---|---|---|---|---|---|
| 2013 | 11 | 2793.50 | 273.38 | 84.32 | 12.37 | 16.58 | 55.38 |
| 2014 | 11 | 2819.04 | 282.90 | 91.33 | 12.44 | 16.63 | 62.27 |
| 2015 | 11 | 2828.03 | 301.79 | 96.70 | 13.43 | 18.50 | 64.77 |
| 2016 | 11 | 2874.72 | 316.93 | 99.47 | 15.56 | 18.59 | 65.32 |
| 2017 | 11 | 2905.33 | 326.75 | 103.44 | 17.08 | 20.56 | 65.80 |
| 2018 | 11 | 2950.79 | 335.12 | 113.62 | 19.03 | 24.58 | 70.01 |
| 2019 | 11 | 2955.80 | 396.35 | 125.86 | 21.95 | 31.39 | 72.52 |
| 2020 | 11 | 2838.78 | 418.12 | 132.21 | 22.27 | 34.98 | 74.96 |

[1]Quantities in [1000 t]
[2]Costs in [Million EUR]

A brief glimpse at the average output and cost quantities of EGF operators by year (see table 6) indicates an upward trend in the quantities of separate waste entering into separate waste management from 2013 to 2020 from about 270,000 to 418,000 tonnes. Not surprisingly, the figures show an increase in the cost of separate waste management across the sample period. Similar trends can be observed for mixed waste quantities and costs. Overall, the fraction of mixed waste entering into treatment is much larger than separate waste.

[33]Again, see more on the computation of the residual service price in the appendix.

# 6 Estimation & Results

## 6.1 Downstream operators

In this subsection, the results of the production function estimation of Portuguese downstream operators are discussed. Equation 1 is estimated for the pooled sample of operators using the OLS estimator. Figure 14 in the appendix confirms that the chosen Cobb-Douglas specification is a good approximation for the downstream operators' production functions. We can observe clear linear relationships between the output and inputs and network size (both in logarithms). This impression is further confirmed by the high $R^2$ achieved in the estimation of both Cobb-Douglas and Translog functions. The models explain a large share of the variation in the observed output.

Looking at the pooled OLS regression results as shown in table 7, indicate a positive and statistically significant relationship between all inputs, as well as network size, and the amount of waste being collected. This association is robust to adding a subset of controls and time-fixed effects. A comparison of the single input elasticities suggests relatively high returns to fuel of around 0.5% while increasing the labor input by 10 % is associated with an increase in the amount of waste collected of 2% (significant at the 1% level), c.p. At the sample average, this would mean that an increase of staff by 4 full-time employees and holding all other factors constant is predicted to increase the amount of waste collected by 3500 tonnes. Returns to capital appear to be fairly low with an estimate of 0.06 (significant at the 10% level). I obtain estimates for the returns to network size of around 0.3 (significant at the 1% level). Evaluated at the sample mean, the model predicts an increase in output by roughly 3500 tonnes after expanding the number of dwellings with separate and mixed collection services in the network by about 3000. Overall, results hint a relatively high energy and labor intensity compared to the low capital intensity of downstream waste collection. The results are robust to the Translog specification of the production function (see tables 24, 22, 23 in the appendix for the detailed results, including regression coefficients and average marginal effects).

The coefficients for the additional control variables show mostly no significant associations.[34] Operators in rural areas (see the next subsection for more details on the classification), appear to be collecting less quantities of waste, while the reverse is true for medium urban areas. The results show no significant difference (both economically and statistically) in output between private and public operators. Nevertheless, the coefficients should be treated with care as the management choice is likely to suffer from selection bias (Ohlsson 2003) and because the great majority of the Portuguese downstream sector are managed publicly. Operators that collect separate waste seem to be collecting less waste in total, but the effect is not statistically significant.[35] Overall, the Translog production function estimation yields similar coefficients for the control variables (evaluated at the

[34] See figure 15 in the appendix on the distribution of outcome and categorical control variables.

[35] The negative relationship could mean that operators reduce their mixed waste collection in order to provide services for separate waste - i.e. that the types of collection act as substitutes. The share of downstream operators with separate waste collection is too small, however, to investigate this question more thoroughly.

the median level of inputs and network size).[36]

Table 7: Total sample estimation results of the Cobb-Douglas production function of waste collection

| | Pooled OLS (I) | Pooled OLS (II) |
|---|---|---|
| | *Dependent Variable*: Log(Waste collected) [t] | |
| (Intercept) | 2.964*** | 3.322*** |
| | (0.231) | (0.259) |
| Log(Nr of Employees) | 0.232*** | 0.214*** |
| | (0.050) | (0.049) |
| Log(Amount of Fuel used) [toe] | 0.515*** | 0.491*** |
| | (0.046) | (0.045) |
| Log(Nr of Collection Vehicles) | 0.039 | 0.060+ |
| | (0.036) | (0.033) |
| Log(Nr of Pickup-points) | 0.344*** | 0.322*** |
| | (0.035) | (0.037) |
| Rural area | | -0.105 |
| | | (0.069) |
| Medium urban area | | 0.119* |
| | | (0.060) |
| Separate collection (0/1) | | -0.022 |
| | | (0.055) |
| Private management | | -0.001 |
| | | (0.038) |
| Time fixed effects | No | Yes |
| Num.Obs. | 1227 | 1227 |
| R2 | 0.947 | 0.952 |
| R2 Adj. | 0.947 | 0.951 |

[1]Standard errors (HC3) (in parentheses) are clustered at the operator level
[2]Results in column 1 can be interpreted as follows: A 1% increase in the number of full-time employees is on average associated with a 0.232% increase in the tonnes of waste collected, c.p.
[3]Reference category for the type of intervention area dummies is "Urban area".
[4]Reference category for the type of management is "Public Management".
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 contains estimates for returns to scale and density from both the Cobb-Douglas and the Translog production function. Both specifications yield similar results. The Translog function allows differentiation between the effects for different operator scales (w.r.t. input quantities and network size). Overall, results hint at slightly decreasing returns to density (statistically significant at the 5% level). That means, that doubling the inputs without altering network size is associated with less than doubling the amount of waste collected. As explained in the theoretical section of this paper, increasing returns to density can indicate that in a given intervention area, it can be more

[36]See table 24 in the appendix.

efficient for one operator to serve the whole network, rather than side-by-side competition between several providers in a given network. Given the market structure of the Portuguese downstream service sector, where most operators are the single providers in their intervention area, results may suggest that potential returns to density have already been exploited and there is no scope for further efficiency gains. Overall, we can observe that the estimates for returns to density diminish as the scale of the operator increases.[37]

More relevant to the Portuguese downstream sector are the estimates for returns to scale. As described above, the market is much more fragmented than the upstream sector. Estimation results from both Cobb-Douglas and Translog functions hint at the existence of increasing returns to scale. Doubling inputs alongside network size is associated with more than a doubling of output quantities. This result holds for different sizes of operators, albeit we observe higher degrees for returns to scale for relatively small operators. For the larger downstream providers, returns to scale are close to being constant. The results thus suggest that the efficiency in the sector can be increased by the merging of particularly small-scale adjacent operators.[38]

#### 6.1.1 Outcome heterogeneity: Type of intervention area

Results from the previous section hint at increasing returns to scale and decreasing returns to density in the Portuguese downstream MSW-management. These returns are predicted to vary, however, in the operator's scale. In this subsection, I will further break down the results by the type of intervention area of a given operator. The reason for this further distinction is to look more closely at the interplay between network size and density when estimating returns.

Following Guerrini et al. (2017) and Rogge and De Jaeger (2013) it is crucial to take into account the type of intervention area an operator is active in when analyzing the efficiency of the waste sector. On the one hand, operators in urban - more and more densely populated areas - may be able to collect more waste compared to rural operators (in areas with less population and less population density) as less time is needed to drive from one pickup point to the other. On the other hand, congestion can introduce constraints to waste collection, e.g. because collection vehicles may not be used (or used less efficiently) in narrow and more densely populated streets. Given these conflicting effects, returns to inputs, network size, and their joint effects are re-estimated for different types of intervention areas. This will allow testing of whether different efficiency patterns exist at different density and network size levels.

I re-estimate equations 1, and 5 by type of intervention area. The variable classifies the intervention area of each operator into *urban*, *medium urban*, and *rural* areas - depending on their population

[37] Since the great majority of operators are monopolists in their network we cannot further investigate the roots for the negative returns to density. We cannot differentiate whether any returns to density have already been exploited or whether it would be more efficient to have side-by-side competition. The fact that the degree of the decreasing returns reduces in magnitude as operators get smaller is suggestive of the former explanation but surely not conclusive.

[38] See e.g. Antonioli and Filippini (2002) who also find evidence for economies of scale in the Italian waste collection sector.

Table 8: Total sample estimates for returns to scale and density in waste collection

| | $H_0$ | Estimate | CI-95 |
|---|---|---|---|
| Cobb-Douglas | | | |
| Economies of Density | $\beta_K + \beta_L + \beta_E \geq 1$ | 0.7644 | $]-\infty, 0.8372]$ |
| Economies of Scale | $\beta_K + \beta_L + \beta_E + \beta_N \leq 1$ | 1.0860 | $[1.0450, \infty[$ |
| Translog function | Median Operator | | |
| Economies of Density | $\beta_K + \beta_L + \beta_E \geq 1$ | 0.7867 | $]\infty, 0.8598]$ |
| Economies of Scale | $\beta_K + \beta_L + \beta_E + \beta_N \leq 1$ | 1.1502 | $[1.1093, \infty[$ |
| Translog function | Small operator (p25) | | |
| Economies of Density | $\beta_K + \beta_L + \beta_E \geq 1$ | 0.8476 | $]-\infty, 0.9342]$ |
| Economies of Scale | $\beta_K + \beta_L + \beta_E + \beta_N \leq 1$ | 1.2305 | $[1.1782, \infty[$ |
| Translog function | Large operator (p75) | | |
| Economies of Density | $\beta_K + \beta_L + \beta_E \geq 1$ | 0.7056 | $]-\infty, 0.7721]$ |
| Economies of Scale | $\beta_K + \beta_L + \beta_E + \beta_N \leq 1$ | 1.0520 | $[1.0193, \infty[$ |

[1]One-sided t-tests are performed at the 95% confidence level
[2]Estimates are obtained using the regression specifications with controls (table 7, II).
[3]For *small operators* the translog function is evaluated where all inputs and network size are at 25th sample percentile, and analogously for median (p50) and large (p75) operators.

size and density.[39] Estimation results are presented in tables 9, and 27. A look at the single input returns seems to confirm the adverse congestion effect mechanisms: returns to vehicles are not statistically different from zero in both urban and medium urban areas, with even a negative coefficient in the former intervention area type. For rural operators, we observe a statistically significant and positive relationship between the amount of waste collected and the number of vehicles used, albeit the returns to capital input remain small in relation to other inputs. Overall, when comparing the coefficients between the subsamples, the relatively small sample size of urban operators has to be taken into account, which will create less precise estimates.

Estimation results for returns to density and scale across the type of intervention areas are illustrated in table 10. Firstly, we can observe decreasing returns to density across all operator types - with medium and urban operators exhibiting lower estimates than rural operators.[40]. As outlined

[39]The classification is defined by the *Portuguese National Institute for Statistic (INE)* and uses a weighted mean between population size and population density in a given municipality. See INE (n.d.) for more details.
[40]Again, given the small sample size, estimates for urban operators are very imprecise and interpretations have to

Table 9: Cobb Douglas production function estimation by type of intervention area

| | Pooled OLS: urban | Pooled OLS: medium urban | Pooled OLS: rural |
|---|---|---|---|
| | *Dependent Variable*: Log(Waste collected) [t] | | |
| (Intercept) | 4.205*** | 4.049*** | 2.914*** |
| | (0.890) | (0.469) | (0.336) |
| Log(Nr of Employees) | 0.233* | 0.219** | 0.240*** |
| | (0.104) | (0.078) | (0.063) |
| Log(Amount of Fuel Used) [toe] | 0.463*** | 0.432*** | 0.506*** |
| | (0.071) | (0.087) | (0.057) |
| Log(Nr of Collection vehicles) | -0.050 | 0.011 | 0.094* |
| | (0.081) | (0.061) | (0.038) |
| Log(Nr of Pickup-points) | 0.284* | 0.296*** | 0.337*** |
| | (0.123) | (0.067) | (0.050) |
| Separate collection (0/1) | -0.065 | 0.126 | 0.056 |
| | (0.080) | (0.081) | (0.107) |
| Private management | 0.032 | -0.086 | -0.003 |
| | (0.059) | (0.064) | (0.054) |
| Time fixed effects | Yes | Yes | Yes |
| Num.Obs. | 109 | 323 | 795 |
| R2 | 0.970 | 0.917 | 0.875 |
| R2 Adj. | 0.966 | 0.915 | 0.874 |

[1]Heteroscedasiticity robust standard errors (HC3) (in parentheses) are clustered at the operator level
[2]Results in column 1 can be interpreted as follows: For urban operators a 1% increase in the number of of full-time employees is on average associated with a 0.233% increase in the tonnes of waste collected (c.p.)
[3]Reference category for the type of management is "Public Management".
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

before, this result is not very surprising given the market fragmentation of the downstream sector. Subsample estimates show increasing returns to scale for rural operators (significant at the 1% level), while medium urban and urban operators exhibit returns that are not statistically different from 1. These more refined results then suggest that incentives for joining adjacent rural operators exist, while no such efficiency-driven incentives are predicted for service providers in urban and medium urban areas.

be treated with care.

Table 10: Cobb Douglas production function: returns to density and scale by intervention area type

| | Rural | Medium Urban | Urban |
|---|---|---|---|
| Returns to Density | 0.840 | 0.662 | 0.646 |
| | [0.733, 0.948] | [0.525, 0.799] | [0.395, 0.897] |
| Returns to Scale | 1.177 | 0.958 | 0.930 |
| | [1.111, 1.244] | [0.8862, 1.029] | [0.832, 1.028] |

[1]Estimates from the Cobb-Douglas estimation with controls (9) are used.
[2]Two-sided 95% confidence intervals are presented in brackets.

#### 6.1.2 Outcome heterogeneity: Density and Size

As explained above the Translog function allows estimating returns to scale and density for different evaluation points in the sample. This is usefuf if we want to separate operator size, from density effects. Figures 16, 18, and 17, show, that there is on average a consistent and statistically significant pattern between the type of intervention area and input quantities, as well as, network size for operators in the downstream sector. Rural operators operate on average in smaller networks and use fewer inputs to collect on average a smaller output quantity than medium urban and urban operators. Analogously, medium urban providers operate on a smaller scale than urban ones to collect on average less waste than their urban counterparts. This means that the Cobb-Douglas regression by type of intervention area cannot separate size from other intervention area specific effects, such as the variation in density. Evaluating the Translog function at different input and network size levels will then be useful for disentangling operator size effects from effects of variation in density and other factors that alter between intervention area types. Unfortunately, this exercise is limited by the relatively small sample and no large within-group variation in operator sizes. Nevertheless, the heterogeneity analysis can deliver suggestive evidence and hint at mechanisms that can be investigated in future research with larger samples.

Results for evaluating returns to scale and density by area type at different points of operator size are presented in table 11. The main trend that we can see is that returns to density and scale tend to remain fairly stable within intervention area groups of operators: returns to scale and density for rural operators of different sizes do not differ from each other significantly (5% level) and the same is true for medium urban operators. For urban operators, we see a variation in returns to density by operator size but estimates are very noisy. Between operator groups, however, such differences in the estimates are observed. Results are in line with the Cobb-Douglas estimation above and yield increasing returns to scale for rural operators (at all levels of operator sizes), whereas medium and urban operators are predicted to exhibit constant returns to scale. Moreover, returns to density remain decreasing across all operators but are larger in magnitude (i.e.closer to being constant) for rural operators than for urban. We can conclude from this analysis, that efficiency patterns differ between rural, urban, and medium urban operators, which cannot be fully explained by the fact that these operator groups vary on average in operation size and scale. Other factors that differ between intervention areas, most notably, the intervention area density, seem to be driving efficiency in mixed waste collection. This result gives a rationale to differentiate regulation policies by the type of intervention area.

Table 11: Translog production function: returns to scale and density by intervention area type

| | Small Operators (Inputs and Network at p25) | Medium Operators (Inputs and Network at p50) | Large Operators (Input and Network at p75) |
|---|---|---|---|
| | **Returns to Density** | | |
| Rural | 0.812 | 0.835 | 0.837 |
| | [0.6288 0.9954] | [0.719, 0.952] | [0.733, 0.941] |
| Medium Urban | 0.715 | 0.738 | 0.800 |
| | [0.556, 0.873] | [0.616, 0.859] | [0.639, 0.961] |
| Urban | 0.675 | 0.388 | 0.3419 |
| | [0.455 0.896] | [0.0542, 0.7224] | [-0.005, 0.689] |
| | **Returns to Scale** | | |
| Rural | 1.247 | 1.228 | 1.187 |
| | [1.156 1.339] | [1.157, 1.300] | [1.135, 1.240] |
| Medium Urban | 0.992 | 0.945 | 0.943 |
| | [0.900, 1.084] | [0.886, 1.005] | [0.841, 1.045] |
| Urban | 0.969 | 0.936 | 0.905 |
| | [0.901, 1.037] | [0.839, 1.032] | [0.775, 1.035] |

[1]Estimates from specification with controls ( 27) are used.
[2]Two-sided 95% intervals are presented in brackets.
[3]Within group percentiles are used: I.e.: for small, rural operators, the translog function is evaluated input quantities and network size are at 25th percentile of *all rural operators* and analogously for medium (p50) and large (p75) operators.

## 6.2 Upstream sector

In this subsection, I discuss the estimation results for the upstream MSW sector. I estimate the cost function, 9, of upstream waste management for the pooled sample of 11 EGF operators between the years 2013 to 2020 using the OLS estimator. For the estimation I follow Antonioli and Filippini (2002) and impose linear homogeneity in input prices by normalizing costs and input prices by the residual service price.[41]

$$
\begin{aligned}
ln\left(\frac{C_{it}^{TOT}}{PS_{it}}\right) \quad = \quad & \alpha_0 + \alpha_{mix}ln(Y_{it}^{MIX}) + \alpha_{sep}ln(Y_{it}^{SEP}) + \alpha_{cc}ln(Y_{it}^{MIX}) \times ln(Y_{it}^{SEP}) + \\
& \alpha_{p_l}lnn\left(\frac{PL_{it}}{PS_{it}}\right) + \alpha_{p_f}ln\left(\frac{PF_{it}}{PS_{it}}\right) + \alpha_{p_e}ln\left(\frac{PE_{it}}{PS_{it}}\right) + \alpha_K ln(K_{it}) + \\
& + density_{it} + LSHARE_{it} + SSHARE_{it} + \gamma_t + \epsilon_{it} \qquad (16)
\end{aligned}
$$

Note, that the small sample size and multicollinearity issues prohibit the estimation of a Translog in addition to the Cobb-Douglas cost function. The main goal of the estimation is to test for the existence of cost-complementarities between treatment/disposal of separate *and* mixed waste streams. A look at figure 30 in the appendix of this article reveals that Cobb-Douglas gives a good approximation of the EGF operators' cost function. Moreover, the figure also highlights a positive correlation between mixed and separate output quantities.

Table 12 summarizes the regression results obtained for different specifications of the cost function. The high $R^2$ indicates that the functional specification does a good job at explaining the variation in operators' costs. Columns vary in the set of control variables that have been added. Looking at the initial specification without controls as given in column $I$, hint at bias arising from selection on unobservables. The results do not resemble a well-behaved cost function with a negative coefficient of labor price. Adding a larger set of control variables, including time fixed effects yields a well-behaved cost function that is increasing in both outputs, and factor prices.[42] Columns III and IV highlight the importance of taking into account the output heterogeneity within mixed and separate waste management. Once controlling for the share of mixed waste being landfilled and the share of separate waste that is entering sorting stations will reduce the bias from column $I$. As suggested by the results in column III, there is a negative and statistically significant association between the total costs and landfill share for Portuguese EGF operators. More precisely, a 1 percentage point increase in the share of mixed waste being landfilled (*relative* to being treated mechanically, or being incinerated), is associated with a reduction in the total costs of waste by about 0.6%.[43] The share of separate waste being sent to sorting stations, on the other side is predicted to increase the overall costs, albeit the estimated effect is only statistically significant when adding the full set of control. The predicted inverse relationship between landfill rates and operating costs seems plausible and stands in line with results in the literature. Landfilling waste will typically entail relatively low transport and processing costs, while, it will create arguably large adverse environmental and health effects (see, e.g. Callan and Thomas 2001; Dijkgraaf and Gradus 2015; Kinnaman, Shinkuma, and Yamamoto 2014).

As expected, results show a positive relationship between both outputs and total costs, which

[41] In plain language, the sum of all input price coefficients $pj$ is constrained to equal one - i.e. $\sum_j \alpha_{pj} = 1$.

[42] Note, that since the fuel price index only varies over time, it is dropped when adding time fixed effects to avoid multicollinearity.

[43] The share variables are already converted to percentages, ranging from 0 to 100

is robust across all specifications. For the preferred specifications in columns III and IV, operating costs are predicted to be more elastic w.r.t to separate than mixed waste output.

Turning to the main coefficient of interest, the OLS regression yields a negative coefficient for the interaction term between both types of outputs that remains fairly stable across all specifications and is statistically significant across columns 2 to 4. Referring to column III, the results suggest that the marginal cost of mixed output is predicted to decrease by roughly 0.9% when increasing separate output by 10%. Overall, the results hint at cost savings that arise from the joint provision of both mixed and separate waste management. This is in line with the results found in Abrate et al. (2014) and Callan and Thomas (2001) who test for cost complementarities and economies of scope between disposal and recycling activities in Italy, and the US, respectively.

Table 13 presents results of cost elasticities and economies of scale for the upstream waste management sector. Different columns present different scales of services (25th, 50th, and 75th percentiles of output quantities). Results are based on the coefficients obtained from table 12, column III. At the median operator size, an increase in the output of separate waste by 10% is associated with an increase in operating costs of roughly 6.8%. This elasticity is about three times as high as for mixed waste. Estimates for economies of scale at the median output levels are close to one indicating very small economies of scale in the upstream sector. These scale economies are predicted to increase for higher scales of output. At the lower quartile of output quantities estimates for economies of scale are not significantly different from 1, hinting at constant returns to scale. Results differ from Abrate et al. (2014) and Callan and Thomas (2001) who find constant economies of scale at varying evaluation points. Unfortunately, the small sample size does not allow the estimation of a translog cost function to test for cross-cost effects that vary in levels of output size.[44] The results of this article can complement Carvalho and Marques (2014) who find evidence for small but increasing economies of scale in the Portuguese recycling sector (using a sample from 2006 to 2010).[45]

[44] The Cobb-Douglas function restricts $\alpha_{cc}$ to be the same across all levels of output size.

[45] The authors find the degree of economies of scale, however, to decrease in overall output quantities. The study, however, focuses only on recycling and does not take into account potential cost complementarities between mixed and separate waste management.

Table 12: Estimation Results of the Cobb-Douglas cost function

| | I: Pooled OLS | II: Pooled OLS | III: Pooled OLS | IV: Pooled OLS |
|---|---|---|---|---|
| | *Dependent Variable*: Log(Total operating costs) | | | |
| (Intercept) | -2.952 | -14.103*** | -7.663* | -13.132*** |
| | (5.775) | (1.754) | (3.088) | (1.578) |
| $\log(Y^{Sep})$ | 1.017 | 1.444*** | 1.771*** | 1.705*** |
| | (0.683) | (0.246) | (0.378) | (0.190) |
| $\log(Y^{Mix})$ | 1.116** | 1.544*** | 1.126*** | 1.259*** |
| | (0.378) | (0.143) | (0.231) | (0.157) |
| log(Labor price) | -0.294+ | 0.385*** | 0.170 | 0.474*** |
| | (0.158) | (0.085) | (0.158) | (0.062) |
| log(Electricity price) | 0.141 | 0.262*** | 0.260*** | 0.331*** |
| | (0.139) | (0.072) | (0.060) | (0.051) |
| Log(Fuel Price) | 0.865*** | | 0.556*** | |
| | (0.175) | | (0.109) | |
| $\log(Y^{Sep}) \times \log(Y^{Mix})$ | -0.058 | -0.113*** | -0.091*** | -0.107*** |
| | (0.050) | (0.016) | (0.026) | (0.015) |
| Log(Nr of plants) | | 0.459*** | | 0.357*** |
| | | (0.058) | | (0.064) |
| Log(Density) | | -0.059** | | -0.026* |
| | | (0.022) | | (0.013) |
| Landfilling share | | | -0.006*** | -0.003** |
| | | | (0.002) | (0.001) |
| Sorting Share | | | 0.003 | 0.005* |
| | | | (0.004) | (0.002) |
| Time fixed effects | No | Yes | No | Yes |
| Num.Obs. | 88 | 88 | 88 | 88 |
| R2 | 0.892 | 0.970 | 0.957 | 0.983 |
| R2 Adj. | 0.884 | 0.964 | 0.953 | 0.980 |

[1]Standard errors (HC3)(in parentheses) are clustered at the operator level

[2]Results in column one can be interpreted as follows: A 1% increase in the electricity price is on average associated with a 0.141 % increase in total operating costs (c.p.).

[3]Share variables are converted to percentages - hence a unit unit change in the share denote a 1 percentage point increase.

[4]Costs and input prices are normalized by the residual service price.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Estimates for cost elasticities and economies of scale in the upstream sector

| | $Y^{Mix} = p50$<br>$Y^{Sep} = p50$ | $Y^{Mix} = p25$<br>$Y^{Sep} = p25$ | $Y^{Mix} = p75$<br>$Y^{Sep} = p75$ | $Y^{Mix} = p25$<br>$Y^{Sep} = p75$ | $Y^{Mix} = p75$<br>$Y^{Sep} = p25$ |
|---|---|---|---|---|---|
| $\epsilon_{CY_{sep}}$ | 0.679 | 0.718 | 0.613 | 0.718 | 0.613 |
| $\epsilon_{CY_{mix}}$ | 0.232 | 0.283 | 0.175 | 0.175 | 0.283 |
| Economies of Scale | 1.096 | 0.999 | 1.270 | 1.120 | 1.116 |
| | [1.018, 1.190] | [0.924, 1.086] | [1.118, 1.469] | [1.035, 1.220] | [1.032, 1.215] |

[1] 95% - Confidence Intervals are displayed in brackets.
[2]The estimates used for the computation are from column III of table 12.
[3]Columns differ in the level of output quantities when evaluating the marginal costs w.r.t both outputs.
[4]Results can be interpreted as follows: for column one, estimates predict economies of scale of around 1.1 for upstream operators at the sample median level of mixed and separate output quantities.

# 7 Robustness Checks:

## 7.1 Downstream: Network and area size

The main problem with the estimation of returns to scale and density by intervention area type is the fact that the number of operators in urban areas is very small compared to the two other operator groups. This makes it difficult to establish whether the absence of statistically significant differences in estimates within the urban subgroup is capturing the true (null) effect, or whether high level of noise in the estimation prohibits us from finding the true effect. Moreover, as it can be seen in figures 17, 16, 18, urban, medium urban, and rural operators vary quite strongly across the whole sample in their network size as well as output and input quantities. This will make it more difficult separate operator size and intervention area effects when estimating the production functions.

A more direct way to investigate how returns to scale vary in operator size and by type of intervention area is to look at the relationship between intervention area size and network size. *Area size* simply refers to the area in $km^2$ that an operator is responsible for, whereas *network size* is measured again by the number of pickup-points, i.e. number of dwellings with mixed or separate collection services, in a given intervention area. Analyzing returns to scale and efficiency by area and network size will allow examining whether efficiency patterns differ for a fixed intervention area size as the network increases (density effect) and whether returns to scale vary for varying operator sizes in a fixed group of intervention area size (size effect).

For the estimation the sample is divided into quartiles of area size (*low*, *lower medium*, *upper medium*, and *top*). Equations 1, and 5, are estimated by quartiles of area size using a pooled OLS estimator. This method has the advantage of creating four equally sized groups of collection operators of different area sizes, that will differ in their network size and the input quantities used. Figures 20, 19, 21 in the appendix, display the distribution and mean estimates for network size, as well as, output, and input quantities by sample quartiles of area size. We see that distributions are quite similar between operators in the four groups of area size, albeit differences in mean estimates exist. Results for the Cobb-Douglas, and Translog function are given in the appendix in tables 25, and 28. Estimates for returns to scale and density are given in the tables 26, 29. The results show a similar pattern to the subsample regressions by area type. In particular, interpreting the estimates in table 29 returns to both density and scale are predicted to decrease in the group of low and lower medium area operators, as operators' network size increases. For upper medium and top area size operators estimates for returns to density and scale vary in the network size as well but this variation is predicted to be less strong. While the small sample size will give in part imprecise estimates, the overall trends from before are confirmed: Increasing returns to scale are estimated across all groups of operators evaluated at a relatively small network size (and with relatively low levels of inputs). For large operators in small areas (high density operators) returns to scale are not statistically significant from 1.

## 7.2 Upstream: Excluding separate collection costs

One might worry that the cost function of upstream operators, see equation 9, does not correctly capture the management of separate waste management. The main shortcoming is, that the current model aggregates *collection* and *treatment/disposal* of separate waste, while these two phases will require different inputs and factor shares and vary in their underlying production processes. One could, for example, expect the collection to be more labor-intensive than treatment of separate waste, and to require different capital inputs (vehicles instead of plants). To see if the aggregation of separate collection and treatment is driving the results, I re-estimate equation 16 but exclude all costs associated with the collection of separate waste for the outcome variable. Hence, I will investigate the existence of economies of scope between mixed and separate treatment and disposal only. Results for the estimation are included in the appendix in tables 31, and 32. Estimates remain mostly unchanged w.r.t to the key parameters of interest. A negative coefficient of $\alpha_{cc}$ is found that predicts marginal costs of both mixed (separate) output to decrease in the quantity of separate (mixed) waste entering into upstream services. The difference in estimates of cost elasticities between separate and mixed waste has decreased in relation to the main specification (including all separate waste management phases). This can be explained by the fact that we have excluded a fairly large share of separate costs from the outcome variable. Despite the reduction in the elasticity gap, costs are still predicted to be more elastic to separate than mixed waste output. Overall, we can conclude, that the results for the upstream sector are robust to including separate collection in the total upstream MSW-cost estimation. However, it might still be appropriate and of interest to estimate the efficiency of separate cost collection independently from other phases of waste management.

# 8 Discussion and Limits

I estimated the cost and production frontier for Portuguese upstream and downstream waste operators. Overall, results suggest that returns to scale exist in particular for rural waste collection services, while upstream services can benefit from economies of scope between managing separate and mixed waste jointly. Moreover, results hint at economies of scale in the upstream management that increase in operator size. In the light of the expected shift away from landfilling waste towards increased separate collection and recycling, this can mean two things:

Firstly, merging adjacent rural collection operators can be a way to better capture economies of scale in the collection of waste. An efficient market structure of the MSW-sector may be more important than ever considering the future investments into MSW infrastructure and technologies needed to achieve European targets (Salvetti 2021). While there is no a priori reason to believe that efficiency patterns differ greatly between *mixed* and *separate* waste collection, it is still an open question whether the results, which are based on a sample of operators who mostly collect mixed waste, will hold for separate collection providers, as well.

Secondly, as outlined above, the transition towards a more circular economy will require a higher share of separate waste and a considerably lower share of mixed waste entering into treatment/disposal. This article has provided suggestive evidence that operating costs react more elastic towards increases in separate than mixed waste, while holding prices, and the allocation of waste to plants within streams fixed. A shift away from landfills and towards treatment of separate waste is thus predicted to drive providers' operating expenditures upwards.[46] This article finds evidence that savings in operating costs exist between managing both streams of waste jointly.[47] Hence, one way to dampen the expected cost increase for operators is to further encourage the joint provision of mixed and separate waste services.

Having discussed the meaning of the results for the Portuguese MSW-sector, I will in the following address several shortcomings of the estimation. Overall, limits due to small sample sizes, and missing variables exist, and results need to be treated with care.

The first limit of the estimation is that estimates may suffer from endogeneity bias. The main sources of endogeneity come from selection on unobservables, attrition, and measurement errors. Attrition bias - the bias that may arise from a selected sample of operators that freely exit and enter the market - is arguable the not a big threat here. For both down- and upstream sectors, we observe great stability in the composition of operators across the sample periods. Attenuation bias -the bias arising from measurement errors in regressors, such as input quantities, - is typically expected to lead to a downward bias in the estimates. It poses a threat to not only the downstream but also the upstream estimation, as input quantities are used to derive input prices. As outlined in Ackerberg,

[46] This is of course only one of many financial challenges that are expected to come along with a transformation of the MSW-sector. Further important examples are the investment costs needed to adapt infrastructure and technology - a point that this article has not focused on.

[47] As argued above, such cost savings could be even larger when taking into account capital expenditures. Unfortunately, data limitations prohibited me from doing so.

K. Caves, and Frazer (2015), measurement errors are a particular problem for the estimation of cost and production function and can be one reason for the bad performance of the fixed effect estimator in practice.[48] In the light of potential measurement errors, estimates can be interpreted as lower bounds for the true associations between inputs and outputs, as well as outputs and costs. A more serious threat to the estimation is the bias arising from potential omitted variables that are correlated with both inputs and outputs in the downstream sector, and outputs and costs in the upstream sector. Examples of such variables are the frequency of collection services per week[49], or the often unobserved management practices that may differ between operators over time. Economic literature has identified several estimation approaches to circumvent the endogeneity bias from selection on unobservables for the estimation of cost and production functions. Most prominent approaches and their refinements come from Olley and Pakes (1996), Levinsohn and Petrin (2003), Blundell and Bond (2000), and Ackerberg, K. Caves, and Frazer (2015).[50] Albeit a thorough discussion of these approaches goes beyond the scope of this article, they suffer from shortcomings that will make their use less appropriate for the application to the Portuguese MSW sector.[51] Yet, further refinement of the listed estimation approaches for an application to the MSW-management sector is a promising avenue for future research.

Another shortcoming that was already mentioned in the theoretical part of the article refers to the external validity of the presented results. Cost and production functions are specified for the Portuguese MSW-sector. As the overall market structure is defined at the national level and no fundamental changes in how the sector is regulated occurred throughout the sample period, an extrapolation of the results to other settings has to be treated with care. Nevertheless, since the design of the Portuguese waste management system - where collection and treatment are disintegrated - is quite common in Europe, the results can still be of value to waste management systems outside of Portugal.

Apart from increasing external validity, a data collection that covers operators of different countries is valuable as it would increase the precision of the results, which are for now based on a fairly small sample of upstream operators. Even though evidence for cost complementarities in the upstream sector remains robust across specifications, any further heterogeneity analysis between different groups of operators is not possible. Moreover, complementing the data with downstream operators from other countries could increase the precision in the estimations by type of intervention

[48] The fixed effects estimator is not performing well for the Portuguese data set. As often observed in the literature (see Ackerberg, K. Caves, and Frazer (2015)) the fixed effect estimator yields unreasonably low estimates for returns to capital and scale. Hence, the pooled OLS specification was chosen.

[49] See e.g. Bel and Fageda (2010) and Antonioli and Filippini (2002) who find the collection frequency to have a positive and significant association with collection costs in Spain, and Italy.

[50] See Ackerberg, K. Caves, and Frazer (2015) for a discussion of these most recent approaches

[51] To be more precise, since the capital stock in the up-and downstream sector shows very little variation within operators over time and no additional data on operators' investment is available, the estimation approach by Olley and Pakes (1996) is less suitable. For the upstream sector, in particular, the small sample size will render the structural approaches less useful, as they will involve a relatively large number of regressors and thus further decrease the degrees of freedom.

areas.[52]

I have put the estimation results of the production and cost function results of the Portuguese MSW-sector into context and discussed their limits. To conclude the discussion section, I will revisit the main lessons that can be learned from this article and similar types of bench-marking models. In the light of small sample sizes, potential measurement errors, and endogeneity bias, results have to be interpreted with great care. As outlined by Farsi, Filippini, and Greene (2006), a direct application of the models to individual operators (i.e. by plugging in individual operator characteristics into the estimated functions) might result in unexpected financial consequences for companies, since many operator-specific factors remain unobserved. The estimations are, however, useful in dividing waste operators into different efficiency clusters - as done for the downstream sector - and to estimate intervals for economies of scale for different groups of operators. Thereby, the estimations can give valuable guidelines for regulators and contribute to decreasing information asymmetries between waste operators and regulation authorities.

# 9 Conclusion and Outlook

This article has investigated the production and cost structure of the Portuguese downstream and upstream municipal solid waste management. Production function estimations of the total sample of Portuguese downstream operators hint at increasing returns to scale in the collection of mixed waste. A further subsample analysis suggests that efficiency incentives exist to merge in particular adjacent rural operators. Cost estimation of a subset of 11 upstream operators highlights that economies of scope exist between managing mixed and separate waste jointly. Joint provision of separate and mixed waste management should be encouraged to exploit the cost complementarities.

There are several avenues to explore in future research. Firstly, since this paper is the first to model all phases of waste management of a given waste management system, its framework can be used to investigate spillovers between both downstream and upstream sectors. It can help to assess how changes in the regulation (e.g. market structure, or tariffs design) in one sector impact production or cost outcomes in the other.

Secondly, further research should focus on collecting data on the final outputs of waste treatment. Most waste management outputs are measured in terms of the amounts having *entered* into treatment sources, rather than in terms of the number of recyclables or energy generated from treatment. Complemented by information on operators' gains from selling recycled and treated waste, this could be used to shed light on the cost recovery of waste management. A better understanding of which operator costs are recovered from selling treated waste and are covered by extended producer responsibility schemes is inevitable to create effective incentives to increase the separate collection and recycling of municipal waste.

[52] Of course, the country-specific contexts and the design of the MSW-sector have to be taken into account for such international estimations.

Thirdly, future research should explore how market structures relate to outcomes other than production and costs. As suggested by Bening, Pruess, and Blum (2021) a closer look at the interaction between transport of waste and market structure is needed to investigate the indirect effects of exploiting economies of scale in waste management. A main channel of interest is the potential growth in the transport of waste between municipalities, and the implied increases in emissions.

Lastly, more data and research is needed to assess municipal waste management and efficient market structures in developing countries. Few studies so far have explored and analyzed municipal waste management in the developing world, which is often suffering from severe mismanagement causing adverse environmental effects (Bening, Kahlert, and Asiedu 2022).

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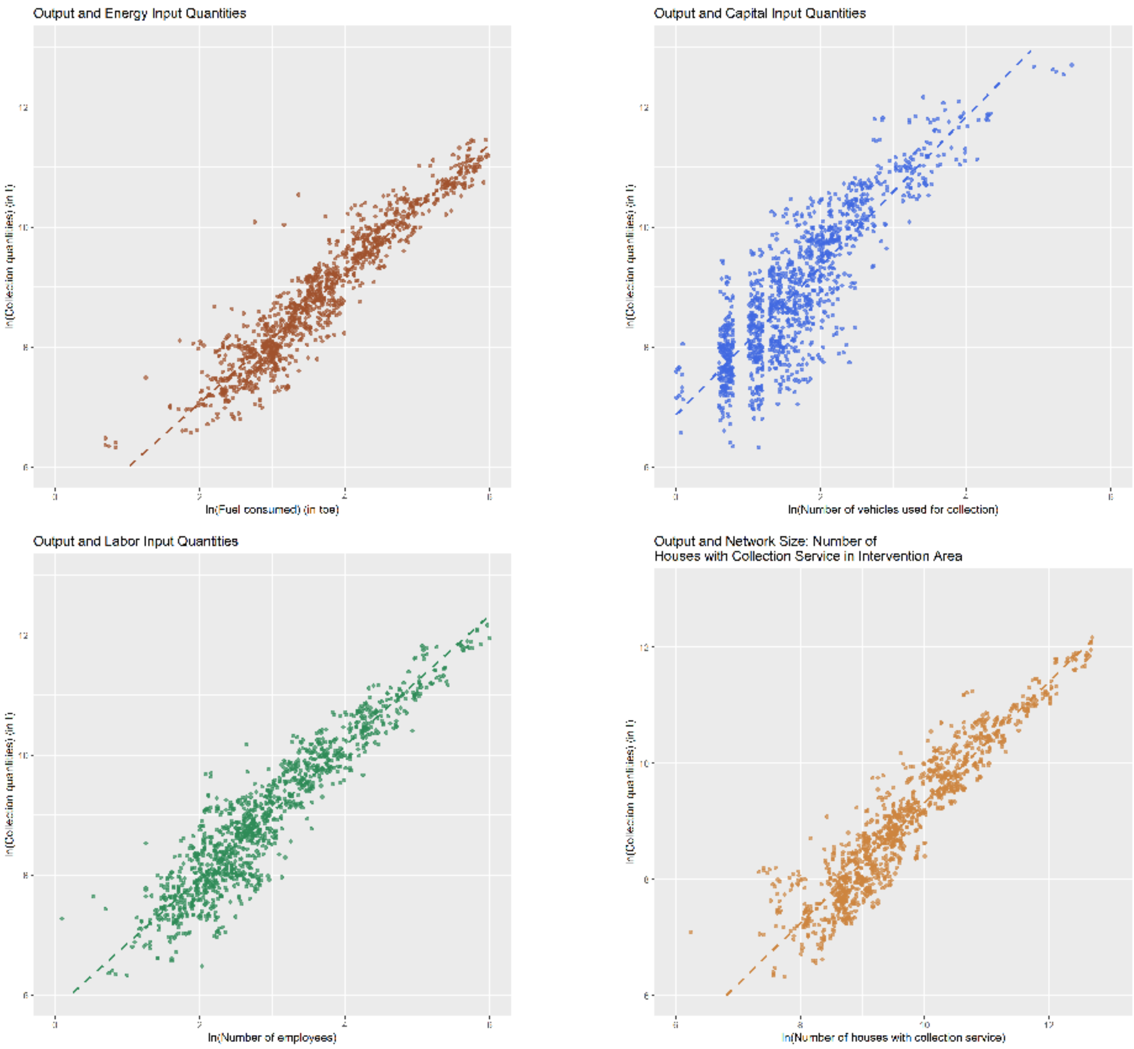
# 10 Appendix

## Downstream sector

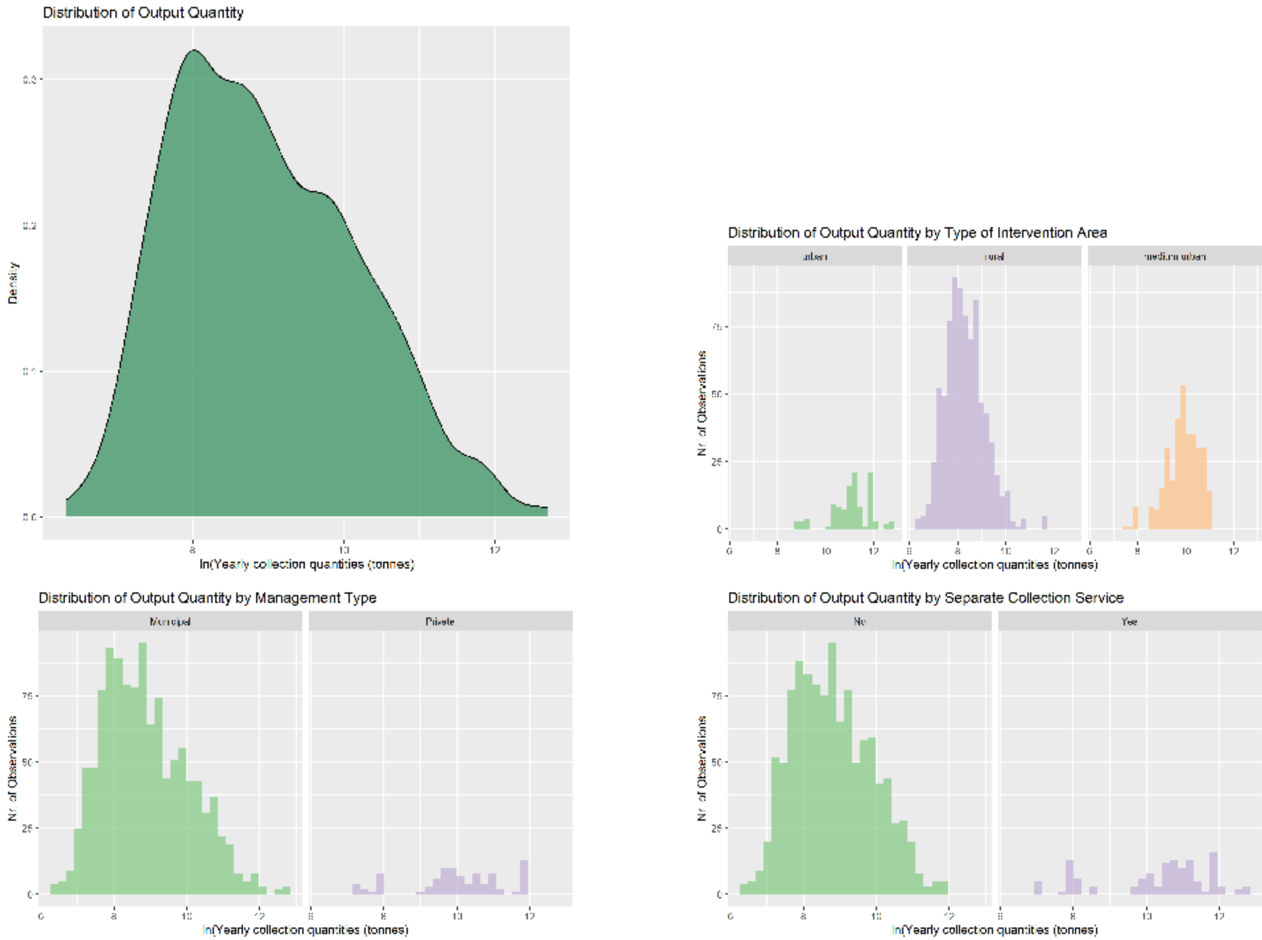
### Distribution of outcome and inputs

Table 14: Downstream operators: Output, Inputs, and Network Size




[1] Dotted line presents estimated linear regression line y=x [2] Note that the x-axes scale differs between the scatter plots

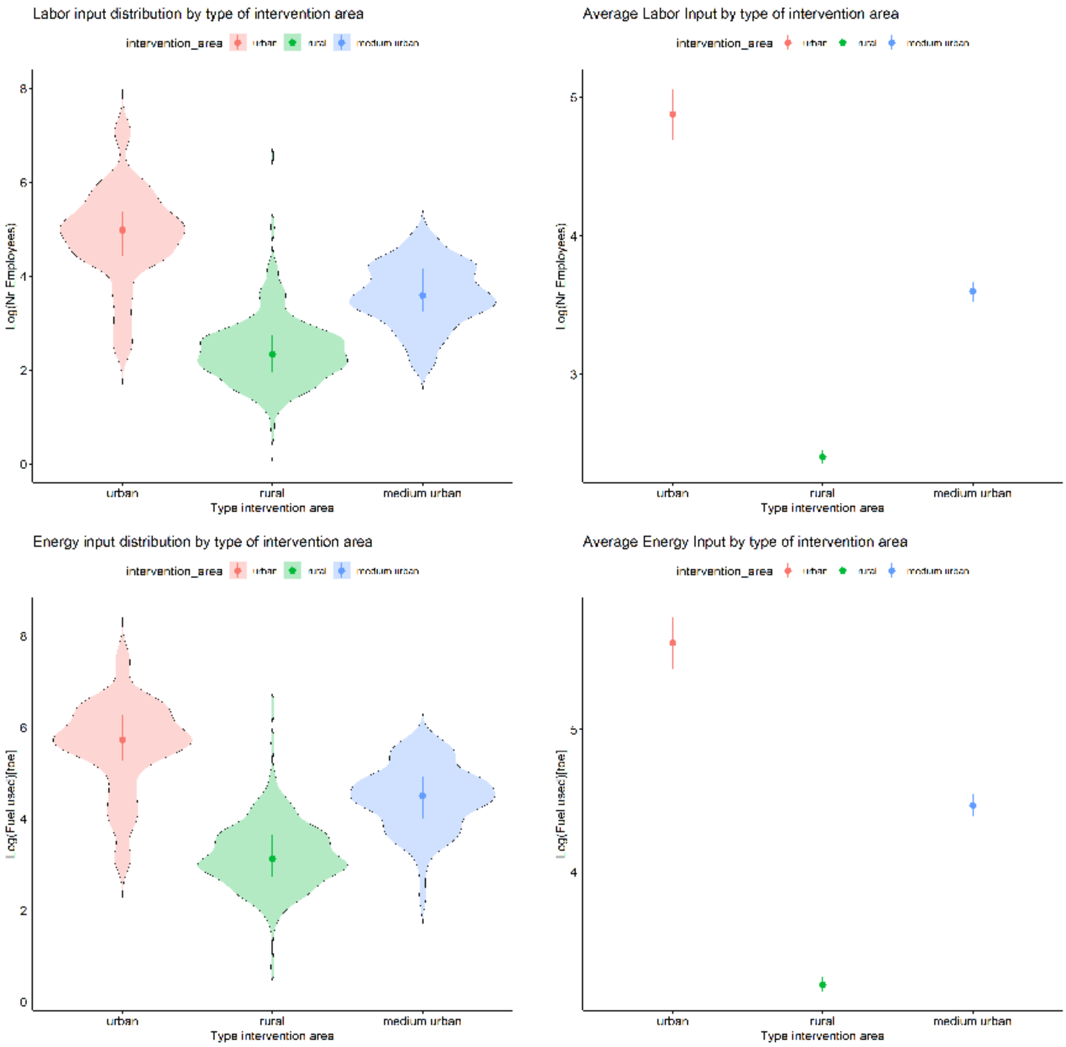
Table 15: Distribution of amount of waste collected - total sample and subsamples




[1]The figures display the output distribution of downstream operators [2]Figures include both total sample and subsample distributions

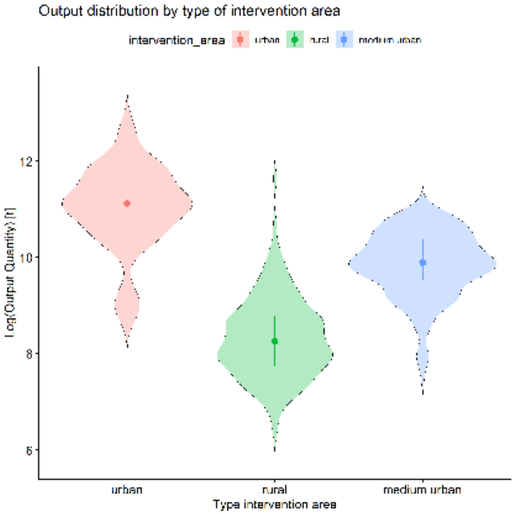
**Distribution of Outcome and inputs by area type:**

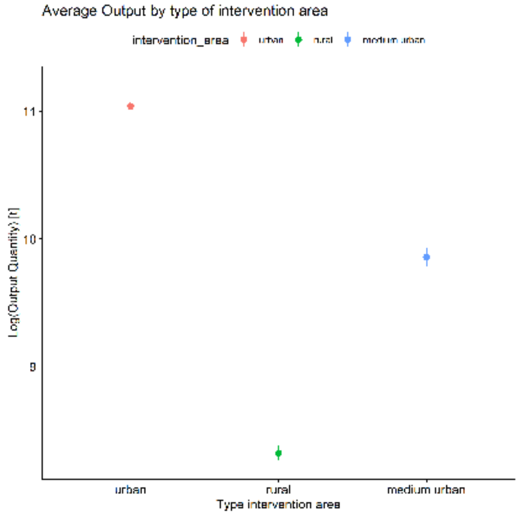
Table 16: Downstream operators by area type: Labor and energy input




[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y
[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

Table 17: Downstream operators by area type: Output quantities

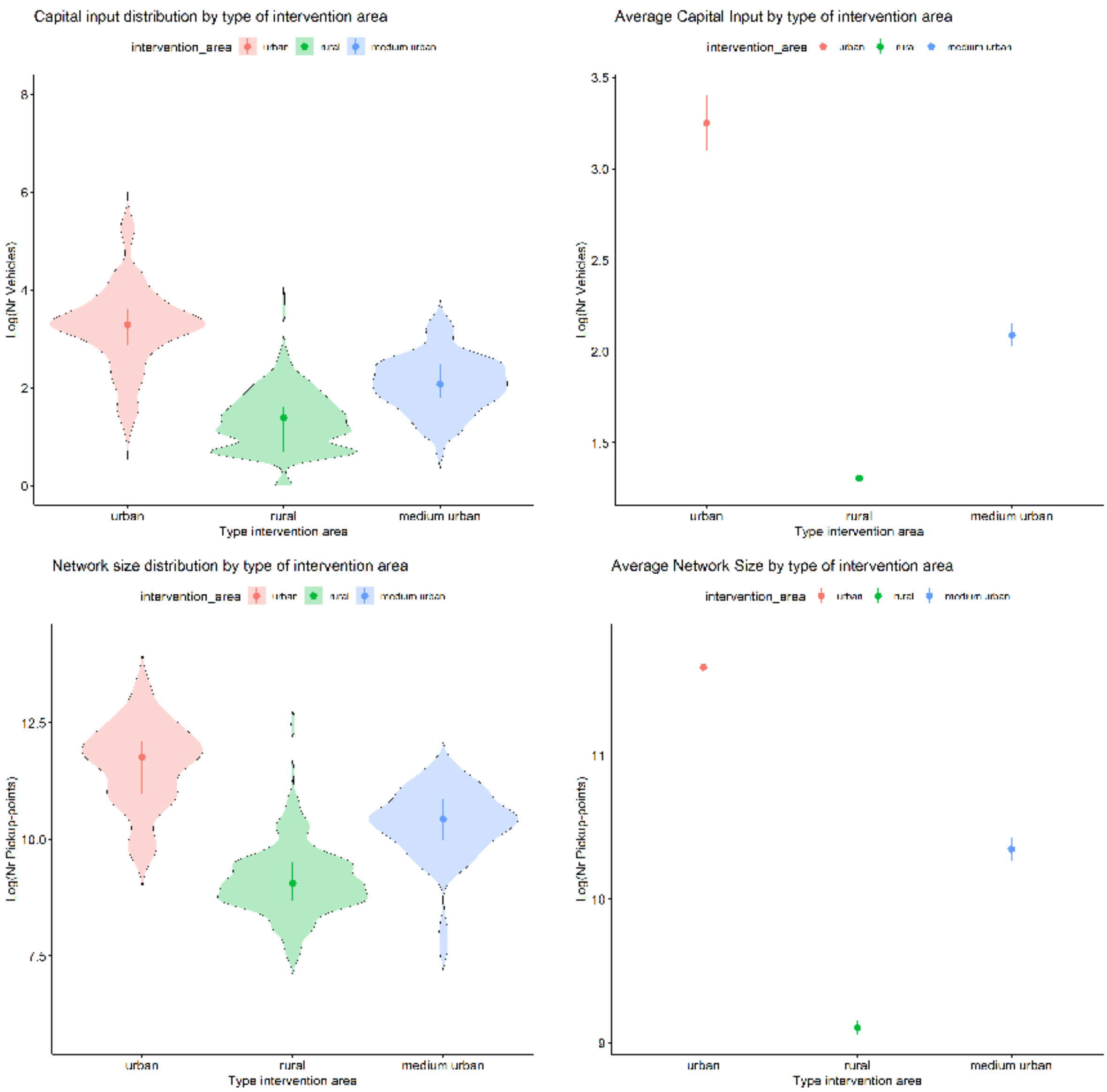



[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y

[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

Table 18: Downstream operators by area type: Capital input and Network size

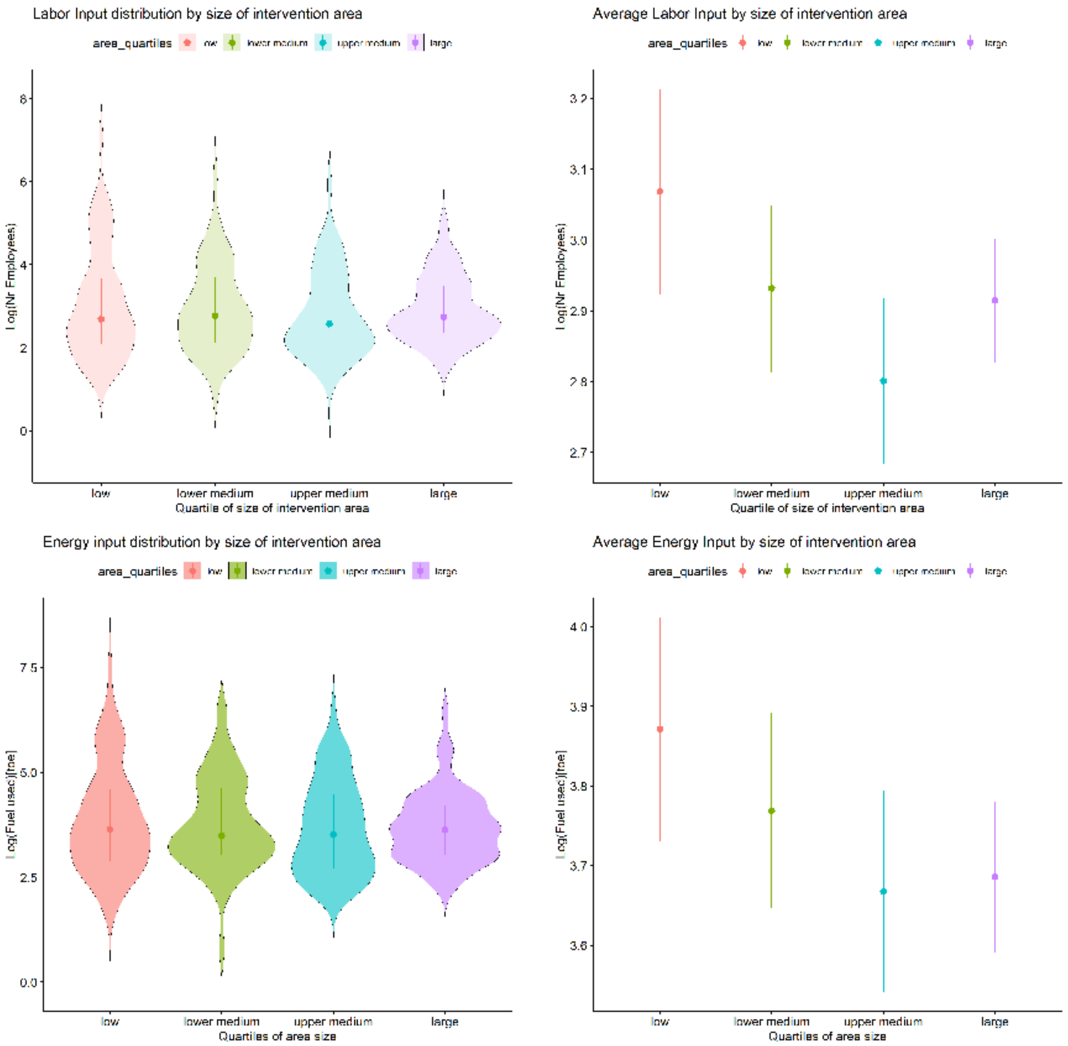



[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y

[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

### Distribution of outcomes and inputs by quartiles of area size

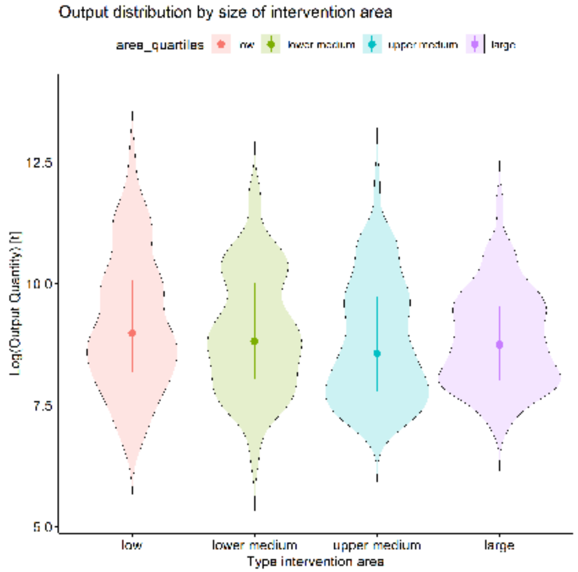
Table 19: Downstream operators by quartiles of area size: Labor and energy input

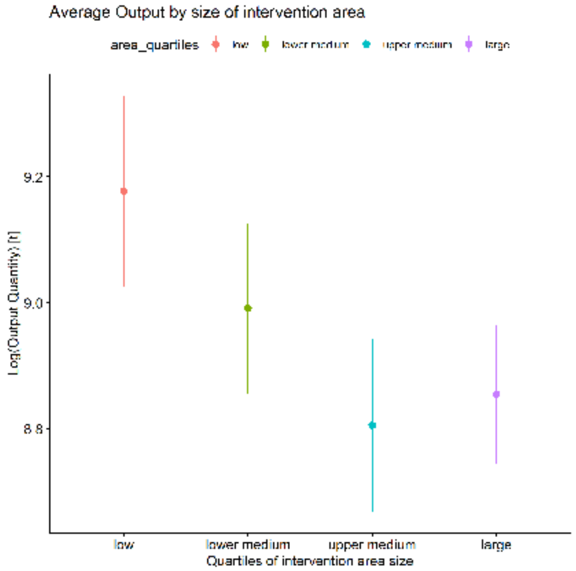



[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y

[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

Table 20: Downstream operators by quartiles of area size: Output quantities

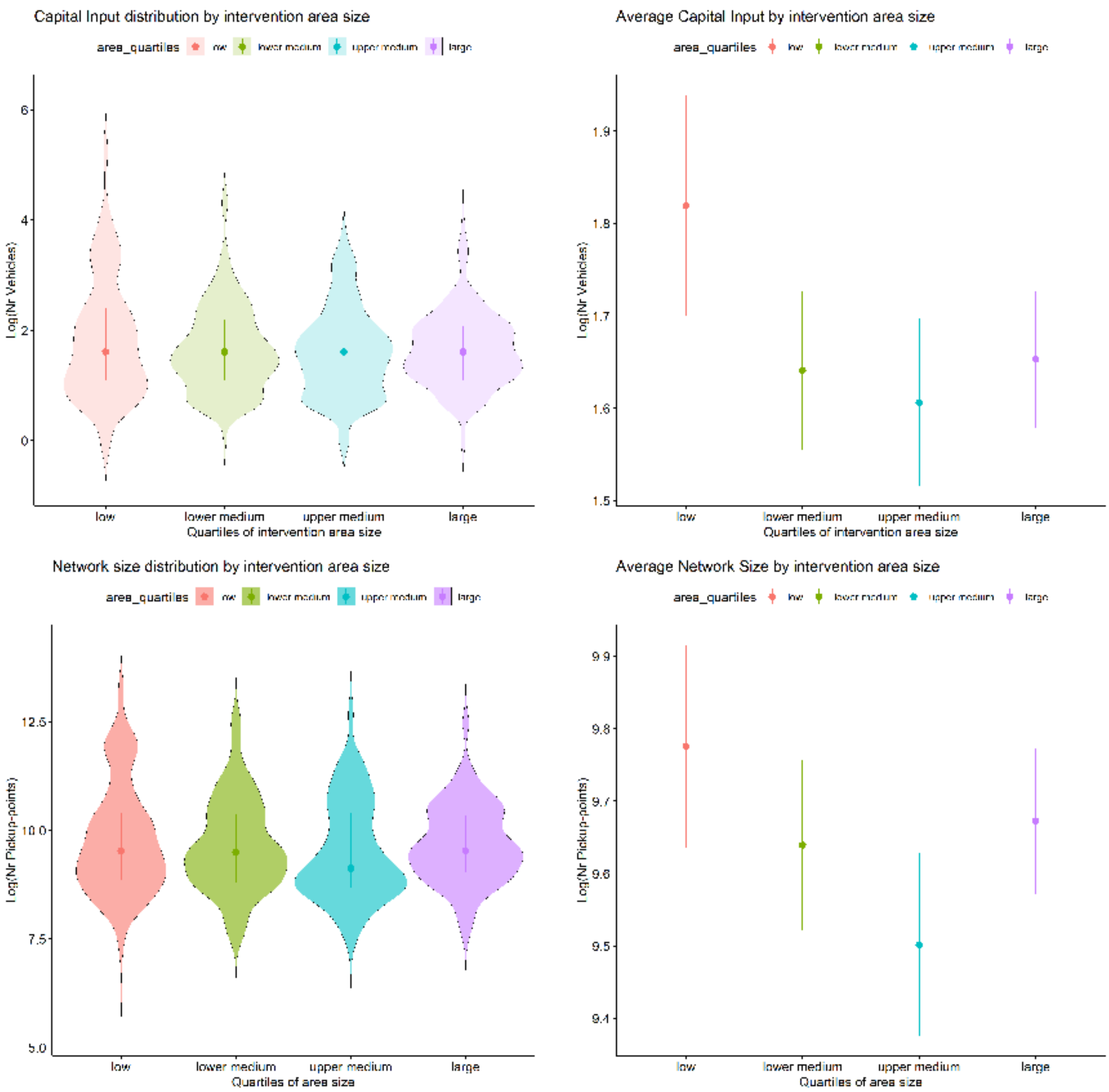



[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y

[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

Table 21: Downstream operators by quartiles of area size: Capital input and Network size




[1] Colored dots indicate sample median
[2] Bars indicate Q1 to Q3 sample quartiles
[3] Violin plots display probability density of y

[4] Colored dots represent mean estimates by group
[5] Bars indicate 95% confidence intervals
[6] Note the varying Y-axis scale between right and left-side plots

**Main Translog production function results**

Table 22: Translog production function: Average marginal effects - No controls

| Variable | AME | SE | Z-Score | P-value | Lower | Upper |
|---|---|---|---|---|---|---|
| log(Fuel consumed) | 0.475 | 0.036 | 13.095 | 0.000 | 0.404 | 0.546 |
| log(Nr employees) | 0.274 | 0.040 | 6.923 | 0.000 | 0.197 | 0.352 |
| log(Nr pickup-points) | 0.387 | 0.040 | 9.695 | 0.000 | 0.309 | 0.466 |
| log(Nr Vehicles) | 0.058 | 0.028 | 2.041 | 0.041 | 0.002 | 0.113 |

[1]This table illustrates the average marginal effects of each input variable.
[2]AME are the average input-specific marginal effects over the whole sample of downstream operators.
[3]Upper and lower bounds are computed at the 95% confidence level.

Table 23: Translog production function: Average marginal effects - Controls

| Variable | AME | SE | Z-score | p-value | lower | upper |
|---|---|---|---|---|---|---|
| Medium Urban Area | -0.003 | 0.042 | -0.067 | 0.947 | -0.086 | 0.080 |
| Rural area | -0.168 | 0.049 | -3.421 | 0.001 | -0.265 | -0.072 |
| log(Fuel consumed) | 0.468 | 0.036 | 13.101 | 0.000 | 0.398 | 0.538 |
| log(Nr employees) | 0.249 | 0.040 | 6.198 | 0.000 | 0.171 | 0.328 |
| log(Nr pickup-points) | 0.362 | 0.041 | 8.813 | 0.000 | 0.281 | 0.442 |
| log(Nr vehicles) | 0.056 | 0.029 | 1.958 | 0.050 | 0.000 | 0.112 |
| Private Management | 0.003 | 0.033 | 0.106 | 0.916 | -0.061 | 0.068 |
| Separate Collection (0/1) | 0.007 | 0.042 | 0.177 | 0.860 | -0.074 | 0.089 |

[1]This table illustrates the average marginal effects of each input variable.
[2]AME are the average input-specific marginal effects over the whole sample of downstream operators.
[3]Upper and lower bounds are computed at the 95% confidence level.
[4]Controls include time-fixed effects.

Table 24: Estimation Results of the Translog production function

| | Pooled OLS (I) | Pooled OLS (II) |
|---|---|---|
| | *Dependent variable:* Log(Waste collected) | |
| (Intercept) | 8.777*** | 8.887*** |
| | (0.020) | (0.050) |
| $\hat{\beta}_L$ | 0.297*** | 0.270*** |
| | (0.043) | (0.043) |
| $\hat{\beta}_K$ | 0.044 | 0.044 |
| | (0.029) | (0.029) |
| $\hat{\beta}_E$ | 0.477*** | 0.472*** |
| | (0.040) | (0.039) |
| $\hat{\beta}_N$ | 0.391*** | 0.364*** |
| | (0.043) | (0.044) |
| $\hat{\beta}_{LL}$ | -0.106** | -0.100** |
| | (0.036) | (0.033) |
| $\hat{\beta}_{KK}$ | -0.026 | 0.005 |
| | (0.093) | (0.088) |
| $\hat{\beta}_{EE}$ | 0.568*** | 0.552*** |
| | (0.092) | (0.086) |
| $\hat{\beta}_{NN}$ | 0.260*** | 0.226** |
| | (0.072) | (0.069) |
| $\hat{\beta}_{LE}$ | -0.094 | -0.103 |
| | (0.074) | (0.070) |
| $\hat{\beta}_{LK}$ | 0.271*** | 0.237*** |
| | (0.070) | (0.069) |
| $\hat{\beta}_{LN}$ | -0.021 | 0.006 |
| | (0.063) | (0.062) |
| $\hat{\beta}_{KE}$ | -0.295*** | -0.278*** |
| | (0.075) | (0.070) |
| $\hat{\beta}_{EN}$ | -0.278*** | -0.273*** |
| | (0.070) | (0.068) |
| $\hat{\beta}_{KN}$ | -0.002 | 0.005 |
| | (0.057) | (0.057) |
| Rural Area | | -0.168*** |
| | | (0.050) |
| Medium Urban Area | | -0.003 |
| | | (0.043) |
| Separate Collection (0/1) | | 0.007 |
| | | (0.043) |
| Private Management | | 0.003 |
| | | (0.034) |
| Time fixed effects | No | Yes |
| Num.Obs. | 1227 | 1227 |
| R2 | 0.958 | 0.960 |
| R2 Adj. | 0.957 | 0.959 |

[1]Input quantities, and network size are normalized at their median point.
[2]Heteroscedasticity robust standard errors (HC3) (in parentheses) are clustered at the operator level
[3]Reference category for type of intervention area is "urban"
[4]Reference category for management type is "public".
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

**Prodcution function results by area type and size**

Table 25: Cobb Douglas production function estimation by size of intervention area (in sample quartiles)

| | Pooled OLS Bottom | Pooled OLS Lower Medium | Pooled OLS Upper medium | Pooled OLS Top |
|---|---|---|---|---|
| | *Dependent variable:* log(Waste collected) | | | |
| (Intercept) | 3.030*** | 2.358** | 3.610*** | 2.526*** |
| | (0.730) | (0.730) | (0.419) | (0.528) |
| log(Nr employees) | 0.251* | 0.206+ | 0.124+ | 0.449*** |
| | (0.119) | (0.119) | (0.075) | (0.076) |
| log(Fuel consumed) | 0.517*** | 0.495*** | 0.720*** | 0.265** |
| | (0.084) | (0.084) | (0.077) | (0.086) |
| log(Vehicles used) | -0.031 | 0.053 | 0.071 | 0.102 |
| | (0.058) | (0.058) | (0.061) | (0.073) |
| log(Nr pickup-points) | 0.352** | 0.425*** | 0.218*** | 0.400*** |
| | (0.113) | (0.113) | (0.063) | (0.077) |
| Separate Collection (0/1) | -0.072 | -0.101 | 0.089 | -0.192* |
| | (0.176) | (0.176) | (0.099) | (0.080) |
| Private Management | -0.031 | -0.151+ | 0.051 | 0.096 |
| | (0.090) | (0.090) | (0.049) | (0.085) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Num.Obs. | 312 | 310 | 300 | 304 |
| R2 | 0.958 | 0.959 | 0.960 | 0.926 |
| R2 Adj. | 0.956 | 0.958 | 0.959 | 0.923 |

[1]Heteroscedasiticity robust standard errors (HC3) (in parentheses) are clustered at the operator level
[2]Bottom group refers to operators in the bottom quartile of intervention area size and analogously for other subsample groups.
[3]Reference category for management type is "Public".
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 26: Cobb-Douglas production function: Returns to Density and Scale by different quartiles of area size

| | Lower | Lower Medium | Upper Medium | Top |
|---|---|---|---|---|
| Returns to Density | 0.737 | 0.754 | 0.916 | 0.816 |
| | [0.565, 0.908] | [0.531, 0.977] | [0.788, 1.043] | [0.644, 0.988] |
| Returns to Scale | 1.088 | 1.179 | 1.134 | 1.216 |
| | [0.989, 1.188] | [1.089 1.269] | [1.080, 1.188] | [1.126, 1.305] |

[1]Estimates from specification with controls (see table 25) area used.
[2]Two-sided confidence intervals are presented in brackets.

Table 27: Translog function results by type of intervention area

| | Pooled OLS: urban | Pooled OLS: rural | Pooled OLS: medium urban |
|---|---|---|---|
| | *Dependent variable:* Log(Waste collected) | | |
| (Intercept) | 11.085*** | 8.216*** | 9.844*** |
| | (0.073) | (0.030) | (0.033) |
| $\hat{\beta}_L$ | 0.190 | 0.331*** | 0.234*** |
| | (0.135) | (0.055) | (0.063) |
| $\hat{\beta}_K$ | -0.033 | 0.089* | -0.013 |
| | (0.092) | (0.039) | (0.054) |
| $\hat{\beta}_E$ | 0.231* | 0.415*** | 0.517*** |
| | (0.096) | (0.050) | (0.066) |
| $\hat{\beta}_N$ | 0.548** | 0.393*** | 0.207** |
| | (0.176) | (0.060) | (0.065) |
| $\hat{\beta}_{LL}$ | 1.398* | -0.106** | 0.526* |
| | (0.592) | (0.039) | (0.214) |
| $\hat{\beta}_{KK}$ | 0.113 | 0.013 | 0.310 |
| | (0.331) | (0.104) | (0.199) |
| $\hat{\beta}_{EE}$ | -0.204 | 0.521*** | 0.530** |
| | (0.311) | (0.114) | (0.165) |
| $\hat{\beta}_{NN}$ | 1.002** | 0.260** | -0.026 |
| | (0.295) | (0.087) | (0.158) |
| $\hat{\beta}_{LE}$ | -0.231 | -0.089 | -0.056 |
| | (0.384) | (0.094) | (0.151) |
| $\hat{\beta}_{LK}$ | -0.295 | 0.283*** | -0.140 |
| | (0.359) | (0.085) | (0.159) |
| $\hat{\beta}_{LN}$ | -0.962*** | -0.014 | -0.174 |
| | (0.254) | (0.082) | (0.159) |
| $\hat{\beta}_{KE}$ | 0.283 | -0.240** | -0.449* |
| | (0.182) | (0.087) | (0.191) |
| $\hat{\beta}_{EN}$ | 0.164 | -0.271** | -0.155 |
| | (0.145) | (0.091) | (0.151) |
| $\hat{\beta}_{KN}$ | -0.159 | -0.044 | 0.273 |
| | (0.223) | (0.072) | (0.168) |
| Separate Collection (0/1) | 0.000 | -0.030 | 0.098 |
| | (0.090) | (0.087) | (0.063) |
| Private Management | 0.071 | -0.034 | -0.033 |
| | (0.065) | (0.051) | (0.065) |
| Time fixed effects | Yes | Yes | Yes |
| Num.Obs. | 109 | 795 | 323 |
| R2 | 0.982 | 0.890 | 0.938 |
| R2 Adj. | 0.978 | 0.887 | 0.934 |

[1]Input quantities, and network size are normalized at their subsample median point.
[2]Heteroscedasticity robust standard errors (HC3) (in parentheses) are clustered at the operator level
[3]Reference category for management type is "public".
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 28: Translog function results by quartiles of area size

| | Pooled OLS: Lower | Pooled OLS: Lower Medium | Pooled OLS: Upper Medium | Pooled OLS: Top |
|---|---|---|---|---|
| | *Dependent variable:* log(Waste collected) | | | |
| (Intercept) | 8.892*** | 8.805*** | 8.713*** | 8.683*** |
| | (0.040) | (0.045) | (0.065) | (0.051) |
| $\hat{\beta}_L$ | 0.263** | 0.257*** | 0.168* | 0.497*** |
| | (0.097) | (0.076) | (0.083) | (0.071) |
| $\hat{\beta}_K$ | -0.005 | 0.066 | 0.039 | 0.085 |
| | (0.055) | (0.053) | (0.047) | (0.077) |
| $\hat{\beta}_E$ | 0.526*** | 0.344*** | 0.613*** | 0.298*** |
| | (0.090) | (0.056) | (0.080) | (0.082) |
| $\hat{\beta}_N$ | 0.435*** | 0.589*** | 0.339*** | 0.419*** |
| | (0.083) | (0.094) | (0.083) | (0.080) |
| $\hat{\beta}_{LL}$ | -0.239 | -0.078 | 0.027 | -0.386 |
| | (0.297) | (0.434) | (0.167) | (0.240) |
| $\hat{\beta}_{KK}$ | -0.023 | -0.108 | -0.058 | -0.140 |
| | (0.185) | (0.197) | (0.181) | (0.262) |
| $\hat{\beta}_{EE}$ | 0.557+ | 0.474* | 0.173 | 0.474** |
| | (0.286) | (0.189) | (0.308) | (0.174) |
| $\hat{\beta}_{NN}$ | 0.256* | 0.727* | 0.563* | 0.210 |
| | (0.110) | (0.313) | (0.227) | (0.182) |
| $\hat{\beta}_{LE}$ | -0.226 | 0.240 | 0.202 | -0.116 |
| | (0.212) | (0.200) | (0.157) | (0.146) |
| $\hat{\beta}_{LK}$ | 0.434* | 0.149 | 0.306* | 0.414** |
| | (0.178) | (0.143) | (0.148) | (0.157) |
| $\hat{\beta}_{LN}$ | 0.099 | -0.356 | -0.434** | -0.002 |
| | (0.158) | (0.338) | (0.152) | (0.137) |
| $\hat{\beta}_{KE}$ | -0.210 | -0.353+ | -0.323 | -0.127 |
| | (0.165) | (0.193) | (0.215) | (0.232) |
| $\hat{\beta}_{EN}$ | -0.229 | -0.471* | -0.212 | -0.198 |
| | (0.198) | (0.205) | (0.178) | (0.156) |
| $\hat{\beta}_{KN}$ | -0.235+ | 0.172 | 0.090 | -0.129 |
| | (0.135) | (0.133) | (0.156) | (0.196) |
| Separate Collection (0/1) | -0.004 | 0.033 | 0.061 | -0.218** |
| | (0.080) | (0.139) | (0.075) | (0.079) |
| Private Management | 0.026 | -0.094 | 0.058 | 0.091 |
| | (0.081) | (0.072) | (0.063) | (0.095) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Num.Obs. | 312 | 310 | 300 | 304 |
| R2 | 0.973 | 0.973 | 0.966 | 0.934 |
| R2 Adj. | 0.971 | 0.971 | 0.963 | 0.930 |

[1]Heteroscedasiticity robust standard errors (HC3) (in parentheses) are clustered at the operator level
[2]Inputs and network size are standardized at their (total sample) median value.
[3]Bottom group refers to operators in the bottom quartile of intervention area size and analogously other subsample groups.
[4]Reference category for management type is "public".
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 29: Translog Estimates: Returns to Density and Scale by quartiles of area size

| | Small Operators | Median Operator | Large Operator |
|---|---|---|---|
| | **Returns to Density** | | |
| Low | 0.859 | 0.784 | 0.650 |
| | [0.644 1.074] | [0.597, 0.971] | [0.463, 0.837] |
| Lower Medium | 0.853 | 0.668 | 0.477 |
| | [0.650, 1.055] | [0.485, 0.850] | [0.194, 0.760] |
| Upper Medium | 0.892 | 0.819 | 0.796 |
| | [0.688, 1.095] | [0.671, 0.968] | [0.643, 0.949] |
| Top | 0.923 | 0.880 | 0.786 |
| | [0.689, 1.156] | [0.717,1.044] | [0.652, 0.920] |
| | **Returns to Scale** | | |
| Low | 1.337 | 1.219 | 1.073 |
| | [1.210, 1.464] | [1.122, 1.316] | [0.999 1.147] |
| Lower Medium | 1.374 | 1.256 | 1.108 |
| | [1.254, 1.494] | [1.181, 1.332] | [1.042, 1.174] |
| Upper Medium | 1.192 | 1.159 | 1.130 |
| | [1.099 1.284] | [1.095 1.222] | [1.066, 1.193] |
| Top | 1.398 | 1.299 | 1.149 |
| | [1.196, 1.600] | [1.165, 1.434] | [1.090, 1.201] |

[1]Estimates from specification with controls (see table 28) area used.
[2]Two-sided confidence intervals are presented in brackets.

## Upstream sector:

### Computing the residual service price

As outlined in the section describing the cost function specification for upstream waste management services, I recover the price of residual services and supplies from the data. Since residual services and supplies mainly refer to repair and maintenance services as well as material supplies (excluding energy supply), their price is expressed per plant an operator owns ($K_{it}$). Yet, plant types[53] that process more quantities of waste are expected to require more external repair services and materials. When computing the residual service price, $PS_{it}$, residual service costs are divided by the total number of plants weighted by the quantities of waste that have entered into the type of plant. This will give plant types that process more quantities more weight in the price computation.
**Unweighted service price:**

$$PS_{it}^{U} = \frac{RC_{it}}{\sum_j P_{jit}} \tag{17}$$

[53]Different plant types considered here are landfills, incinerators, mechanical treatment plants, sorting stations, biological treatment plants, and eco-centers.

**Weighted service price:**

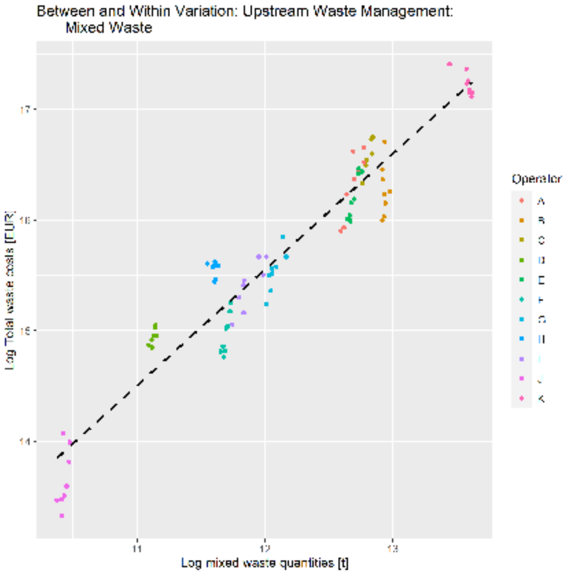
$$PS_{it} = \frac{RC_{it}}{\frac{\sum_j q_{jit} P_{jit}}{\sum_j q_{jit}}} \tag{18}$$

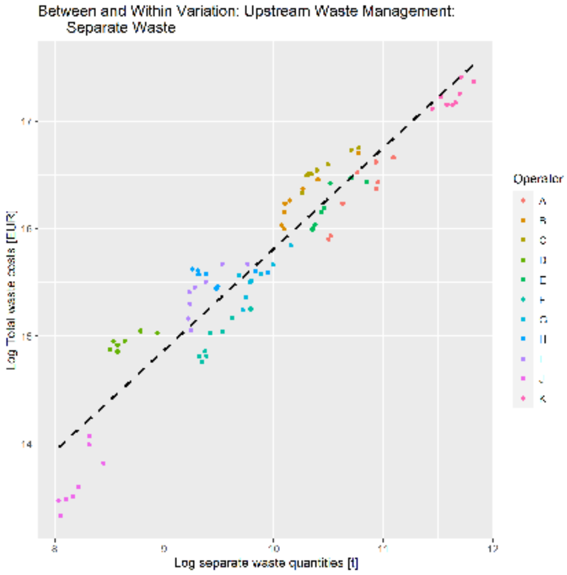
where $P_{jit}$ denotes the number of plants of type $j$, operator $i$ owns in period $t$, $RC_{it}$ denote the residual service expenditures of $i$ in $t$, and $q_{jit}$ refer to the quantities of waste processed by plant type $j$ of operator $i$ in period $t$.

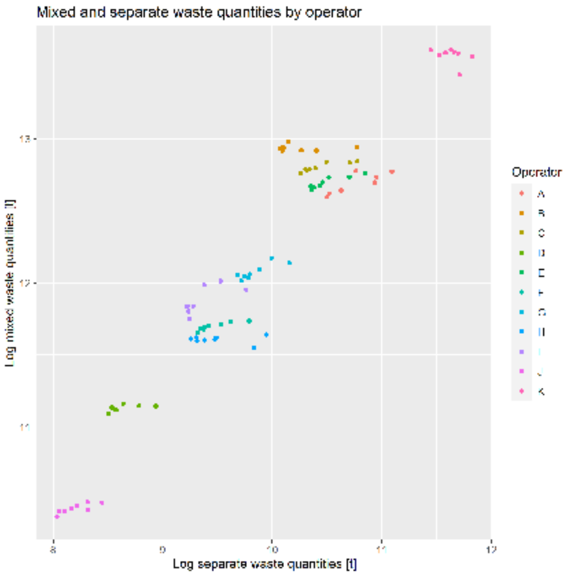
Due to data limitations this price measure, however, cannot take into account that different types of plants may face different a priori levels of services and materials expenditures irrespective of the quantities of waste processed. One could for example imagine, that landfills may need less repair services that mechanical treatment plants, irrespective of its output. Furthermore, no data on the age of plants and machines are available.

### Distribution of costs and output

Table 30: Upstream operators: Costs and Output quantities




[1]Dotted line represents estimated linear regression line y=x [2]Note that the x-axis scale differs between the single plots
[3]The 11 operators are referred to by different letters in the legend. [4]Observations by a given operator are depicted in the same color

### Robustness Check Results: Excluding collection costs

Table 31: Estimation Results of the Multi-product Cobb-Douglas Cost function - excluding collection costs

| | I | II: Controls | III: heterogeneity | IV: heterogeneity+ controls |
|---|---|---|---|---|
| (Intercept) | -1.487 | -11.956*** | -6.823** | -11.400*** |
| | (6.326) | (1.882) | (2.418) | (1.155) |
| $\log(Y^{Sep})$ | 0.641 | 1.163*** | 1.493*** | 1.497*** |
| | (0.764) | (0.277) | (0.281) | (0.150) |
| $\log(Y^{Mix})$ | 0.932* | 1.269*** | 1.068*** | 1.044*** |
| | (0.388) | (0.151) | (0.231) | (0.144) |
| log(Labor Price) | -0.342* | 0.346** | 0.128 | 0.437*** |
| | (0.162) | (0.103) | (0.124) | (0.072) |
| log(Electricity Price) | 0.187 | 0.174+ | 0.303** | 0.274*** |
| | (0.189) | (0.088) | (0.110) | (0.068) |
| log(Fuel Price) | 0.761*** | | 0.481*** | |
| | (0.212) | | (0.101) | |
| $\log(Y^{Sep}) \times \log(Y^{Mix})$ | -0.034 | -0.092*** | -0.076*** | -0.091*** |
| | (0.055) | (0.018) | (0.021) | (0.011) |
| Log(Nr of Plants) | | 0.529*** | | 0.396*** |
| | | (0.062) | | (0.048) |
| Log(Density) | | -0.054* | | -0.019+ |
| | | (0.026) | | (0.011) |
| Landfill Share | | | -0.007*** | -0.004*** |
| | | | (0.001) | (0.001) |
| Sorting Share | | | 0.000 | 0.004* |
| | | | (0.004) | (0.002) |
| Time period effects | No | Yes | No | Yes |
| Num.Obs. | 88 | 88 | 88 | 88 |
| R2 | 0.865 | 0.964 | 0.958 | 0.984 |
| R2 Adj. | 0.855 | 0.958 | 0.954 | 0.981 |

Heteroscedasticity robust standard errors (HC3)(in parentheses) are clustered at the operator level
[2]Results in column one can be interpreted as follows: A 1% increase in the electricity price is on average associated with a 0.19 % increase in operating costs (c.p.).
[3]Share variables are converted to percentages - hence a unit unit change in the share denote a 1 percentage point increase.
[4]Costs and input prices are normalized by the residual service price.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Estimates for cost elasticities and economies of scale in the upstream sector: Excluding collection costs

| | $Y^{Mix} = p50$<br>$Y^{Sep} = p50$ | $Y^{Mix} = p25$<br>$Y^{Sep} = p25$ | $Y^{Mix} = p75$<br>$Y^{Sep} = p75$ |
|---|---|---|---|
| $\epsilon_{CY_{sep}}$ | 0.574 | 0.607 | 0.519 |
| $\epsilon_{CY_{mix}}$ | 0.317 | 0.359 | 0.268 |
| Economies of Scale | 1.122 | 1.034 | 1.271 |
| | [1.056, 1.197] | [0.958, 1.124] | [1.117, 1.396] |

[1] 95% - Confidence Intervals are displayed in brackets.
[2]The estimates used for the computation are from column III of table 31.
[3]Columns differ in the level of output quantities when evaluating the marginal costs w.r.t both outputs.