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A food bank supply chain model: Optimizing investments to maximize food assistance

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ABSTRACT

Food banks are initiatives that redistribute food at risk of becoming waste to people that are food insecure in middle- and high-income countries. These initiatives, which have become more prevalent in recent years, face high levels of uncertainty in their supply chain. Inspired by challenges facing the food banks in The Netherlands, this paper describes an optimization model that can assist food bank supply chains with the distribution of an available investment budget in order to increase the number of beneficiaries that can receive food assistance. Strategic investments can be used to tackle shortages in transport, storage, and food donations. The optimization model prioritizes investments that will have the largest positive social impact, which we define as the number of beneficiaries that can be served by the food banks. Furthermore, the model deals with real-world circumstances, such as decentralized organizations, data scarcity, location-specific transport and storage capacities, and strong diversity in food bank operations. The model is applied using real-life data from the food bank supply chain in The Netherlands and the results establish investments that increase capacity and will serve 32% more beneficiaries. The association of Dutch food banks has made practical application of these findings.

1. Introduction

Food insecurity affects millions of people across the world. While most hunger arises in low-income countries, food insecurity also remains an issue in middle- and high-income countries, where 14.5% of the people do not have enough food to live a healthy and productive life (FAO et al., 2021). Despite the fact that food insecurity in these countries is on the rise, each person wastes on average around 78 kilograms of food every year (United Nations Environment Programme, 2021). Reducing the amount of food waste provides an opportunity to improve food security and can therefore contribute to the goal of zero hunger by 2030, as set out in the second of the United Nations' Sustainable Development Goals.

Food banks are an example of how food at risk of becoming waste can be redistributed to people in need in middle- and high-income countries. Eisenhandler and Tzur (2019) define food banks as warehouses or depots for agencies such as food pantries, community kitchens, or shelters that provide food assistance to beneficiaries that are food insecure. The supply to food banks consists mainly of donated products that are no longer suitable for the intended use in the retail sector, for example mislabeled products or foods nearing their best before date.

The typical food bank is initiated and managed locally, it operates with limited resources and faces high levels of uncertainty in the supply chain (Ataseven et al., 2018). The supply of foods, for example, relies on the availability of donations, leading to variation and/or uncertainty in the frequency, type, quality, and amount of food provided. This supply is often limited, and an important consideration is fair allocation across the food bank supply chain. Furthermore, food banks heavily rely on volunteers, and this may entail an inexperienced workforce, resistance to change, high staff turnover, problems with accountability, etc.. See, for example, Billis and Harris (1996). Because of these challenges, managing food bank supply chains can be complicated.

This study is motivated by a challenge that the food banks faced in the Netherlands. The national association of Dutch food banks (hereafter called DFB) represents 10 food banks and 171 food agencies in the Netherlands.[2] In 2019, DFB redistributed 74 million euros worth of food to 160,500 people, supporting approximately 1% of the country's population. The start of COVID-19 in the Netherlands in March 2020 confronted DFB with a potential growth in users up to 50% in some

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regions – and they suspected that their supply chain would not be able to accommodate this increase. Meanwhile, financial donations rose, providing budget to invest in operational changes such as the expansion of storage and transport capacity. However, finding the best way to use the budget posed a challenge. To help DFB with this investment problem, we developed an optimization model that we will discuss in the remainder of this paper.

Recent literature indicates that food bank supply chain enhancement is important in countries other than the Netherlands (Mahmoudi et al., 2022; Martins et al., 2019; Alkaabneh et al., 2021). Declining food donations are one reason for this. The increasing importance of food waste reduction interventions in the food supply chain, for example at supermarkets (Närvänen et al., 2019, p.89 – p.112), reduces the supply of food donations to food banks. Recent initiatives such as platforms or apps that redistribute surplus food for discount prices, e.g. "Too Good To Go" (Too Good To Go, 2022), reduce the supply further. Assisting as many beneficiaries as possible with the given supply, has therefore become more important.

The Food Bank Supply Chain Model (FBSCM) presented in this paper deals with the food bank context and can assist food bank supply chains in identifying strategic investments that will tackle supply chain problems and increase the number of beneficiaries of a food bank supply chain. It is a programming model that proposes investments for the efficient tackling of problems in transport, storage, and food donations. Growth scenarios are used to ensure that the supply chain can accommodate an expected increase in demand. Given the available budget, the FBSCM will suggest investments that will have the greatest social impact, defined as the number of beneficiaries that can be served. The FBSCM is applied to data from DFB and results have been used in practice for budget allocation decisions.

Our contribution in this paper is threefold. First, the FBSCM and the types of decisions involved, i.e., how to choose investments optimally, has not previously been studied in the food bank context. Second, we introduce transport and storage capacity constraints in which the size and efficiency of capacity can vary across food banks in a practical and realistic manner. This methodology addresses some of the issues in previously proposed food bank models, that typically simplify food bank transport and storage capacity (Mahmoudi et al., 2022). Third, the FBSCM is used by DFB and the steps of implementation are described in this paper. This focus on a practical implementation of research findings is rare among the existing food bank publications.

This paper is further structured as follows. Section 2 provides a review of related literature along with an expanded summary of the contributions of this paper. The problem context is described in Section 3 after which Section 4 presents the mathematical formulation of the FBSCM. An application of the FBSCM using real-life data from DFB is discussed in Section 5. Section 6 contains a summary and conclusion of the study.

2. Related literature

Food security is defined by FAO et al. (2021) as "A situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life". There are many factors that influence food security such as conflict, climate change, economic fluctuations, economic inequality, and poverty. These drivers are often interrelated and understanding exactly how they lead to food insecurity can be difficult; see FAO et al. (2021) and Godfray et al. (2010) for a more in-depth explanation. Finding solutions to food insecurity is, as a consequence, also challenging. Some authors, such as Godfray et al. (2010), suggest direct actions such as changing diets or reducing food waste, while others (e.g. FAO et al. (2021)) propose working on the drivers behind food insecurity. In fact, multiple interventions will have to be undertaken in parallel to achieve food security.

As a result of recent research in the field of humanitarian aid and disaster relief, an important step in this process can be offered by Operations Research (OR) (Besiou et al., 2018; Altay and Green, 2006). Many researchers describe OR applications that improve food security, some (diverse) examples include solutions for emergency response management by the World Food Programme (Peters et al., 2021), helpful approaches to child stunting in Ethiopia (Fenn et al., 2012) and sustainable farming in Africa (Schweigman, 2008).

Food assistance programs are a possible response to food insecurity. These programs include a variety of initiatives, from humanitarian relief efforts in low income countries to the provision of school meals and food banks in middle- and high-income countries. The focus of this paper is on food banks. Recently, this context and its relevance for possible OR applications has been the focus of increasing academic attention. For a recent survey of this literature, see Mahmoudi et al. (2022). In dealing with OR for food banks, literature identifies certain challenges and research gaps that can be categorized under three headings: (i) types of optimization models, (ii) transport and storage capacity constraints, and (iii) applied research focus. These topics will serve as a framework for the remainder of this literature study.

2.1. Types of optimization models

The existing studies on supply chain optimization models for food banks focus on three sub-problems. The first is vehicle routing (e.g. Gunes et al. (2010) and Nair et al. (2016, 2018)) and the second is resource allocation (e.g. Alkaabneh et al. (2021) and Orgut et al. (2016a, 2017, 2018)). In their most basic forms, respectively they deal with choosing the best possible routes and allocation of food supplies throughout the food bank supply chain. Several authors, for example Reihaneh and Ghoniem (2018) and Eisenhandler and Tzur (2019), have proposed optimization models that combine routing and resource allocation.

The third sub-problem, facility location, deals with finding the best location for supply chain facilities. This topic has received most attention in the food bank literature when modeled together with the other sub-problems of routing and/or resource allocation. For example, a combination with vehicle routing that focuses on food banks in remote areas is proposed by Solak et al. (2014). They consider separating the transportation between food bank and agency into two legs, due to long distances: the first leg is carried out by the food bank and the second by the agency. The authors describe an optimization model that determines the best geographic locations for cross-docking from food bank to agency as well as the best delivery routes.

Although different in the type of question to be answered, the facility location sub-problem comes closest to the FBSCM discussed in this paper because of the level of strategic decision making involved: decisions concern the structure of the food bank supply chain for the upcoming years (Mahmoudi et al., 2022). Facility location problems are typically concerned with choosing where a facility should be located geographically, while optimizing facility capacities such as transport and storage (e.g., Martins et al. (2019)). In comparison, the FBSCM does not aim to change the physical location of facilities, but instead the FBSCM decisions are related to investments in transport and storage capacity, as well as supplied donations. To the best of our knowledge, there is no single optimization model yet available for these strategic decisions.

2.2. Transport and storage capacity constraint

Given the complexity of the food bank setting, the OR studies in this context are sometimes forced to simplify certain operational characteristics to be able to model them. One such assumption concerns transport capacities. Most studies model this by setting the capacity of all vehicles to the same finite number (e.g. Nair et al. (2017) and Gunes et al. (2010)) and some consider capacities to be infinite (e.g. Lien et al. (2014) and Balcik et al. (2014)). However, differences in transport capacities are quite common in the real-world food bank setting since, amongst other reasons, they are managed individually and purchases of new vehicles are not always coordinated. This typically results in a heterogeneous fleet of vehicles, for instance consisting of large trucks, small delivery vans, and even passenger cars. In addition, in practice there can be prominent differences in the efficiency of food banks' transport capacity. For example, the availability of drivers and dexterity in loading can cause differences in the utilization of vehicle capacity. The literature review by Mahmoudi et al. (2022) identifies a research opportunity by acknowledging that certain realistic elements of transport capacity have not yet been studied. The FBSCM presented in this paper aims at closing this gap by assuming that the current payload transport capacity of agencies and food banks is known, and measuring the efficiency of transport with location-dependent utilization parameters. Hence, our method realistically applies to vehicles that are different in terms of capacity and/or utilization.

A second common abstraction is to leave out the food banks' storage capacity. In other words, excluding modeling constraints that verify whether the operational activities in given scenarios still fit within the available storage capacities. The real-world warehouse capacity limits are thereby not considered, while, in reality, food banks vary in size, layout, equipment, and available storage facilities. To the best of our knowledge, Martins et al. (2019) are the only researchers to consider such storage constraints. Their study describes a multi-objective mixed-integer linear programming model developed for the Portuguese Federation of Food Banks.[3] Their model can be used for decisions on opening new food banks, closing existing ones, and adjusting capacities in transport and storage. These decisions are subject to storage capacity constraints that depend on the type of product to be stored. Mahmoudi et al. (2022) also state that further research is worthwhile on how to model storage capacities in the food bank setting. In this paper, we propose a new methodology for this, where the size and efficiency of storage capacity may vary across food banks.

2.3. Applied research focus

Studies that have successfully applied OR solutions to food banks in practice are relatively scarce. Mohan et al. (2013) is an exception, by studying the operational planning of the food supply chain of the Society of Saint Vincent de Paul (SVdP).[4] The SVdP is an international organization located in 130 countries with the objective of helping the poor. A collaboration between the Arizona state University and the SVdP focused on applications of OR to improve the effectiveness and efficiency of the SVdP supply chain. The study's recommendations were put into practice, increasing the amount of food delivered to beneficiaries while maintaining the same costs and warehouse space.

A second notable implementation oriented work is Blackmon et al. (2021) that describes a Decision Support System (a mixed-integer linear program) applied in response to the growing imbalance between supply and demand at food banks in the Los Angeles County as a result of the COVID-19 pandemic. The Los Angeles Regional Food Bank,[5] Salesforce, and UCLA Anderson School of Management collaborated to create this system, which made it possible for families to directly pick up fresh food boxes from suppliers when the food bank facilities are completely utilized. In these cases, some steps in the supply chain can be skipped. The results of Blackmon et al. (2021) provided all involved parties with a simple, easily understandable, and immediately usable system.

To the best of our knowledge, the above two publications are the only ones to have put their research findings into practice. Hence, there seems to be few optimization models being implemented by food banks. This paper attempts to fill this gap by proposing a practical model (the FBSCM) that deals with real-world circumstances, such as location-specific transport and storage capacities and strong diversity in food bank operations. Another practical circumstance in the food bank setting that can be an obstacle of implementation-oriented research is the lack of reliable data. Advanced information systems are not commonly used by food banks, partly due to unfamiliarity and the associated costs. Little academic attention has been paid to dealing with this data scarcity problem. Despite this challenge, the FBSCM findings are used successfully by DFB and the steps of implementation, including dealing with data issues, are described in this paper.

3. Problem description

This paper describes the FBSCM that focuses on strategic supply chain optimization in the context of food banks. In this section, we highlight several assumptions regarding the setting of the problem. Consider a food bank supply chain consisting of three levels: (i) a national organization facilitating supply chain coordination, (ii) food banks that act as a distribution center, and (iii) agencies that provide food assistance to beneficiaries. All food banks and agencies have a location for logistics purposes while the national organization does not; there the non-physical and administrative tasks take place. The relationships among the stakeholders as well as the distribution of goods are illustrated in Fig. 1. Food donations enter the supply chain at different stages: the red, orange and yellow arrows indicate the national, regional, and local donations, respectively. The solid black arrows indicate the physical shipments of goods, and the dashed black arrows the information flows. The national donations are administered by the national organization and are shipped directly from the donor to the food banks. The total service area is split into different regions, with each agency assigned to exactly one region and every region containing exactly one food bank. A food bank covers all redistribution activities within a pre-specified region, resulting in a single internal shipment to each agency. These internal deliveries plus the local donations add up to the agency's supply. The allocation of donations is governed by proportionality considerations: each agency should receive a portion of national and regional donations, depending on the number of people they currently serve. The FBSCM applies to different units of measurement for donations and shipments of goods. Examples include weight in kilograms or consumer units, i.e., the unit in which an item is purchased from a retailer. Note, however, that the problem considers a single dimension (e.g., size and weight cannot be treated simultaneously), but this assumption can easily be generalized. The frequency of these donations and shipments of goods can differ among food banks and agencies, usually ranging from daily to several times a week. Due to the strategic purpose of the FBSCM, all donations and shipments of goods are aggregated to represent an average week.

The FBSCM aims to detect and solve supply chain bottlenecks, revealing shortages in transport capacity, storage capacity, and received donations. There is a finite investment budget available to spend on issues in these three areas, of which costs are assumed to be known. The costs associated with donations are indicative and can relate to the purchase of additional food items, and acquisition initiatives to reach out to new donors. The problem is to decide which bottleneck to tackle, how much to invest in each of them, and at which food bank or agency.

The transport capacity of a food bank or agency is determined by the payload of their fleet of vehicles. Food banks generally use their transport capacity to collect goods from donors and to distribute to agencies in their region or to other food banks. The transport capacity of agencies is often used to collect from local donors, but can also be used to collect from the regional food bank. The storage capacity is equal to the total number of square meters of space available to a food bank or agency, while the layout and organization of this space varies per location. These differences in storage management can cause variations in terms of output efficiency. For example, one

[3] See https://www.bancoalimentar.pt/ (in Portuguese).

[4] See https://ssvp.ca/.

[5] See https://www.lafoodbank.org/.

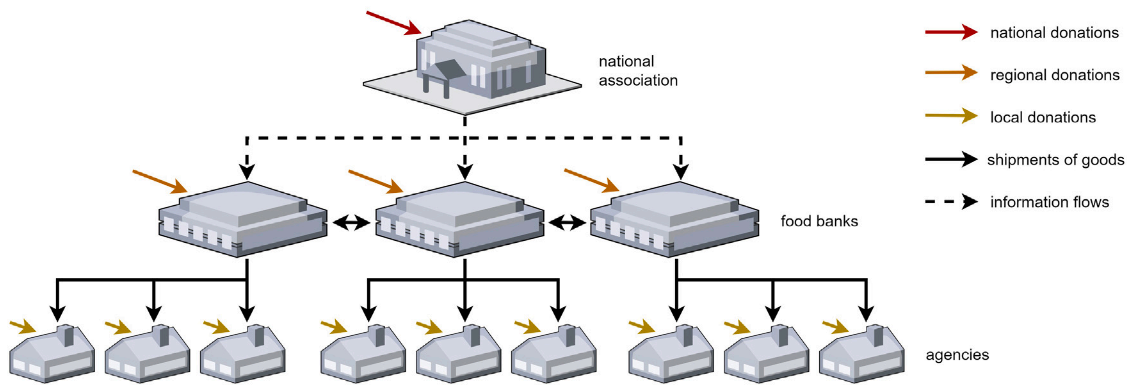

Fig. 1. Schematic overview of the FBSCM entities and shipments of goods. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

agency may be able to help more beneficiaries compared to another agency with the same space. We assume the current capacity levels of storage and transport to be heterogeneous and known, but the day-to-day utilization of capacities to be unknown. To determine the capacity levels that are needed at agencies, we assume that the capacity that is required to serve one beneficiary is known or can be approximated. For food banks, a similar assumption is made: the capacity that is needed to serve one beneficiary in the food bank's region is known. Hence, for an agency we look at the beneficiary who receives food assistance directly, while for a food bank we look at the beneficiary that is helped indirectly (i.e., through the agencies in the region). Benchmarking is one example of the methods that can be used for approximation, as we will illustrate for DFB.

These transport and storage capacity assumptions are made to tune the FBSCM to real-world circumstances. Another practical assumption is that the investment decision depends on the needs directly expressed by a food bank or agency. That is, if a food bank or agency does not see the need for an expansion, no investment will be proposed.

4. Mathematical formulation

The above description of the problem establishes the mathematical formulation of the FBSCM presented in this section. We first introduce notations, which are also summarized in Table 1. Let $\mathcal{N}_F$ be the set of food banks, $\mathcal{N}_A$ the set of agencies and $\mathcal{N} = \mathcal{N}_F \cup \mathcal{N}_A$ the set of all locations. The sets $\mathcal{N}_{P_T}$ and $\mathcal{N}_{P_S}$ denote the collections of locations that have indicated potential capacity shortages related to transport or storage, respectively, where $\mathcal{N}_{P_T} \subseteq \mathcal{N}$ and $\mathcal{N}_{P_S} \subseteq \mathcal{N}$. The set $\mathcal{R}_i$ defines a region, i.e., it denotes the agencies that are served by food bank $i \in \mathcal{N}_F$. The food bank to which agency $i \in \mathcal{N}_A$ is connected is denoted by $\mathcal{D}_i$.

The parameter INV represents the available investment budget. The unit costs of installing transport capacity (CT), installing storage capacity (CS), and acquiring new donations (CA) are the same across locations. All cost and budget parameters are expressed in euros. Parameters ET_i and ES_i represent, respectively, current capacities for transport and storage of location $i \in \mathcal{N}$. The tonne and square meter are the respective units of measurement for transport and storage. The capacity that is required to serve a beneficiary is denoted by transport parameter RT_i and storage parameter RS_i for $i \in \mathcal{N}$. Note that this service to a beneficiary can be of two types: (i) direct, i.e., when the end user receives food assistance from the agency, and (ii) indirect, i.e., the preparatory activities at a food bank that facilitate the eventual assistance provided by the agencies in the region. For ease of notation, these slightly different implications for agencies and food banks are integrated into the same parameters RT_i and RS_i. The number of beneficiaries that receive food assistance from agency $i \in \mathcal{N}_A$ is specified by B_i. Parameter U_i denotes the goods handed out per beneficiary by agency $i \in \mathcal{N}_A$. The donation parameters are named according to their entrance in the chain: at the national level (ND), at the regional level (RD_i, $i \in \mathcal{N}_F$) and at the local level (LD_i, $i \in \mathcal{N}_A$). Donations and the goods handed out per beneficiary can be expressed in any unit of measurement, as long as all parameters are defined accordingly. For simplicity, we refer in the text to "quantity". All parameters are non-negative.

Table 1
Notations.

Sets	
$\mathcal{N}_F$	Food banks
$\mathcal{N}_A$	Agencies
$\mathcal{N}$	All locations, i.e., $\mathcal{N} = \mathcal{N}_F \cup \mathcal{N}_A$
$\mathcal{N}_{P_T}$	Locations with potential transport capacity shortages, where $\mathcal{N}_{P_T} \subseteq \mathcal{N}$
$\mathcal{N}_{P_S}$	Locations with potential storage capacity shortages, where $\mathcal{N}_{P_S} \subseteq \mathcal{N}$
$\mathcal{R}_i$	Agencies in a region, i.e., agencies that are served by food bank $i \in \mathcal{N}_F$
$\mathcal{D}_i$	Food bank to which agency $i \in \mathcal{N}_A$ is connected
Parameters	
INV	Investment budget (€)
CT	Unit costs of installing transport capacity (€)
CS	Unit costs of installing storage capacity (€)
CA	Unit costs of acquiring new donations (€)
ET_i	Current capacity for transport of location $i \in \mathcal{N}$ (tonnes)
ES_i	Current capacity for storage of location $i \in \mathcal{N}$ (square meters)
RT_i	Transport capacity required to serve a beneficiary at location $i \in \mathcal{N}$
RS_i	Storage capacity required to serve a beneficiary at location $i \in \mathcal{N}$
B_i	Number of beneficiaries that receive food assistance from agency $i \in \mathcal{N}_A$
U_i	Quantity handed out per beneficiary by agency $i \in \mathcal{N}_A$
ND	National donations: quantity donated to the national association
RD_i	Regional donations: quantity donated to food bank $i \in \mathcal{N}_F$
LD_i	Local donations: quantity donated to agency $i \in \mathcal{N}_A$
Decision variables	
t_i	Transport capacity at location $i \in \mathcal{N}$ (tonnes)
s_i	Storage capacity at location $i \in \mathcal{N}$ (square meters)
a_i	Acquired donations at location $i \in \mathcal{N}$ (quantity)
$x_{\mathcal{R}_i}$	Goods from the national organization that are allocated to region $\mathcal{R}_i$, $i \in \mathcal{N}_F$ (quantity)
x_{ij}	Goods transported from food bank $i \in \mathcal{N}_F$ to agency $j \in \mathcal{N}_A$ or food bank $j \neq i$, $j \in \mathcal{N}_F$ (quantity)
Auxiliary variable	
b_i	Number of beneficiaries that can be served at agency $i \in \mathcal{N}_A$

Variable t_i, $i \in \mathcal{N}$ denotes the transport capacity in tonnes and s_i, $i \in \mathcal{N}$ the storage capacity in square meter. The acquired donations of the optimized food bank supply chain are denoted by a_i, $i \in \mathcal{N}_A$. The goods from the national organization that are allocated to region $\mathcal{R}_i$, $i \in \mathcal{N}_F$ are specified by $x_{\mathcal{R}_i}$. These goods can in turn be shipped to either the agencies or the other food banks. These shipments of goods are denoted by variable x_{ij}, where $i \in \mathcal{N}_F$ and $j \in \mathcal{N}_A$ or $j \neq i$, $j \in \mathcal{N}_F$. Finally, auxiliary variables b_i indicate the number of beneficiaries that theoretically can be served at agency $i \in \mathcal{N}_A$, based on the optimized food bank supply chain, considering: (i) the supply of donations, (ii) the storage capacity, (iii) the transport capacity, (iv) the uncertainty scenario on demand, and (v) the expressed needs of the food banks and agencies.

This auxiliary variable b_i is used as the objective of the FBSCM, i.e., we maximize the number of beneficiaries that can be supported with food assistance:

$$\max_{t_i, s_i, a_i, x_{\mathcal{R}_i}, x_{ij}} \sum_{i \in \mathcal{N}_A} b_i. \tag{1}$$

This objective is subject to various groups of constraints, which are now explained below.

Investment constraint

$$CT \sum_{i \in \mathcal{N}} (t_i - ET_i) + CS \sum_{i \in \mathcal{N}} (s_i - ES_i) + CA \sum_{i \in \mathcal{N}_A} a_i \leq INV \tag{2}$$

Constraint (2) ensures that the total investments consisting of (i) transport capacity expansions, (ii) storage capacity expansions, and (iii) acquiring additional donations, cannot exceed the budget.

Capacity lower bounds and qualification constraints

$$t_i \geq ET_i \qquad \forall\, i \in \mathcal{N}_{P_T} \tag{3}$$

$$s_i \geq ES_i \qquad \forall\, i \in \mathcal{N}_{P_S} \tag{4}$$

$$t_i = ET_i \qquad \forall\, i \in \mathcal{N} \setminus \mathcal{N}_{P_T} \tag{5}$$

$$s_i = ES_i \qquad \forall\, i \in \mathcal{N} \setminus \mathcal{N}_{P_S} \tag{6}$$

Inequalities (3) and (4) limit the transport and storage capacity values. These lower bounds stipulate that capacities cannot be smaller than the current levels. This relationship holds with equality when food banks express no capacity problems. These qualification constraints are imposed by equalities (5) and (6).

Capacity utilization constraints

$$b_i \leq \frac{t_i}{RT_i} \qquad \forall\, i \in \mathcal{N}_A \cap \mathcal{N}_{P_T} \tag{7}$$

$$b_i \leq \frac{s_i}{RS_i} \qquad \forall\, i \in \mathcal{N}_A \cap \mathcal{N}_{S_T} \tag{8}$$

$$b_i \leq \max\left\{\frac{ET_i}{RT_i},\ B_i\right\} \qquad \forall\, i \in \mathcal{N}_A \setminus (\mathcal{N}_{P_T} \cap \mathcal{N}_A) \tag{9}$$

$$b_i \leq \max\left\{\frac{ES_i}{RS_i},\ B_i\right\} \qquad \forall\, i \in \mathcal{N}_A \setminus (\mathcal{N}_{P_S} \cap \mathcal{N}_A) \tag{10}$$

$$\sum_{j \in \mathcal{R}_i} b_j \leq \frac{t_i}{RT_i} \qquad \forall\, i \in \mathcal{N}_F \cap \mathcal{N}_{P_T} \tag{11}$$

$$\sum_{j \in \mathcal{R}_i} b_j \leq \frac{s_i}{RS_i} \qquad \forall\, i \in \mathcal{N}_F \cap \mathcal{N}_{S_T} \tag{12}$$

$$\sum_{j \in \mathcal{R}_i} b_j \leq \max\left\{\frac{ET_i}{RT_i},\ \sum_{j \in \mathcal{R}_i} B_j\right\} \qquad \forall\, i \in \mathcal{N}_F \setminus (\mathcal{N}_{P_T} \cap \mathcal{N}_F) \tag{13}$$

$$\sum_{j \in \mathcal{R}_i} b_j \leq \max\left\{\frac{ES_i}{RS_i},\ \sum_{j \in \mathcal{R}_i} B_j\right\} \qquad \forall\, i \in \mathcal{N}_F \setminus (\mathcal{N}_{P_S} \cap \mathcal{N}_F) \tag{14}$$

Constraints (7)–(10) state the relationship between the capacity utilization and the number of beneficiaries that can be assisted by an agency. A distinction is made between agencies that report having capacity problems ($\mathcal{N}_A \cap \mathcal{N}_{P_T}$ and $\mathcal{N}_A \cap \mathcal{N}_{S_T}$) and those who report not having any problems with capacity ($\mathcal{N}_A \setminus (\mathcal{N}_{P_T} \cap \mathcal{N}_A)$ and $\mathcal{N}_A \setminus (\mathcal{N}_{P_S} \cap \mathcal{N}_A)$). For the former group, the available transport and storage is translated into a maximum number of beneficiaries using parameters RT_i and RS_i. No investments are considered for the latter group (see constraints (5) and (6)) and so the number of beneficiaries that can be assisted at these agencies depends on the current capacities ET_i and ES_i. It can occur, however, that the approximations ET_i/RT_i and/or ES_i/RS_i exceed the current number of beneficiaries (B_i). The extent to which this appears depends on the values of RT_i and RS_i. No fewer beneficiaries in the optimum than in the current setting are allowed and so constraints (9) and (10) prohibit this. A similar method is used to specify the capacity utilization for food banks, as presented in constraints (11)–(14). While the agency constraints, discussed above, each relate to their own optimization variable b_i, $i \in \mathcal{N}_A$, the required capacity for a food bank is determined by looking at the beneficiaries in a region combined, i.e., $\sum_{j \in \mathcal{R}_i} b_j$, $i \in \mathcal{N}_F$.

Uncertainty on the number of beneficiaries

$$B_i \leq b_i \leq B_i \times (1 + \alpha) \qquad \forall\, i \in \mathcal{N}_A \tag{15}$$

Constraint (15) specifies bounds on the number of beneficiaries that can be served at every agency. These bounds indicate the uncertainty on demand, where we assume that there will be no reduction in demand. The maximum growth of b_i, $i \in \mathcal{N}_A$ is restricted by the growth factor α.

Distribution constraints

$$ND \geq \sum_{i \in \mathcal{N}_F} x_{\mathcal{R}_i} \tag{16}$$

$$x_{\mathcal{R}_i} + \sum_{j \neq i,\, j \in \mathcal{N}_F} x_{ji} + RD_i \geq \sum_{j \neq i,\, j \in \mathcal{N}} x_{ij} \qquad \forall\, i \in \mathcal{N}_F \tag{17}$$

$$x_{D_i,i} + a_i + LD_i \geq U_i \times b_i \qquad \forall\, i \in \mathcal{N}_A \tag{18}$$

$$x_{ij} = 0 \qquad \forall\, i \in \mathcal{N}_F,\ j \notin \mathcal{R}_i \tag{19}$$

$$x_{ij} = -x_{ji} \qquad \forall\, i \in \mathcal{N}_F,\ j \in \mathcal{N}_F \tag{20}$$

Flow preservation constraints (16)–(18) are defined for each entity in the supply chain. They guarantee that outgoing flows do not exceed incoming flows for the national organization, food banks, and agencies. For the national organization this implies that the allocations to the food banks may not exceed the national donations. The incoming flows to the food banks, as expressed in constraint (17), consist of: (i) the allocation from the national organization, (ii) the incoming flows from other food banks and (iii) regional donations. On the agency level, constraint (18) ensures that the quantity handed out to beneficiaries does not exceed the quantity available. The quantity received from a food bank, the additionally acquired donations and the local donations sum up to the incoming flow to an agency. Constraint (19) ensures that agencies can only receive goods from the food bank in its region. That is, flows from food banks to agencies outside their service area are set to zero. Constraint (20) preserves flows between food banks.

Proportionality constraints

$$\left|\frac{x_{D_i,i} - \gamma_i \times ND}{\gamma_i \times ND}\right| \leq \beta \qquad \forall\, i \in \mathcal{N}_A \tag{21}$$

Constraint (21) ensures that the national donations are proportionally distributed to the agencies where β is the fractional deviation from perfect proportionality and $\gamma_i = B_i / \sum_{j \in \mathcal{N}_A} B_j$ the share of beneficiaries currently served by food bank $i \in \mathcal{N}_A$ as fraction of the total number of beneficiaries currently served. Ideally, proportionality should be established according to the expected number of beneficiaries requesting food assistance in the near future. The FBSCM is intended to assist with making investment decisions by solving the model once or twice a year using the updated current number of beneficiaries, and therefore we believe B_i is a good proxy for controlling proportionality. Moreover, computing the proportionality according to the variable b_i has the disadvantage that it comes with additional calculation complexity due to increased nonlinearity of the model. Note that when using B_i in the proportionality constraint, a simple manipulation of the absolute value expression allows a fully linear reformulation of constraint (21), e.g., $|A| \leq B$ can be replaced by $A \leq B$ and $-A \leq B$. A linear reformulation is useful to reduce the complexity of the model.

Non-negativity constraints

$$x_{\mathcal{R}_i} \geq 0 \qquad \forall\, i \in \mathcal{N}_F \tag{22}$$

$$x_{ij} \geq 0 \qquad \forall\, i \in \mathcal{N}_F,\ j \in \mathcal{N}_A \tag{23}$$

$$a_i \geq 0 \qquad \forall\, i \in \mathcal{N}_A \tag{24}$$

Constraints (22)–(24) specify the domains of the corresponding variables. In addition, inequalities (22) and (23) enforce that goods cannot flow "up" in the chain: distributing goods from agencies in the direction of the national organization is not possible. Non-negativity constraints for t_i, s_i and b_i are redundant due to constraints (3)–(6), and (15).

5. Application: Dutch food bank supply chain

In this section, we present the results of a numerical experiment conducted to test the applicability of the FBSCM described in this paper. The analysis was performed using real data from DFB and results are successfully used in their organization. This numerical experiment was coded in Python 3.10.5 and Gurobi 9.5.2 using a machine equipped with an Intel i7-1165G7 2.8 GHz processor and a limit of 16 GB of RAM. Specifics of this numerical experiment are presented in Section 5.1 after which the data collection is described in Section 5.2. Next, Sections 5.3 and 5.4 discuss the results and how these results have impacted DFB.

5.1. Specifics of DFB

DFB contributes to food security in the Netherlands by facilitating the Dutch food bank supply chain as the national organization (cf. Fig. 1). To provide food support throughout the Netherlands, the country is divided into ten regions where each region has exactly one food bank. These food banks act as distribution centers for the agencies in their region, but also house their own agency.[6] This network consists of 171 agencies and is run by 13,000 volunteers.[7]

New challenges arose for DFB in 2020 with the onset of the COVID-19 pandemic. They had to deal with greater uncertainty, such as volunteer absences due to illness, decreasing food donations, and drastic changes in demand. In particular, the demand uncertainty created alarming scenarios, where demand could potentially grow as much as 50%. This would inevitably cause capacity problems in the supply chain. At the same time, monetary donations in this year were five times higher than expected. DFB decided to use this budget to make the supply chain resilient in a way that best serves its beneficiaries.

DFB uses consumer units as a measurement of the food aid provided to these beneficiaries. A consumer unit is the unit in which the item is purchased from a supplier or retailer. When items are packaged together, such as in a bag of apples or a box of eggs, this counts as a single consumer unit. DFB agencies then bundle these consumer units in food packages, that supplement the meals of beneficiaries at home. This is a different type of food assistance from that discussed more extensively by related publications (e.g. Davis et al. (2014) and Orgut et al. (2016b)), where ready-cooked meals are provided by e.g., community centers, churches, soup kitchens, or nursing homes. Additionally, some food banks, for example in Canada, combine both methods (Tarasuk and Beaton, 1999; Tarasuk et al., 2014). Although this numerical experiment considers the food package-type, the developed FBSCM applies to all above-mentioned variants of food assistance.

[6] The agency activities of nine out of ten food banks take place at the same location. One food bank, to the contrary, uses two separate locations for this. Given their proximity, however, we consider them as one location. Hence, for the numerical experiment we have $\mathcal{N}_F \subset \mathcal{N}_A$ and so $\mathcal{N} = \mathcal{N}_A$.

[7] See https://voedselbankennederland.nl/ (in Dutch).

Table 2
Summary of data.

Information	Notation	Value
Number of food banks	$\|\mathcal{N}_F\|$	10
Number of agencies[a]	$\|\mathcal{N}_A\|$	131
Number of locations with transport capacity problems	$\|\mathcal{N}_{P_T}\|$	23
Number of locations with storage capacity problems	$\|\mathcal{N}_{P_S}\|$	58
Total number of beneficiaries assisted	$\sum_{i\in\mathcal{N}_A} B_i$	82,550
Average size of a food package in consumer units	$\frac{1}{\|\mathcal{N}_A\|}\sum_{i\in\mathcal{N}_A} U_i$	31
Total transport capacity in tonnes	$\sum_{i\in\mathcal{N}} ET_i$	390,613
Total storage capacity in square meters	$\sum_{i\in\mathcal{N}} ES_i$	60,448
Demand uncertainty parameter	α	0.5
Fractional deviation from perfect proportionality	β	0.2

[a]Only the agencies that replied to the survey (response rate of 77%) are part of the data.

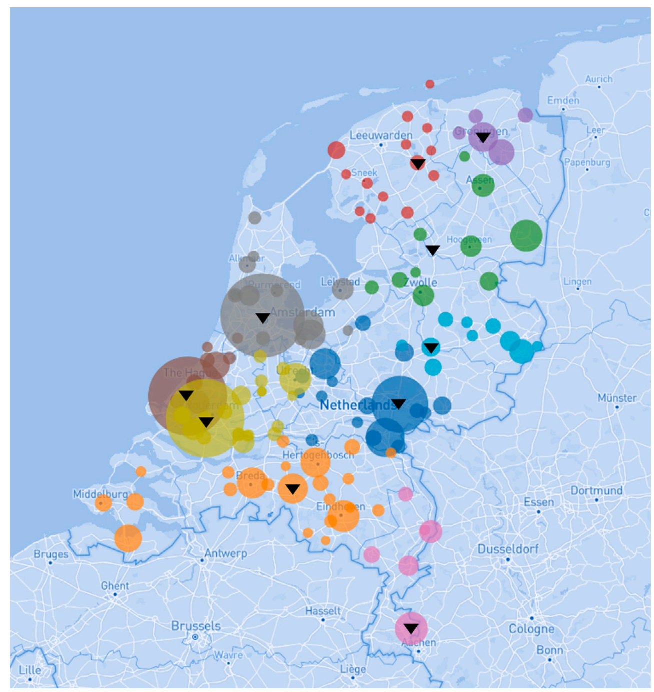

Fig. 2. Map showing the locations of food banks (triangles) and agencies..

5.2. Data collection

The data used for this numerical experiment were gathered from: (i) surveys, (ii) internal data systems, (iii) expert knowledge, and (iv) approximations using benchmarking.

Location-specific data on beneficiaries, transport, and storage were collected through a survey that was sent out to all food banks and agencies affiliated with DFB. This survey was created by the authors in collaboration with the board of DFB, took place in March 2021, and resulted in 131 complete responses (response rate of 77%). The food banks and agencies that did not reply are excluded from the analysis. Another survey, conducted by DFB in 2020, provided the information on local donations and the cost of acquiring additional donations. In addition, data on the national donations over 2020 were provided by the DFB volunteers responsible for the acquisition of food donations and were retrieved from DFB's internal data system. The location independent parameters, such as the investment budget and costs of transport and storage capacity expansions, were provided by the logistics experts of DFB. Finally, the parameters for the capacity that is required to serve a beneficiary (i.e., RS_i and RT_i for $i \in \mathcal{N}$) are approximated by comparing the efficiency of food banks and agencies using a multiple linear regression method, see Appendix for more details on this approximation method.

Finally, the collected data is normalized to represent an average week in 2021. Table 2 provides a summary of the data. Fig. 2 shows the

Table 3
Main results of FBSCM for DFB.

	Extra	Distribution of investment			Increase		
	Beneficiaries $\frac{\sum_i(\bar{b}_i-B_i)}{\sum_{j\in\mathcal{N}_A}B_j}$	Storage $\frac{\sum_i(\bar{s}_i-ES_i)CS}{\bar{\kappa}}$	Transport $\frac{\sum_i(\bar{t}_i-ET_i)CT}{\bar{\kappa}}$	Donations $\frac{\sum_i(\bar{a}_i)CA}{\bar{\kappa}}$	Storage $\frac{\sum_i(\bar{s}_i-ES_i)}{\sum_i ES_i}$	Transport $\frac{\sum_i(\bar{t}_i-ET_i)}{\sum_i ET_i}$	Donations $\sum_i \bar{a}_i$
$i\in\mathcal{R}_1$	16%	11%	1%	1%	30%	10%	5,802
$i\in\mathcal{R}_2$	30%	9%	0%	2%	9%	0%	9,894
$i\in\mathcal{R}_3$	35%	2%	3%	3%	4%	7%	15,453
$i\in\mathcal{R}_4$	39%	8%	5%	10%	9%	10%	57,742
$i\in\mathcal{R}_5$	42%	2%	1%	6%	2%	4%	33,910
$i\in\mathcal{R}_6$	36%	7%	9%	5%	4%	9%	28,695
$i\in\mathcal{R}_7$	33%	1%	1%	4%	1%	1%	25,210
$i\in\mathcal{R}_8$	17%	0%	0%	2%	0%	0%	11,457
$i\in\mathcal{R}_9$	47%	1%	0%	3%	2%	0%	14,320
$i\in\mathcal{R}_{10}$	11%	2%	2%	0%	5%	9%	1,508
$i\in\mathcal{N}_A$	32%	42%	22%	36%	5%	4%	203,992

The bar mark is used for the solution values of the decision variables, with $\bar{\kappa} = CT\sum_{i\in\mathcal{N}}(\bar{t}_i - ET_i) + CS\sum_{i\in\mathcal{N}}(\bar{s}_i - ES_i) + CA\sum_{i\in\mathcal{N}_A}\bar{a}_i$.

locations of the 131 food banks and agencies in the data set. The black triangles indicate the food banks and the bulbs the agencies, where the size of the bulb is an indication of the number of beneficiaries assisted. The coloring indicates the regions in the country.

5.3. Results

The solution as presented in this section is obtained by solving a second-stage optimization model with cost minimization objective:

$$\min_{t_i,s_i,a_i,x_{\mathcal{R}_i},x_{ij}} CT\sum_{i\in\mathcal{N}}(t_i - ET_i) + CS\sum_{i\in\mathcal{N}}(s_i - ES_i) + CA\sum_{i\in\mathcal{N}_A} a_i, \tag{25}$$

subject to all constraints of the FBSCM as specified in (2)–(24) and additional constraint:

$$\sum_{i\in\mathcal{N}_A} b_i = \sum_{i\in\mathcal{N}_A}\bar{b}_i, \tag{26}$$

where $\bar{b}_i$ denotes the optimal solution for b_i when solving the FBSCM (first-stage). This methodology of minimizing costs in a second-stage was required because investment constraint (2) was not binding for this numerical experiment. Without this constraint being binding, there is no incentive for using the available donations before acquiring additional donations.

The results for the DFB numerical experiment are presented in Table 3. In column 1 we describe the region. Column 2 gives the extra beneficiaries that can be served as a percentage increase relative to the current number of beneficiaries served. Columns 3 – 5 present the distribution of investment for extra storage, transport and donations, respectively, as a percentage of the total investments. Finally, columns 6 – 8 show the increase in storage, transport, and donations of the optimized supply chain. For storage and transport, the percentage change is presented relative to the current supply chain, while for donations the sum of the additionally acquired donations is given in consumer units.

Because of the second-stage methodology, the presented results correspond with a solution in which all donations are distributed and only part of the investment budget is used. Additionally, no consumer units are distributed between food banks. The findings in Table 3 show that the number of beneficiaries that can be assisted can increase by 32% on the national level when increasing the total storage capacity by 5%, the transport capacity by 4% and acquiring a total of 203,992 additional donations. In absolute numbers, this means that the number of beneficiaries as presented in Table 2 can increase to 109,223. On the regional level, the possibility of increasing this number varies between 11% for Region 10 and 47% for Region 9. The largest investment is suggested for storage, to which 42% of the budget is assigned. With 22% of the total investments, transport requires least investment. Table 3 shows that the type and size of investment strongly differ per region. For example, for Region 8 no transport or storage investments need to be made, whereas for Region 1, a big part of the investment is to be made in storage. When comparing the optimized supply chain to the current supply chain, Table 3 shows that Region 1 should be expanded by 30% additional storage space, which is the largest percentage increase.

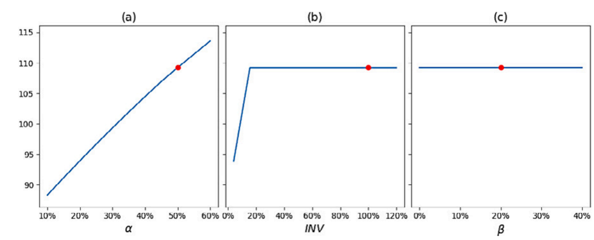

Fig. 3. Sensitivity results. The y-axis indicates the number of beneficiaries in thousands, i.e. $\sum_{i\in\mathcal{N}_A} b_i$.

It is worth noting that these results can not only be attributed to the FBSCM, but also to the specific conditions at time of running the experiment. It is a special situation, for example, that a relatively large available investment budget is available to DFB. Under different conditions the possible increase in the number of beneficiaries, as well as other results, would be different.

The results in Table 3 provide a base case, and sensitivity results are presented in Fig. 3. The y-axis is the same for the three plots in the figure, indicating the number of beneficiaries in thousands, i.e., the objective value of the FBSCM. The base case solution is indicated in all plots by means of a red dot. Plot (a) provides information on the dependence of this objective value on the uncertainty of demand (α). It shows that there is a positive linear relationship between the demand uncertainty and the objective value. That is, the model provides more capacity when demand is more uncertain. Next, plot (b) shows the effect of the investment budget (INV) on the objective, where the 100% on the x-axis corresponds to the base case investment budget. Twenty per cent of this budget gives the same objective value as for the base case. Hence, after making the suggested investment, there is still budget available to DFB for other investment opportunities or to accommodate even larger uncertainty in demand. Finally, plot (c) shows the objective as a function of the percentage deviation from perfect proportionality (β). It turns out that this proportionality scenario does not affect the objective value. This is because the investment budget is not binding. Regardless of how strictly the national goods are allocated over the agencies, there is always sufficient budget to increase donations. Though the objective is not affected, a larger β does bring higher costs.

5.4. Impact for DFB

Several steps were taken to translate the above results into meaningful actions for DFB. First, together with DFB we investigated the potential bottlenecks in the food bank supply chain. To gain a good understanding of the operational challenges, this exploration consisted of visiting food banks, frequent team discussions, and conducting a survey. The model was then developed in an iterative manner where model components and solutions were constantly verified with DFB. Initially, we found the reliability of the data to be a problem and additional data gathering and validation was done to improve this. Although several data mistakes were corrected, we decided on an implementation method that deals well with possible discrepancies left in the data. Finally, the above results are implemented by DFB in the following ways[8]:

1. Our results were used to increase inter agency-learning on the regional level: food banks and agencies within a region discussed our results and shared ideas and solutions related to identified bottlenecks and possible causes.
2. Investments were made by combining our results with a funding application procedure for food banks and agencies. They were asked to apply for a specific investment and only if this was supported by our model, was the investment made.
3. Our results were used to improve collaboration between agencies and food banks. Whenever there were two or more parties within close proximity for which our findings indicate small capacity investments, the opportunity of intensified collaboration was proposed.

6. Conclusion

This paper focuses on the issue of distributing an available investment budget to increase the number of beneficiaries that can receive food support through a food bank supply chain. Investments can be used to address shortages in transport, storage, and food donations. The nature of the problem required designing an objective function that models the social impact of the food bank supply chain while dealing with challenging real-world circumstances of this setting. Some examples include limited resources, high uncertainty levels, strong diversity in operations across the different agencies, and limited availability of data that complicates the use of decision support models. We propose an optimization model for this setting that aims to assist decision making at the strategic level of (national) food bank organizations and to advise on the structure of the food bank supply chain.

The applicability of this optimization model was tested using real-world data from the national association of Dutch food banks (DFB). This organization represents 171 agencies and contributes to food security for 160,500 beneficiaries in the Netherlands every year. The results show that the suggested investments can provide capacity for serving an additional 32% of beneficiaries. These findings have successfully enhanced DFB's operational activities.

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[8] As of November 2022, DFB has implemented 2 million euros worth of supply chain changes in response to the results. The results are expected to contribute to another 2 to 3 million in investments in the coming year.

Appendix. Benchmarking

For the DFB numerical experiment we consider a setting with $\mathcal{N} = \mathcal{N}_A$, as all food banks also house their own agency. Approximations for RT_i and RS_i are made for $i \in \mathcal{N}$ using two consecutive multiple linear regressions. The interpretation of each of these regressions is as follows. The first compares agencies and selects agencies that are efficient, controlling for the following independent variables: (i) the sizes of the agencies in terms of beneficiaries, (ii) whether or not the agency is also a food bank, (iii) the number of issuing points where beneficiaries can pickup food packages and (iv) the degree of choice a beneficiary has in the composition of the food package. Then, the second regression is performed only on the efficient agencies to find an efficiency performance, given the above four characteristics of an agency. In more detail, the steps are:

1. **Find efficient agencies.** Specify the set of efficient agencies using a least squares linear fit with k independent variables, i.e.:

$$ES_i = \alpha_{0i} + \alpha_{1i}x_{1i} + \alpha_{2i}x_{2i} + \cdots + \alpha_{ki}x_{ki} \qquad \forall i \in \mathcal{N}_{P_S} \tag{27}$$

$$ET_i = \beta_{0i} + \beta_{1i}x_{1i} + \beta_{2i}x_{2i} + \cdots + \beta_{ki}x_{ki} \qquad \forall i \in \mathcal{N}_{P_T}, \tag{28}$$

where $\{x_1, \dots, x_k\}$ are the independent variables. Using Ordinary Least Squares (OLS) gives coefficients $\hat{\alpha}_{ji},\ \hat{\beta}_{ji},\ j \in \{1, \dots, k\}$ and the estimates $\hat{ES}_i$ and $\hat{ET}_i$ can be derived for all $i \in \mathcal{N}$. Specify the set of efficient agencies for transport and storage, individually, such that:

$$\mathcal{E}_T = \{i : ES_i < \hat{ES}_i, i \in \mathcal{N}\}$$
$$\mathcal{E}_S = \{i : ET_i < \hat{ET}_i, i \in \mathcal{N}\}.$$

2. **OLS on efficient agencies.** Compute OLS for the same independent variables as in (27) and (28), using $i \in \mathcal{E}_T$ and $i \in \mathcal{E}_S$. This produces new OLS estimates $\tilde{\alpha}_{ji},\ \tilde{\beta}_{ji},\ j \in \{1, \dots, k\}$ that we use to obtain $\tilde{ES}_i$ and $\tilde{ET}_i$.
3. **Calculate RS_i and RT_i.** Then the parameters RS_i and RT_i are equal to:

$$RS_i = \frac{\tilde{ES}_i}{B_i} \qquad \forall i \in \mathcal{N}$$
$$RT_i = \frac{\tilde{ET}_i}{B_i} \qquad \forall i \in \mathcal{N}.$$

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