Food Aid Logistics in Resource-Constrained Environments

by

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Dedicated to the memory of Mustafa Kemal Atatürk,
the founder of the modern Republic of Turkey,
for his vision and persistent championing of Turkish women's rights,
especially in education.

Abstract

This thesis focuses on the logistical challenges that the humanitarian agencies face while delivering food aid to regions suffering chronic hunger. Although the problems described in the thesis are common among the humanitarian organizations and the outcomes are transferable to other settings, they are inspired by the world's largest humanitarian organization fighting against hunger: United Nations' World Food Programme (WFP). This thesis consists of three research projects. In the first project, I conducted a field research in WFP Kenya headquarters in order to understand the major challenges that WFP faces in the transportation domain. I have visited critical points in the WFP's food aid supply chain, conducted interviews with WFP officers and the third-party transporters contracted for food aid delivery. These interviews revealed that the WFP is facing considerable challenges with the transporters. First, WFP signs contracts with transporters that provide the lowest bid for a six-month period. This mechanism enables WFP to decrease its logistics costs, however, the contracted rates usually fall below the average market rates. In addition, the transportation cost fluctuations due to oil price changes are not reflected in the contracts. Second, the transporters usually turn down the requests from WFP for better paying opportunities since there are neither penalty nor bonus clauses in WFP contracts. Third, there is a significant variance among the rates for different origin-destination pairs as well as different contracts. To address these challenges, in my second project, I develop a framework that calculates contract rates reflecting the market dynamics and provides the necessary adjustments in the contracts, so that the transporters respond WFP's cargo requests on time. Using the market rate data gathered from the Kenyan transporters, I build an econometric model that captures the variation in transport market prices. In addition, I devise a new barrier-type option contract that can increase the transporters' service levels by updating the rates according to the oil price fluctuations during the course of the contract. The numerical experiments on real-life data demonstrate that significant improvements in service levels without incurring additional costs to WFP can be achieved for certain origin-destination pairs that are not desirable for the transporters. In the third project, I explore a more radical solution to the excessive logistics costs and related operational challenges: providing cash and vouchers instead of physical food distribution. Recently, many humanitarian organizations ran pilot studies on these newer aid modalities. Empirical evidence emanated from these studies shows that implementing cash and voucher programs can improve three main objectives: the logistics costs, the nutritional outcomes, and the contribution to the local economy. I develop a generic model that selects the aid modalities by measuring the improvements in these three program objectives. In addition, I incorporate the consumption behaviour of the beneficiaries in a bilevel optimization model structure to capture their cash spending preferences. Finally, I show how this model can be used for aid program design and policy evaluation purposes by using a real-data set for Garissa county of Kenya.

Résumé

Cette thèse se penche sur les défis logistiques auxquels font face les agences humanitaires en livrant de l'aide alimentaire dans des régions souffrant de malnutrition chronique. Bien que les problèmes décrits dans cette thèse s’appliquent à plusieurs organisations humanitaires et que les résultats soient généralisables à d'autres contextes, ceux-ci sont principalement inspirés des défis encourus par la plus grande organisation humanitaire luttant contre la faim: le Programme alimentaire mondial de l’Organisation des Nations unies (PAM). Cette thèse comporte trois projets de recherche portant sur la distribution de l’aide alimentaire dans des pays en voie de développement. Dans le premier projet, j'ai mené une recherche sur le terrain au Kenya afin de comprendre les principaux défis auxquels le PAM était confronté en ce qui concerne le domaine du transport. J'ai visité des points critiques de la chaîne d'approvisionnement du PAM (p. ex., le bureau principal, des entrepôts et un camp de réfugiés) et j’ai mené des entretiens avec des agents du PAM ainsi qu’avec des transporteurs contractés pour distribuer de l'aide alimentaire. Ces entretiens ont révélé que le PAM fait face à des défis considérables avec ses transporteurs. Premièrement, le PAM établit des contrats, pour une période de six mois, avec les transporteurs qui offrant les prix les plus bas sur les différents segments du réseau. Cette stratégie permet au PAM de réduire ses coûts logistiques, mais on constate que les taux contractés sont généralement inférieurs aux taux moyens du marché, ce qui génère certaines difficultés. De plus, les fluctuations des coûts encourus par les transporteurs, causés par les variations du prix du pétrole, ne sont pas reflétées dans ces contrats. Deuxièmement, les transporteurs refusent souvent les requêtes de transport du PAM afin de profiter de meilleures possibilités sur le marché puisqu’il n'y a pas de clauses de pénalités ni de primes dans les contrats établis entre le PAM et ses transporteurs. Troisièmement, il existe des écarts importants entre les taux des différentes paires origine-destination ainsi que pour différents contrats. Dans le deuxième projet, j’ai développé un cadre méthodologique qui estime les taux contractés et qui reflètent la dynamique du

marché en apportant les ajustements nécessaires aux contrats lorsque le prix du pétrole augmente considérablement afin d'inciter les transporteurs à répondre à temps aux requêtes du PAM. En utilisant les données sur des prix de marché recueillis auprès de plusieurs transporteurs du Kenya, j'ai construit un modèle économétrique qui saisit des prix du marché du transport. De plus, j'ai proposé une nouvelle forme de contrat, basé sur des options de type barrière, qui permet d'améliorer le niveau de service des transporteurs en actualisant les tarifs en fonction des fluctuations du prix du pétrole pendant la durée du contrat. Les tests numériques effectués sur des données réelles montrent que des améliorations significatives du niveau de service peuvent être réalisées pour certaines paires origine-destination, celles moins désirables auprès des transporteurs, et ce sans générer des coûts supplémentaires pour le PAM. Dans le troisième projet, j'analyse une solution plus radicale aux coûts logistiques et aux défis opérationnels associés: des transferts en espèces et en bons d'échange pour l'aide alimentaire en contrepartie à la distribution physique de nourriture. Récemment, de nombreuses organisations humanitaires ont mené des études sur ces nouvelles modalités d'aide. Les résultats empiriques de ces études montrent que la mise en œuvre de programmes de transferts en espèces et de bons d'échange peut améliorer trois objectifs à considérer lors de la distribution de l'aide alimentaire: les coûts logistiques, les bénéfices nutritionnels et la contribution à l'économie locale. Ainsi, j'ai développé un modèle mathématique qui permet de sélectionner les modalités d'aide en optimisant ces trois objectifs d'un programme d'aide alimentaire. En outre, j'ai incorporé le comportement des bénéficiaires dans une structure de modèle d'optimisation à deux niveaux afin de considérer leurs préférences en ce qui concerne leurs dépenses en espèces. Enfin, je montre comment ce modèle peut être utilisé pour la conception de programmes d'aide et pour l'évaluation de politiques en utilisant un ensemble de données réelles pour la région de Garissa au Kenya.

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Preface

Statement of the co-authorship

The following manuscript is based on this thesis:

Sahinyazan FG, Rancourt ME, Verter V. 2017 "Price Flexible Transportation Contracts for Food Aid Delivery." *Working Paper.* CIRRELT-2017-65

The first author (student) conducted a field research in Kenya to collect the qualitative and the quantitative data-sets, cleaned the quantitative data, constructed the two-phase contracting framework, performed econometric analyses for the first phase, and built the real-options model and contract design for the second phase. During the study, the first author was the main responsible for conducting the research, writing the manuscript and developing the computer models required to solve the problem. The second and third co-authors contributed during modelling and computational analysis phases. Also, they provided guidance to the first author for interpreting the results. Finally, they reviewed the manuscript and provided editing suggestions.

Disclaimer

The content of this thesis does not reflect the official opinion of the World Food Programme. Responsibility for the information and views expressed in the thesis lies entirely with the author.

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List of Abbreviations

APR. *Asia Pacific Region*

DALY. *Disability Adjusted Life Years*

ECA. *East and Central Africa*

ERDO. *Emergency Relief & Development Overseas*

FAIMS. *Food Aid Modality Selection Problem*

FAO. *Food and Agricultural Organization of the United Nations*

GIS. *Geographical Information System*

KSh. *Kenya Schillings*

LAC. *Latin America and the Caribbean*

MENA. *Middle East and North Africa*

MS. *Management Science*

OR. *Operations Research*

RFQ. *Request for Quotation*

SA. *Southern Africa*

SDG. *Sustainable Development Goals*

USAID. *United States Agency of International Development*

WA. *West Africa*

WFP. *World Food Programme*

WHO. *World Health Organization*

Chapter 1

Introduction

1.1 Chronic Hunger Response

Almost 800 million people, one ninth of the world population, is facing hunger on a daily basis (WFP, 2018b). These people do not have access to the food required to maintain a healthy lifestyle, in other words they are *food insecure*. As of 2018, hunger is still the greatest health risk to the population. It affects more people than AIDS, tuberculosis and malaria combined. Governments and international organizations work towards achieving “zero hunger” under the leadership of the United Nations (UN) through building sustainable agricultural practices and supporting rural livelihoods. However, food insecure populations are in immediate need of food aid until these long-term solutions succeed.

People who are in need of food aid might be affected by natural disasters (e.g., Haiti, Pakistan, Myanmar), by infectious disease outbreaks such as Ebola (e.g., Liberia, Guinea, Sierra Leone), by armed conflicts and wars (e.g., Syria, South Sudan, Afghanistan) or by living in developing countries with not sufficient agriculture and purchasing power (e.g., India, Kenya, Peru). Among all these cases, long term food aid distribution against chronic hunger in developing countries constitutes more than 64% of the total aid distributed by World Food Programme (WFP), the largest humanitarian organization fighting the hunger (WFP, 2017a). The food aid is predominantly distributed in Sub-Saharan African countries, where hunger is the most prevalent. The concentration of beneficiaries served by WFP can be seen in Figure 1-1.

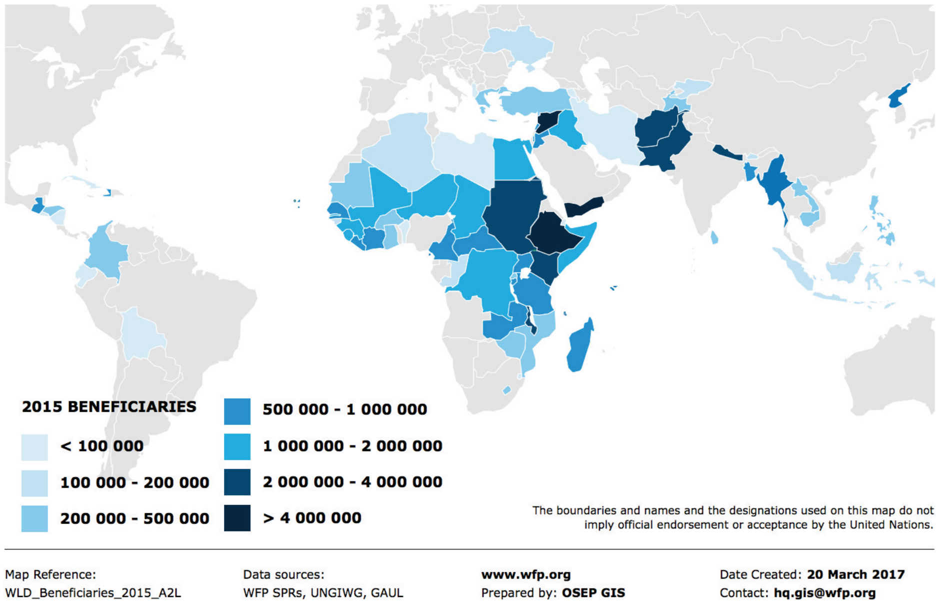


Figure 1-1 Map of the locations of the beneficiaries served by WFP in 2015 (WFP, 2017b)

The most common practice of delivering food aid is distributing food commodities to the beneficiaries, i.e., *in-kind food aid*. Although, there is an increasing trend of providing aid through different modalities such as *cash* or *vouchers* (i.e., food coupons that can be redeemed in local retailers) to the beneficiaries instead of in-kind food aid, 94% of the humanitarian aid distributed is in-kind (Overseas Development Institute, 2015). Thus, delivering in-kind food aid to geographically dispersed beneficiaries all over the world requires effective supply chain management solutions. However, operating food aid programs in development contexts is associated with certain financial and logistical challenges as summarized below.

- **Access:** Populations who are in need of food aid reside in regions harder to reach by humanitarian actors due to climatic conditions (e.g., heavy rains and floods), lack of infrastructure, non-cooperative official or unofficial authorities, and insecurity in the region (e.g., attacks by armed groups). Most of the times more than one of these factors are present simultaneously. Timely distribution of food commodities is critical for beneficiaries' well-being. However, operating in a context with access issues strain the supply chain of humanitarian organizations direly. Also, food aid transportation is costlier than non-food aid items since food is perishable and, therefore, brings additional storage and handling requirements for conservation. Increased costs of physical food aid delivery in environments with access constraints urge the humanitarian organizations to plan and improve their logistics operations continuously.

- **Conflicts:** People living in regions affected by conflicts are three times more likely to suffer from malnutrition. Conflicts force people to flee from their homes and livelihoods and become Internally Displaced People (IDPs) or refugees. Due to the extended nature of conflicts, a large number of people require food aid for prolonged periods in such cases (FAO, 2010).
- **Funding:** Long-term humanitarian crises, such as hunger, receives less media attention in comparison to sudden-onset disasters. In fact, there should be more than 19,000 deaths from hunger to receive an equal media coverage for each person who dies in an earthquake (Eisensee & Stromber, 2007). This is reflected in the donations received by the organizations responding to such crises. WFP's funding gap, i.e., the difference between the funding needed and received increased from US$ 1 billion in 2013 to US$ 4 billion in 2017. Although the received funds are insufficient and delayed, the major cause of the widening gap is the increase in the operational costs.
- **Immature markets:** Due to erratic climate and other access issues, commodity costs, especially food commodities tend to rise and fall sharply in rural markets. Physically and economically isolated regions suffer from high commodity prices, yet these regions are often the most impoverished. Thus, the purchasing power of the population residing in these regions decreases while their risk of becoming malnourished increases. For the same reasons that surges the commodity prices, food aid transportation to

these regions are challenging. Cost and availability of the trucks that carry food aid to these regions are also highly volatile.

Global trends, such as climate change and population growth, exacerbate the impact of these challenges on food aid operations in recent years. For example, climate change causes more extreme weather events disrupting food aid supply chains. Indeed, food assistance expenditures have increased by 230% between 2009 and 2016, whereas the total number of beneficiaries have declined (WFP, 2017b). Among six regional operation areas of the United Nations, namely Asia and Pacific Region (APR), East and Central Africa (ECA), Latin America and the Caribbean (LAC), the Middle East and North Africa (MENA), Southern Africa (SA), and West Africa (WA), the ECA region has increasingly the highest expenditure per beneficiary, as shown in Figure 1-2.

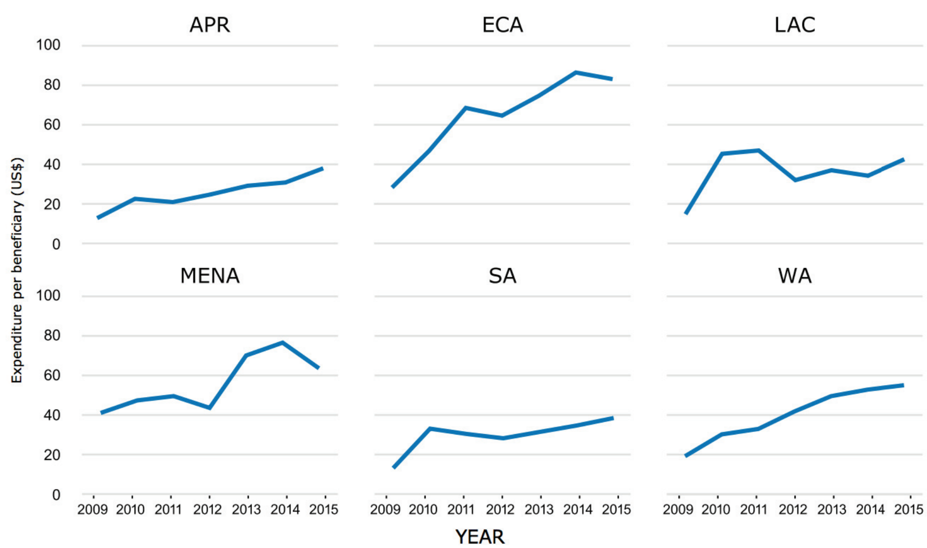


Figure 1-2 Expenditure per beneficiary by region by WFP (WFP, 2017b)

This disproportionate increase in expenditures within the ECA region is associated with the share of the logistic costs within the overall aid program budget. The ECA region suffers from access, conflict and immature market issues simultaneously. In addition, ECA persisted in in-kind food aid distribution while other regions swiftly adopted cash and voucher-based programs. In comparison to 2009, the overall share of cash-based transfers within WFP aid modalities surged from less than 1 percent to 20 percent, but the increases were uneven in different regions: they were fastest in Latin America and the Caribbean and the slowest in East and Central Africa. As cash and voucher programs eliminate the need for food transportation to the beneficiary settlements, the ECA remained the only region where the share of the logistics costs does not follow a decreasing pattern as it can be seen in Figure 1-3.

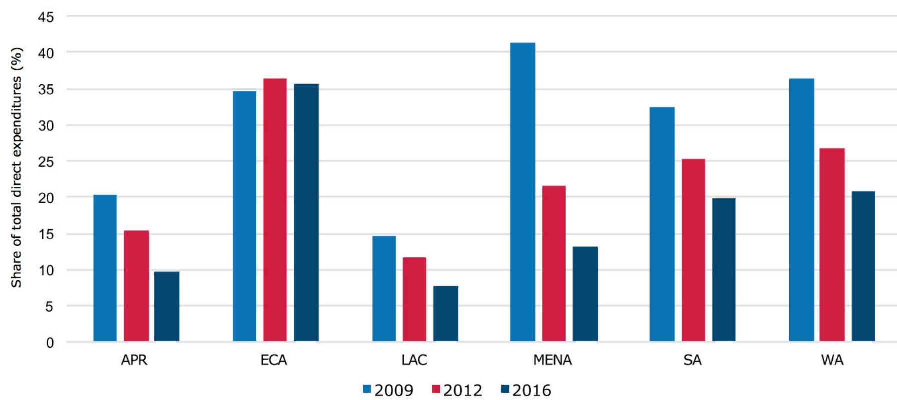


Figure 1-3 Share of logistics costs in the total expenditure

In this thesis, I aim to understand the underlying mechanisms that drive the logistics costs of food aid delivery and provide effective, but most importantly, applicable solutions to decrease these costs. To do so, I have collaborated with the WFP Kenya office, which serves the ECA region by distributing more than 350,000 tonnes of in-kind food aid annually. I approach this problem from two different angles. First, I examine the existing food aid transportation mechanisms of WFP Kenya and explore possible improvements in these practices. Then, I develop a methodology to determine whether it is beneficial for WFP to implement cash and voucher programs, and, if so, which beneficiary groups and locations WFP should prioritize. In the next subsection, I explain the structure of the thesis in detail and list its contributions.

1.2 Thesis Structure and Contributions

This thesis can be classified as an action research. Action research is a term that describes the type of studies where the researchers and the subject organization, in this case WFP, work collaboratively towards targeted outcomes. It is an interactive, data-driven process that aims to reveal the underlying causes of the problems that practitioners face and to develop practically sound solutions that rely on reasonable assumptions (Bradbury, 2007). Throughout this thesis, I combine qualitative and quantitative research methodologies. I designed and performed a field trip to understand the food aid supply chain in Kenya and collect qualitative data. The quantitative models developed in this thesis are based on the insights and observations gathered in the field. The developed frameworks are tested with real data provided by WFP. In the remainder of this chapter, I summarize the content and contributions of each chapter.

In Chapter 2, I review the growing humanitarian logistics literature in the operations research (OR)/management science (MS) domain. I provide the major differences between the humanitarian aid supply chains and the commercial supply chains. In addition, I explain how the humanitarian logistics studies can be classified in terms of the disaster response phases and disaster types. As chronic hunger is classified as a long-term development issue, I also present the OR/MS literature focusing on this domain. This literature review revealed that the humanitarian logistics literature focusing on long-term development problems is rather scarce.

Holguín-Veras *et al.* (2014) claim that the major issue of the humanitarian logistics research is that the realities of the operations are poorly understood. Thus, studies emanated from empirical foundations based on field research achieved a better grasp on the context and relevant parameters and assumptions convincingly grounded in the reality (Sohn, 2018). To this end, I explain the field research that I conducted in collaboration with WFP Kenya office in Chapter 3. For a thorough understanding of the major logistical challenges and their root causes, I have visited the critical points of WFP Kenya's food aid distribution network, I have also interviewed the officers in the field as well as the contracted transporters that carry WFP cargo to the aid distribution points. In this chapter, I provide my observations in the field trip, interview results, and how these findings shape the rest of the thesis.

In an understudied applied research domain, where little work is done, few models exist and little is known about the research context, qualitative data collection is a logical starting point to gain an understanding of the context and ongoing challenges (Patton, 2002). Performing a field trip is the most crucial way forward to qualitative data inquiry. The gained insights from the field trip can enable researchers to develop hypotheses that are built upon real problems faced by practitioners with well-grounded assumptions (Besiou & Van Wassenhove, 2015; Chopra *et al.,* 2004). On the other hand, conducting a field trip can be time consuming and costly. In many cases, the security level of the field, especially in development contexts, discourage researchers to design a study that includes a field trip. For these reasons, the field work presented in Chapter 3 is exceptional in the sense that the studies in a development context based on a field trip are quite rare (Sohn, 2018). The invaluable insights gained through the field trip allowed me to build a stream of research that is based on first-hand knowledge of the context and the ongoing practices.

In Chapter 4, I explain the major problems in WFP's existing contracting mechanism and why determining accurate transportation rates is important, both for WFP and the contracted transporters. Then, I describe the proposed two-step data-driven framework for improving the service levels of the contracted transporters. In the first phase, I develop an econometric model based on a set of contracts provided by transporters that predicts the transportation market rates. In the second phase, I develop a barrier-type options contract design that adjusts WFP's rates if the market rates increase beyond a threshold during the course of the contract. I measure the reduction in the transporters' potential losses under all possible market rate realizations and compare their losses under the current contract settings to demonstrate the value of introducing flexibility to the contracts. In addition, I discus which types of origin-destination pairs this new contract design would be most beneficial for WFP.

The data sources covering the transport market prices in East Africa are rather limited. The econometric model presented in Chapter 4 is built upon a data set that contains more than 200 contracts from over 60 carriers operating in Kenya and it is rather unique given the scarcity of information over African transportation markets. The econometric model built on these contracts enables us to identify the factors determining the market rates and the potential fluctuations throughout the course of the contract. In the second phase, I incorporate the estimations of this econometric model in a real options scheme, which enables WFP to adjust in the contract rates based on these fluctuations. These flexible contracts resulting from this approach let WFP to share the transporter's risk associated with the market volatility. By partially covering these risks, WFP can incentivize the transporters to provide better service without paying extra fees. The novelty of this study lies within the flexibility of the contracts, which incentivize the transporters to provide a higher service level even if WFP's contracts do not contain penalty or bonus mechanisms.

In Chapter 5, I discuss an alternative approach to the logistical challenges associated with physical (in-kind) food aid distribution: cash and voucher transfers. After reviewing the current practices of the humanitarian agencies on cash and voucher modalities as well as the randomized controlled trials ran by economists, I define a new problem, namely the Food Aid Modality Selection Problem (FAIMS), that determines the modality and the amount of aid to be allocated for a selected group of beneficiaries. The developed model for FAIMS evaluates three objectives to assess the potential solutions: program costs, beneficiaries' nutrition levels, and the aid program's economic contributions to the local economy. In addition, beneficiaries' consumption behavior is incorporated to this model through a bi-level optimization structure to capture and prevent inefficient cash use by beneficiaries.

Food aid not only aims to save lives in the short term but also improve the livelihoods economically to end hunger in the medium to long term. Thus, aid organizations implement instruments such as cash and voucher transfers alongside providing in-kind aid. These instruments can increase the agricultural productivity by promoting local purchases and can improve nutrition of the beneficiaries by providing a more diverse diet. In addition, these modalities decrease logistics costs by eliminating the transportation and handling requirements of in-kind aid. The choice of which instrument or modality of food aid should be determined according to the program objectives, market conditions and implementation capacity of the organization (WFP, 2017b). Although, there are simplistic guidelines developed by aid agencies for the aid modality selection, the model presented in Chapter 5 is the first formulation proposed in the literature that determines the aid modality based on these factors and calculates the implications of the chosen modality on program costs, beneficiary's nutritional status as well as the economic contributions to the local community. Unlike the agency guidelines, this model considers the solutions where more than one modality is administered simultaneously. Another contribution of this model is to incorporate the beneficiaries' consumption behavior by modeling them as economic agents maximizing their utility. Many aid agencies are distant to cash distributions since their donors believe the distributed cash can be spent on items such as alcohol or drugs by the beneficiaries. By modelling the beneficiaries' consumption behavior, my model can evaluate the outcomes of a cash distribution program and can avoid cash distribution to the households with potential misuse behavior, instead of completely abandoning this modality for the whole beneficiary population.

In Chapter 6, I adapt the devised generic model for the FAIMS problem to the WFP Kenya setting. I explain the parameter estimation procedure required to establish results as realistic and applicable as possible. I validate the model using the data from the Garissa region of Kenya. Furthermore, I run sensitivity analyses on different cost components, including food commodity prices and operational costs, to measure the robustness of the model to these parameters. Finally, I demonstrate how this model can be used to evaluate different policies commonly used in practice to improve the food aid program outcomes, such as educating beneficiaries on nutrition or fortifying local food commodities.

Although there exist numerous pilot studies indicating that cash and vouchers are more cost-efficient than in-kind distribution, our results for the Garissa region show that in-kind aid distribution is the least costly option. The FAIMS model enables aid organizations to assess the outcomes of different modalities in terms of costs, nutrition outcomes and economic contributions. The use of the model can prevent untimely implementations of a modality simply because that modality performed well in different contexts. With the help of the FAIMS model, we not only decide on the best aid modality, but also explore under which circumstances different modalities would provide better program designs through sensitivity analyses. Our analyses for the Garissa region revealed that the food commodity prices in local retail markets are rather high for cash and voucher distribution at the time of the data collection. However, these modalities can become viable if the food prices decrease in the future. In addition, the FAIMS model can be used for policy evaluation purposes. Many agencies and governments reinforce the aid programs by supporting them with certain policies, such as educating the beneficiaries on nutrition or fortifying food commodities with vitamins and minerals. FAIMS model can be used to determine how the aid programs should be altered in the existence of such policies.

Finally, in Chapter 7, I conclude this thesis by revisiting the results of the thesis and discussing the potential extensions of the studies presented.

Chapter 2

Literature Review

The aim of this chapter is reviewing the existing studies in the humanitarian logistics domain and identifying the research opportunities. This chapter is divided into two sections. In Section 2.1, I explain the typical operations research (OR) and management science (MS) problems that can arise in humanitarian logistics. Two alternative classifications of the literature are also discussed: based on the disaster response phase and based on the disaster type. In Section 2.2, I provide a review of the studies that focus on the long-term development problems including chronic hunger. Then, I summarize the research gaps revealed by the literature review. While this chapter provides a review of contextually relevant studies to this thesis, methodologically relevant papers and their connections to the proposed methodologies in Chapters 3, 4, 5, and 6 are discussed within those chapters.

2.1 Humanitarian Aid Logistics

The World Health Organization (WHO) defines a disaster as: "A serious disruption of the functioning of a community or a society causing widespread human, material, economic or environmental losses which exceed the ability of the affected community or society to cope using its own resources". Between 1970 and 2010, 3.3 million people (82,500 per year) died due to disasters, and droughts are the deadliest disaster type compared to earthquakes, floods, storms and others. Almost one million people died because of African droughts (United Nations & World Bank, 2010).

People affected by such disasters are usually in immediate need of food, water, medicine, shelter and other critical items. Although many governments have disaster response plans, depending on the magnitude of the disasters, they often need external support from other countries and non-governmental organizations (NGO). The needs of the affected people should be delivered in a very short time span, but demand for relief items can last for very long time periods depending on the magnitude of the disaster.

Humanitarian logistics coins the term for the science of effective and efficient logistics and supply chain management operations that aim to deliver aid to the affected people by humanitarian crises (Van Wassenhove, 2006). Similar to the commercial supply chains, humanitarian aid supply chains also aim to deliver the right amount of aid at the right time to the right people (Balcik & Beamon, 2008). However, the associated uncertainties at each step of the supply chain further complicate the supply chain planning efforts. A detailed discussion on the similarities and the differences between humanitarian and supply chains is provided by Holguín-Veras *et al.* (2012) and by Sabri (2017). Some of the differences between these two types of supply chains are provided below.

- **Objectives:** Commercial supply chains mostly focus on maximizing profit and improving service. In general, humanitarian logistics focus on broader impacts of the delivered items within the community as a social welfare objective rather than individual satisfaction of needs. Another commonly used objective is the economic value of human suffering in the absence of relief items such as food, water, and shelter.
- **Demand:** A great level of uncertainty is associated with humanitarian aid operations in terms of time, location and size of the demand. In commercial settings, demand can be estimated using past sales data; this approach is not applicable to the humanitarian settings. Unlike commercial customers, the beneficiaries cannot switch to another brand, therefore loss of goodwill type of costs are not relevant in humanitarian settings.

- **Infrastructure:** After a disaster, the existing supply chain infrastructures can be heavily damaged. This situation can be exacerbated if the disaster strikes to an under-developed country, where the initial infrastructure is already inadequate. As a result, the relief efforts can be significantly delayed, and/or the costs may disproportionately increase.
- **Financial resources:** Private sector is funded with investments aiming a monetary return. Humanitarian operations, on the contrary, heavily rely on individual and organizational donations, and the donations usually do not create a steady stream of finances. Although aid organizations receive generous donations in the aftermath of a disaster well-covered by media, such donations are often earmarked to that specific disaster[1], i.e., it cannot be used for disaster preparedness for another disaster. The lack of continuous stream of resources direly strain humanitarian logistics operations.

Although humanitarian logistics is a relatively new field of research, there is a plethora of researchers focusing on this field with a diverse set of approaches and methodologies. A quick search in Web of Science database returns 440 articles on the subject and this number goes up to 6,400 in Google Scholar. One way to classify these studies is to group them based on the disaster response phase they are targeting.

Figure 2-1 shows the generic disaster response phases. First phase, the preparedness phase, signifies the efforts to prevent a disaster or reduce the effects of an anticipated disaster by taking the required measures and preparing the community. Second phase, the response phase, defines the immediate actions taken by the stakeholders right after the disaster occurred. In the first 24 hours, the host nation makes a quick analysis of the situation, deploys local resources to the incident area and, if the national resources are not sufficient, declares a disaster status and seeks international help. Any disaster response

[1] Earmarked donations refer to the donations dedicated to a specific disaster, or a specific operation.

teams or organization cannot enter a disaster effected country unless this call for international help comes from the host nation. During the response phase, local and international NGOs pursue activities including search and rescue, needs assessment analysis, and relief item demand estimation. After a few days, relief phase starts. During the relief phase NGOs distribute relief items such as shelter, food, water and hygiene kits. Meanwhile, plans for long-term recovery are built with the community. This phase can take up to 6 months. Any activities taking place in the disaster region beyond the first six months are considered as recovery activities. The main aim of this phase is replenishing the lost resources and infrastructure and bring the community back to the state before the incident happened. The longest phase of the disaster response cycle is the recovery period. If the community can manage to go back to pre-disaster state, the preparedness efforts start again. These phases are commonly referred as the "disaster management cycle".

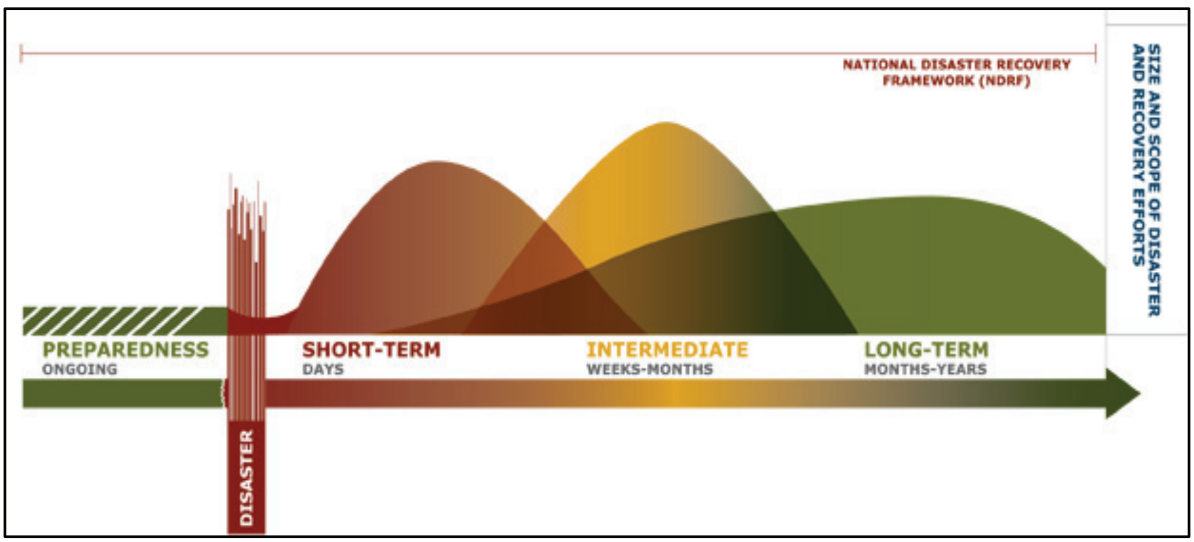


Figure 2-1 Timeline of the disaster response by FEMA(Federal Emergency Management Agency) (2015)

Altay and Green (2006) are the first authors that classify the humanitarian logistics papers in the operations research (OR) and management science (MS) domains based on the disaster response cycle phases. Their review of 77 articles published in OR/MS journals review that, a great majority of these papers (67.6%) focus on the pre-disaster preparedness efforts, 26% on response phase and only 6.4% of them are targeting the recovery phase.

Another way to review the humanitarian logistics literature is by classifying the papers based on the disaster types that they are focusing. Table 2-1 shows the classification by Van Wassenhove (2006). This two-dimensional classification differentiates the disasters based on their time period (slow-onset, sudden-onset) and cause (natural, man-made). The term disaster is mostly associated with the events classified as sudden-onset, natural disasters. Indeed, the disaster response phases are well-defined within a sudden-onset disaster context. However, for a chronic problem such as persisting poverty or hunger in Sub-Saharan Africa, distinguishing these stages is not trivial. We can imagine the ever-going hunger relief efforts as a very long recovery period aiming to establish a "zero-hunger" state for the affected communities.

Table 2-1 Classification of disasters in the context of humanitarian logistics

	Sudden-onset	Slow-onset
Natural Disasters	Earthquake Hurricane Tsunami	Poverty Famine (Hunger) Drought
Man-made Disasters	Terrorist attack Nuclear accident Coup-d'état	Political Crisis Refugee Crisis

Sudden-onset, natural disasters usually receive an extensive media coverage and as a result a significant amount of "earmarked donations" received in a short time span. On the other hand, slow-onset disasters receive much less coverage in the media. For instance, in order to receive the equal media coverage for each person who dies in an earthquake, there should be more than 19,000 deaths from hunger (Eisensee & Stromber, 2007). Yet, hunger kills more people every year than AIDS, malaria, and tuberculosis combined. There are 795 million people who are facing hunger in the world currently and nearly half of the child deaths under age five are caused by hunger (Food and Agriculture Organization (FAO), 2015). Yet, compared to the needs of the agencies dealing with hunger the attention and donations that they receive are much limited. In addition, hunger is geospatially prevalent, many countries in Sub-Saharan Africa and South-East Asia are experiencing hunger-related issues, especially in the rural regions. Operating in such a disperse region significantly inflates the logistics costs of food aid organizations, which are already receiving very limited amount of donations.

The lack of attention to the slow-onset disasters in developmental contexts is also present in the OR/MS literature. In their more recent literature reviews, Çelik *et al.* (2012) and Kara and Savaşer (2017) both demonstrate that, there is an extensive literature in sudden-onset disaster relief operations whereas humanitarian efforts on slow-onset disasters are usually overlooked. Among the 87 humanitarian logistics studies published in years between 2007-2012 that Çelik *et al.* (2012) reviewed, 14 of them belong to long term slow-onset disaster problems. Kara and Savaşer (2017) extend the review to the year 2017 and find 11 new studies on long term development context versus 125 new studies on sudden-onset relief. Çelik *et al.* (2012) conclude their review by drawing attention to the increasing number of people affected by slow-onset disasters such as food and water shortages, pandemics, and refugee crises, which are further exacerbated by global warming and invite the academic community to work towards the Millennium Development Goals (MDGs) defined by United Nations (UN). By answering this call, we review the limited literature on long term development context after we introduce the Sustainable Development Goals (SDGs), renewed version of the MDGs.

2.2 Literature on Long Term Development Issues

Sustainable Development Goals, also known as Global Goals, were adopted by UN member states on 25$^{\text{th}}$ September 2015 as an extension of Millennium Development Goals declared in 2000. Encouraged by the success of their predecessors, MDGs, these interrelated goals are built on specific themes including ending poverty, fighting inequality and protecting the planet. Each goal has specific targets to be reached by 2030 in collaboration with governments, private sector, NGOs and society. For example, Goal 2 is achieving zero hunger, means providing food security to 795 million people who are facing chronic hunger through strategies such as targeting malnutrition of children and mothers, thriving agriculture sector, eliminating food waste, and evolving food sector to respond climate change. Figure 2-2 lists all 17 sustainable development goals.

Figure 2-2 Sustainable development goals by UN (United Nations, 2015)

Almost all these goals aim to ameliorate the outcomes of slow-onset disasters taking place in developmental contexts. Governments and NGOs working towards these goals can substantially benefit from OR/MS approaches to reduce their operational costs and to improve the efficiency, especially given that the resources are scarce, and the demand is overwhelming. As mentioned in previous subsection, more recent reviews on humanitarian logistics domain revealed that, although not extensively, researchers started to cover the development problems as well. In this section, I provide a selection of such studies. I benefited from previous reviews by Çelik *et al.*, (2012) and Kara and Savaşer, (2017), as well as Google Scholar and Web of Science database. I classified the most relevant papers according to the SDGs that they are targeting, and, in each table, I provided the main decisions, solution evaluation criteria, methodology.

Studies that focus on hunger and poverty related problems (SDG#1,2), are listed in Table 2-2. Epstein *et al.* (2002) design a combinatorial auction for school meal catering firms which provide single-round close bids. They test their results for Chile school feeding program run by the government, providing lunch to 1,300,000 children from low-income families. This study is a good example how the SDGs are interrelated, since state-provided school meals contribute both to zero hunger and to education related goals. Trestrail *et al.* (2009) develop a model that selects the best bids after an auction for ocean transportation of the food aid provided by United States Department of Agriculture. De Angelis *et al.* (2007) build a model that generates weekly routes for food aid transportation by air in WFP Angola Office. Rancourt *et al.* (2015) develop a location model for food distribution centers also in collaboration with WFP. All these papers evaluate different solutions based on their cost to the decision maker. One study that adopts a different objective function is by Huh and Lall (2013). Their model selects the best crops and irrigation patterns given the scenarios of the rainfalls and market outcomes, to prevent harvest failures causing food insecurity.

Although the majority of the studies in the intersection of health care and humanitarian logistics domain (SDG#3) are designed for sudden-onset disaster response, there are few studies in the development context as listed in Table 2-3. Malvankar-Mehta and Xie (2012) design a multi-level (country and regional-level) fund allocation for HIV prevention campaigns. The other three studies (Griffin *et al.* 2013; Ekici *et al.* 2014; Cao *et al.*, 2016), are adaptations of location-allocation problem to different humanitarian contexts. Unlike the studies targeting hunger reduction, health studies adopt a variety of objective functions such as equity and case prevention. This factor allows the decision makers to attain solutions that prioritize the well-being of the beneficiaries rather than simply minimizing the program costs.

Table 2-2 Long-term development logistics literature targeting SDGs #1 and #2 (No Poverty, Zero Hunger)

Decisions	Cost/criteria	Methodology	Papers
Auction winners for school meals	Total cost	Mixed Integer Programming	(Epstein *et al.*, 2002)
Routes for food aid distribution	Total cost	Mixed Integer Programming	(De Angelis *et al.*, 2007)
Auction winners for food aid transporters	Total cost	Mixed Integer Programming	(Trestrail *et al.*, 2009)
Crop choice, Irrigation pattern	Farmers' revenue	Stochastic Programming	(Huh & Lall, 2013)
Location of food distribution centers	Total cost	Mixed Integer Programming	(Rancourt *et al.*, 2015)

Table 2-3 Long-term development logistics literature targeting SDG #3 (Health and well-being)

Decisions	Cost/criteria	Methodology	Papers
Field vehicle fleet management	Equity, efficiency	Field Research	(Pedraza Martinez *et al.*, 2011)
Resource allocation for HIV prevention	Equity, efficiency	Linear Programming	(Malvankar-Mehta & Xie, 2012)
Location of malaria prevention centers, team scheduling	Prevented cases of malaria	Mixed Integer Programming	(Griffin *et al.*, 2013)
Re-designing drug supply chain	Reducing stock shortages	Field Research	(Jahre *et al.*, 2012)
Facility location	Total cost	Mixed Integer Program	(Ekici *et al.*, 2014)
Location of breast-milk banks	Equity	Mixed Integer Program	(Cao *et al.*, 2016)

Table 2-4 Long-term development logistics literature targeting SDG #4 (Education)

Decisions	Cost/criteria	Methodology	Papers
Location and capacity of schools	Total cost	Mixed Integer Program	(Araya *et al.*, 2012)
Routes of school buses	Travel cost & Equity	Bi-criteria optimization solved with metaheuristics	(Pacheco *et al.* 2013)

Table 2-5 Long-term development logistics literature targeting SDG #7 (Affordable and clean energy)

Decisions	Cost/criteria	Methodology	Papers
Selection of energy generators	Total cost, Improvement in rural livelihoods	Multi-criteria optimization	(Henao *et al.* 2012)
Location of wind generators	Total cost	Mixed Integer Programming	(Ferrer-Martí *et al.* 2013)

In other development research domains, namely education (SDG#4) and clean energy (SDG#7), we observe a tendency to employ multi-criteria optimization approaches as seen in Table 2-4 and Table 2-5, respectively. Facility location-allocation problems in these contexts (Araya *et al.*, 2012; Ferrer-Martí *et al.*, 2013) still use a cost-minimization objective. On the other hand, Pacheco *et al.* (2013) take into consideration the equity alongside the costs while designing school-bus routes for rural neighborhoods. Furthermore, Henao *et al.* (2012) not only consider the improvements in rural livelihoods as an objective but model these improvements as a combination of five aspects: social, physical, natural, financial and human capital.

This brief review of the literature reveals that humanitarian logistics domain mainly focus on the sudden-onset disasters, whereas slow-onset disasters and chronical development issues are mostly overlooked. Similarly, the organizations targeting development problems are receiving less attention from the donors and the media. Although the United Nations aim to change this situation by introducing sustainable development goals to increase awareness of the public, the academic community also needs to respond to this call and collaborate with the actors in this neglected research domain. This thesis is a step towards closing this gap in the literature by addressing the operational challenges encountered by the WFP, one of the world's largest humanitarian agencies, in collaboration with their logistics team.

Second short-coming of the existing studies targeting hunger and poverty is the lack of variety in the objective functions of the developed models. These studies targeting hunger and poverty mostly focus on minimizing cost objective. The programs targeting long-term chronic problems last for years, or even decades. Thus, models that design such chronic problems should incorporate the perspective of different stakeholders involved. Failing to consider the effects of these programs on the stakeholders, such as the local governments or the beneficiaries themselves, may lead to undesirable outcomes. Indeed, in their review that discusses the gaps between the practice and literature in humanitarian logistics domain, Bhimani and Song (2016) underline the importance of producing research from a policy evaluation mind-set with customized objectives for the problem context. In this thesis, I incorporate the perspective of the other stakeholders to our models and designed our frameworks accordingly. In particular, in Chapter 4, I design a transportation contracting framework between WFP and the transporters and I reflected the motivations and the benefits of both parties in our design. Similarly, in Chapter 5 I develop an optimization model that selects the food aid modalities distributed in a region. The model selects the best fitting modality not only from a cost minimization perspective, but it also takes into account the beneficiaries' and the local communities' well-beings.

Finally, the need for well-structured field researches is evident to conduct more realistic and applicable studies. As Starr and Van Wassenhove (2011) state comprehending the context of the humanitarian problems (i.e., beneficiaries, stakeholders, environment, infrastructure, etc.) is central to building models and assumptions that can be robust enough for use in practice. Field researches conducted at early stages of the progress enables the researchers to establish the research priorities, to understand the context and to contact with the stakeholders for determining the research agenda (Patton, 2002). In an exploratory research setting, the main motivation of a field trip is to achieve a deeper understanding level that can only be attained by observing the context, attending the activities and getting to know the program staff. Also, field work sets a firm ground for further quantitative research and serves as a preparatory stage. However, the number of studies that emerges out of an exploratory field research is disproportionately low within the humanitarian logistics domain. Among the studies I reviewed, I found three such examples: Pedraza Martinez *et al.* (2011); Jahre (2012); and Rancourt *et al.* (2015). As an addition to these studies, this thesis is also emanated from a field research, which is discussed in the next chapter.

Chapter 3

Field Research: World Food Programme Kenya Office

3.1 Introduction

World Food Programme (WFP) is the world's largest humanitarian agency fighting against hunger worldwide. Each year WFP reaches more than 80 million people with food assistance in 82 countries. Unlike other UN agencies, WFP entirely relies on donations from governments, corporations and individuals for financing its operations. The donations can be either in the form of food commodities or cash. The total annual funds donated to WFP is as large as US$ 5.38 billion and in return WFP distributes 3.5 million metric tons of food to the people mostly residing in developing countries or in refugee camps (WFP, 2018a).

To maintain supply chain efficiency, WFP uses different strategies including:

- Continuous price index monitoring and purchasing in bulk when the prices decrease,
- Contracting with local transporters, food producers and retailers to decrease the transportation and fleet maintenance costs,
- Continuous optimization and improvement of contracting and food delivery practices.

In accordance to these strategies, WFP's Kenya office wanted to improve its current logistics operations and contacted our research team in 2014, via Kimetrica Limited, a Kenya-based consultancy company that provides research support to humanitarian agencies. As Kenya is strategically located in WFP's global supply chain as the gateway to East and Central Africa, WFP's Kenya office delivers food aid to surrounding countries in addition to the operations within the country.

For food aid delivery, WFP Kenya procures transportation service from local transporters instead of managing its own fleet. In recent years, the demand for transport services in Kenya has increased, as the countries in the region are experiencing considerable economic growth rates. Consequently, the transportation sector thrived with increased demand for the transportation and logistics services. As an organization that delivers more than 350,000 tonnes of food commodities annually by spending more than US $50 million on transportation, WFP Kenya wanted to understand the driving factors of the transport market and to improve the efficiency of the current food aid delivery system, accordingly.

In particular, WFP Kenya had two main agenda items for us to investigate:

Item 1: Contracting Practices

WFP Kenya deliver food commodities to beneficiaries residing in remote, dispersed, and insecure destinations where the road infrastructure is damaged and the market information is not transparently available. These conditions expose WFP Kenya to the risk of inflated transportation rates.

- There is a need for a data-driven transportation cost model that provides reasonable estimates of transportation rates. WFP would use this model to improve their bargaining position in rate negotiations and thereby ensure cost-efficiency in contracting operations.
- Currently, WFP signs fixed rate contracts with transporters for extended time periods to reduce the bid collection and contracting efforts. However, extension

of contracts at fixed rates cause transporters to bid higher rates to cover for potential market risks during the contract. It also causes WFP possibly not accruing the benefits of downward price reduction due to potential oil price decreases during, the contract period. Therefore, a new contract design that reduces the price fluctuation risks for both parties is needed.

Item 2: Delivering aid in alternative modalities

- WFP faces excessive logistics costs for large scale food aid operations. These costs can be reduced by decreasing the in-kind operations and providing alternative aid modalities such as cash or voucher. Indeed, WFP Kenya started pilot cash and voucher projects within the refugee camps and wants to explore the possibility of abandoning in-kind aid distribution for beneficiaries other than the ones in refugee camps. An analytical model that examines the best aid modality for other regions of Kenya and reports the effects on the logistics costs is needed.

After this request from WFP, we held Skype meetings with the logistics department to clarify the context and scope of the problems. These initial meetings made it clear that the logistics practices involved with WFP's supply chain are significantly different than the North American context. The number of stakeholders involved (more than 90 transportation companies, WFP field officers, border clearance agents, etc.) and their perspectives are too complex to capture accurately over Skype interviews. At this point, performing a field trip to Kenya in order to closely observe WFP's supply chain and the associated challenges has become critical. In the remainder of this chapter, I describe the methodology and the findings of the field research as well as how these findings shape the rest of this thesis.

3.2 Methodology

Field work sets a firm ground for further quantitative research and serves as a preparatory stage, especially if conducted in an exploratory research setting. It enables the researcher to develop the hypotheses and to define the research questions through formal interviews and informal discussions. In addition, field visits demonstrate the researchers' commitment to the subjects, increase the mutual trust among stakeholders, creates an environment for more detailed and transparent data sharing. As Jahre (2012) stated, one of the major achievements of performing a field study in a humanitarian logistics context is to observe and to understand the challenges faced by the stakeholders on a day-to-day basis. During these field studies, the researchers use the same roads as the transporters use and encounter the same security issues as the logisticians encounter.

Although field researches can be conducted for multiple reasons including direct observation, data collection, and running experiments, our field visit is organized more as an exploratory research. This type of research aims to establish research priorities, to understand the context and to contact with the stakeholders for determining the research agenda. In an exploratory research setting, the main motivation of a field trip is to achieve a deeper understanding level that can only be attained by observing the context, attending the activities and getting to know the program staff (Patton, 2002). As the time and the resources to perform a field trip is usually very limited, the field should be planned and executed carefully.

While designing our field research we heavily relied on qualitative research guides by Patton (2002) and Sreejesh *et al.* (2014) as well as previous case study examples in the humanitarian logistics domain (Pedraza Martinez *et al.* 2011; Jahre, 2012). The rest of the Section 3.2 is organized as follows: in Section 3.2.1, I explain the steps we have taken to get prepared for the field study. Then, I present the details of the field research in two parts. In Section 3.2.2, I list the visited strategic points of WFP's supply chain and provide my observations on operational challenges. In Section 3.2.3, I provide the details of the interviews that I have conducted with the transportation companies that provides service to WFP.

3.2.1 Preparation and Initial Findings

Before arriving in the field, I started to investigate the primary data provided by WFP's Kenya Office (e.g., food aid distribution network in Kenya, Excel spreadsheets of WFP's transportation rates, and previous contracts), as well as the secondary data available online (e.g., WFP's strategic plans, evaluation reports, maps and related literature). This data enabled me to understand WFP's in-kind food aid transportation and distribution operations, and to overview the challenges and the best practices observed by similar organizations.

Although the initial communication between our research team and WFP Kenya started in September 2014, the field trip took place in the Spring of 2015. The time in between was spent on initial data collection and preparation for the trip. By the time I arrived in Kenya, I already had a broad understanding of the logistics operations of the organization. Next, I summarize the findings of this preliminary research, namely the structure of the WFP Kenya's supply chain network and their contracting practices at that time.

3.2.1.1 WFP Kenya's Supply Chain Network

As one of the largest countries in East Africa, Kenya is the host of the United Nations and WFP headquarters in Africa. WFP's Kenya Office serves the food aid demand both in Kenya and also other surrounding countries that do not have access to marine transportation such as Uganda, Burundi, Congo and South Sudan. Although WFP delivers aid to people affected by emergencies, 90% of WFP Kenya's operations are focused on slow-onset disaster recovery (hunger, drought and refugee crisis). Unconditional food aid is distributed to beneficiaries suffering from chronic hunger in two main modes.

- **In-kind Food Distribution:** This is the most common food aid activity that WFP consistently pursues for the last couple of decades. This program delivers in-kind food rations (including oil, pulses or cereals and salt) to meet an immediate need. Food rations can show variability between nations and seasons, but usually, they are sufficient to cover a family's food demand until the next distribution.
- **Cash and Vouchers:** This program is developed as an alternative to traditional food distribution to decrease costs. Compared to in-kind aid, it is quite new, but shown to be cost efficient in certain contexts. It is predominantly applied in the regions where there is plenty of food available in the markets, but poor people do not have sources to buy them. Cash is a direct money transfer to the beneficiary whereas vouchers are coupons that are redeemable for food items at selected markets. The success depends on the local market dynamics. Cash and voucher programs can be advantageous for all parties: they bring a freedom of choice between different food varieties for the beneficiaries, they can reduce the logistics costs of WFP, and the money spent in retailers stays in the community. Currently, WFP operates pilot projects on cash and voucher distribution in two refugee camps located in Kenya with the intention of eventually expanding the program to the whole country.

In-kind food aid requires physical and periodic food distribution to beneficiaries mostly inhabiting in remote areas where the roads are in poor quality and insecure. Considering that the distributed food is usually donated by or procured from overseas, associated logistics activities are rather complex. Once the commodities are procured, they are shipped to the receiver country mostly with maritime transportation. After the food enters to the nearest port of the receiving country, it is transported to the intermediate or final destinations by trucks.

Each aid receiving country has at least one point of entry (POE). The point of entry is often the port of the country, if available. If not, then it is the border of a neighboring country. After their entrance to the country, the commodities travel along first the major hubs, then extended delivery points (EDP) and final delivery points (FDP) where they are distributed to the beneficiaries.

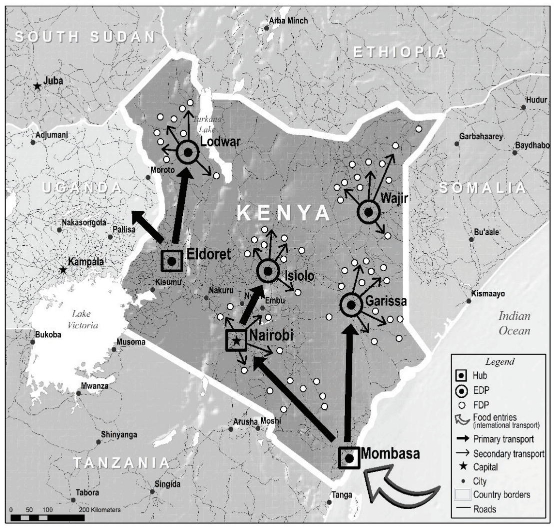


Figure 3-1 Representation of WFP Kenya's Supply Chain

Figure 3-1, shows the food aid supply chain network of WFP Kenya. Mombasa Port is the POE for Kenya. In addition, there exists three major hubs in Kenyan supply chain: Mombasa (right next to the port), Nairobi and Eldoret. Most of the food entered the country are stocked in Mombasa warehouses or shipped to the Nairobi and Eldoret for long term storage. These major hubs enable planners to stock the food in proximity to the beneficiaries before the aid demand is known. Once the stock levels in the EDPs decreases or the demand estimates are known, commodities are shipped from the major hubs to the EDPs. Transportation from major hubs to the EDPs (called primary transportation) are operated by WFP but executed by the contracted transportation companies in Kenya. This is a common practice for WFP. Indeed, the organization chooses to use the local capacity instead of building its fleet wherever possible.

EDPs can also store food for couple of months, if necessary. However, the commodities are usually stored in major hubs instead of EDPs for long term storage because (i) warehouses located in these major hubs are more secure compared to EDPs, (ii) capacity of the major hubs are ampler, and (iii) in case of changes in the distribution plans relocating commodities between EDPs is costlier than a direct shipment from major hub to the new EDP. As of 2014, there were 17 EDPs and two refugee camp depots in Kenya. From the EDPs, food is transferred to FDPs (secondary transportation) on the day of last mile food distribution to the beneficiaries since the FDPs are not suitable for storage. An example of FDPs can be seen in Figure 3-2. The secondary transportation activities are usually supervised by local partners, such as World Vision, ChildFund, and Kenyan Red Cross, etc. The local partners are responsible of finding, contracting the transporters, monitoring the transportation and performing the distribution collaboratively with the local community, but WFP covers the transportation costs.

The beneficiaries need to travel to their assigned FDPs on the day of distribution, to collect their ration, a month-worth of food for the family. Although, the locations of FDPs are chosen in the proximity of the villages, some beneficiaries have to travel either by foot or with an animal up to eight to ten kilometers with approximately 50 kilograms of food.

Figure 3-2 An FDP near Lodwar, Kenya

3.2.1.2 Current Practices on Transportation Contracting

WFP contracts with local transporters for the primary transportation activities from hubs to EDPs and to other countries. Considering the fact that WFP needs to transport several hundred thousand tonnes of food each year, constructing the best contracting terms is crucial. In order to reach the lowest rates, WFP sends a Request for Quotation (RFQ) to the shortlist of transporters for each origin destination (O-D) pair with an estimation for that season's total tonnage to be delivered. The shortlist of transporters consists of the transporters who were on the shortlist in the previous bidding season with an adequate performance level and new transporters who responded to WFP's expression of interest published in local newspapers.

Once the transporters receive WFP's RFQs, they choose the O-D couples that they want to provide service and submit their bids (quotes) to the WFP. Based on these bids, WFP chooses the transporters that is awarded (i.e., signed a contract with). Prior to 2013, WFP awarded the transporters with lowest bids if their bids were within the 10% of the fifth lowest bid. In this way, WFP prevented aggressive bidding and avoided disturbing the market dynamics. WFP updated its awarding mechanism as of 2013. In order to decrease the high logistics costs, WFP started to use the lowest bid received as a counter-bid to be sent to the five lowest bidders. In this new scheme, these five transporters could either accept the lowest-bid made for that O-D or they are not contracted at all. Rest of the transporters do not receive a counter-bid, unless the capacity of the five lowest bidders are sufficient for the expected transportation load for that period. Otherwise, more than five transporters receive counter-bids to ensure adequate *effective transporter capacity*, i.e., 25% of the overall truck capacity. Bidding and awarding processes are performed separately for each O-D.

Once the contracts are awarded, WFP can reach one of their contracted transporters for a transportation request whenever there are goods to be transferred between an O-D. If that transporter does not have capacity to respond the request, WFP proceeds to another transporter who has a contract for that O-D. Once the transporter verbally agrees to carry the cargo, WFP issues a formal Landside Transportation Instruction (LTI). LTI is a document which represents the origin, destination, total tonnage, and the expected time of delivery. LTIs are issued without a prior notice and the time frame starts on the day of the LTI issued and ends at the expected travelling time between the origin and destination. Each time a new cargo is available, a new LTI is issued.

Our initial Skype meetings with WFP officers revealed that, this new contracting scheme and the current LTI practice direly strained the transportation operations of WFP. Although the new contracting scheme provides significant cuts in the transportation costs, the quality of the service claimed to be declined. Inexperienced transporters, who just started their businesses, considers WFP contracts as an opportunity to promote themselves in the market. As a result, they submit aggressively low bids, but then they cannot fulfill the LTIs in a timely fashion. In addition, not knowing the transportation requests before an LTI is issued catches all transporters unprepared most of the time, so they have to decline the request. Also, other transporters, who accept to fulfill the LTIs, sometimes send their trucks to other customers who pay higher rates and look for ways to delay the LTI expiration time. On the other hand, contracts have no consequences or penalty fees for delayed shipments. Consequently, WFP deliveries are delayed multiple times.

For the field trip, the following actions are prioritized.

- Observing WFP's supply chain network as well as the transportation infrastructure of Kenya to identify the opportunities and challenges associated with the food aid delivery operations,
- Understanding the main drivers of the transportation rates and identifying the practices that yields smoother operations for both WFP and the transporters.

For the first action part, I visited a number of destinations that are critical in WFP Kenya's supply chain. For the second one, I interviewed leading actors in Kenyan transportation market. In the next two sections, I elaborate on the site visits and the interviews conducted.

3.2.2 Site Visits

After arriving in Nairobi in April 2015, I immediately had meetings with the logistics and the contracting departments of WFP Kenya. Except the time that I spent in site visits, I was based at the logistics departments throughout my field research. So, I had the chance to observe the daily operations closely and to have formal interviews and informal conversations with the officers. Within the first week, we have arranged the dates, and the routes for the site visits for all three major hubs, namely Mombasa, Nairobi and Eldoret warehouses; the EDP in Lodwar and an FDP which receives service from that EDP; the Kakuma Refugee Camp, and the EDP and FDPs that serves to the camp; and finally, the Ugandan border at Malaba. These points are marked on a map of Kenya in Figure 3-3. Most of these destinations can be reached by plane, but I deliberately travelled the lanes between Lodwar-Kakuma and Eldoret-Malaba as a round-trip by road to observe the road conditions. After each site visit, I went to back to Nairobi and debrief with the logistics departments. For all these destinations, except Mombasa, I was accompanied by one WFP officer. In all destinations, we were greeted by local officers working on the field.

While planning for the site visits and conducting interviews with the local officers, I took the steps to triangulate the data from as many different sources as possible to ensure the quality and the reliability of the data collected as suggested by Akhtar (2018). Strategic themes that we kept in mind while designing the field work interviews were:

- *Naturalistic inquiry.* This theme suggests designing interviews and collecting data in a non-manipulative, unassuming way, so that the emerging results can be free of pre-determined hypotheses and constraints.
- *Inductive analysis.* This theme recommends an initial data collection with open-ended questions to unveil the categories and the interrelationships among them rather than trying to fit the context to pre-existing theories and models. Unlike

> the hypothetical deductive approach that requires the identification of the independent variables and the research question before the data collection period, inductive analysis enables the subjects to express the important factors in open-ended questionnaires, so that the researcher can select the variables by following the emerged patterns in the responses (Patton, 2002).

In the following subsections, I summarize the observations acquired through these visits. First, I explain the warehousing operations and relevant challenges observed in all three major hubs, namely Nairobi, Mombasa, and Eldoret. Then, I list my observations at the border crossing point at Malaba and related transportation challenges. Finally, I provide the details of food aid distribution operations in both refugee camp settings and in hunger response settings based on my observations in Kakuma Refugee Camp and distribution points of Lodwar. All the photos in these subsections are captured by myself.

3.2.2.1 Major Hubs

Nairobi

WFP's Nairobi Office is located in the UN headquarters of Africa. This enables WFP to collaborate with other UN offices such as UNHCR (United Nations High Commission for Refugees), FAO (Food and Agriculture Organization for the United Nations) and World Bank and yields operational efficiency due to the strategic importance of Nairobi and Kenya in the region. Nairobi is located on the Northern East African Corridor, which is the autoroute that connects Mombasa to other landlocked countries that have a WFP office including Uganda, South Sudan, Burundi, Rwanda, and Democratic Republic of Congo.

Besides the meetings that I attended in the Nairobi Office, I also visited the warehouse in Nairobi, which is approximately 35 kilometers outside of the city. There are four warehouses with much smaller capacities compared to the ones in Mombasa since most of the commodities are shipped directly from Mombasa. In addition, I interviewed representatives of five Nairobi-based transportation companies which have contracts currently or had in the past with WFP. The content and outcomes of these interviews are summarized in Section 3.2.3.

Figure 3-3 Visited sites throughout the field trip

Mombasa

During the three-day trip to Mombasa, I visited the Mombasa hub, observed the ongoing operations, and interviewed with the director of the Mombasa hub. I also interviewed the representatives of five Mombasa-based transportation. Mombasa Port is the main point of entry to Kenya for the donated or internationally procured food since it is one of the largest ports in the East Africa Region. Mombasa hub consists of 24 leased warehouses and eight silos just next to the Mombasa port. The commodities are stocked there before the shipment to other major hubs or extended delivery points (EDPs). Figure 3-4 depicts examples for those silos and warehouses.

It is preferred to directly send the cargo to the EDPs and bypassing the Nairobi or Eldoret hubs. However, since Kenyan road network is not well-connected with high quality roads, most of the cargo has to first travel to Nairobi and then use the roads that connects Nairobi to the final destination. In theory, this approach lengthens the total distance that has to be travelled. Yet, in practice, this longer route is much safer and quicker compared to shorter alternatives.

Almost 90% of WFP's transportation activities are originated in Mombasa. Operational challenges the Mombasa office has to address on a daily basis are numerous:

- For each arriving cargo by sea, monitoring the clearance of the cargo from the port customs bureau,
- Maintaining the food commodities in good condition in the warehouses by periodic checks for leaks, pests, damaged packages, and manage the heat, the humidity, and the air ventilation within the depots. Keeping track of the expiration dates of the commodities,
- Following-up the transporters from the moment that the office issues an LTI until the transportation is complete,
- Providing feedback on the performance of the transporters regularly.

Since the contracting office is in Nairobi, but the transportation activities are mostly started from Mombasa, the communication between these offices is essential. In fact, the anecdotes shared by the Mombasa officers revealed that the transporters started to respond less eagerly after the new contract awarding mechanism lowered the rates. It is claimed that the transporters are following the transportation spot markets closely and when the market rates are on the rise they reserve their trucks for those opportunities and disregard WFP's requests.

Figure 3-4 Silos and warehouses of Mombasa

Eldoret

Eldoret is the third largest hub of WFP Kenya's supply chain. Most of the commodities that are stored in this hub are sent from Mombasa and almost all of them are shipped to either Lodwar EDP or Kakuma Refugee Camp. The major problem faced by this EDP is the low level of security and quality of the roads that are connecting Kakuma and Lodwar to this hub. The security issues in the region are discussed in detail where we explain the site visits to Lodwar and Kakuma.

3.2.2.2 Border Operations

Ugandan Border at Malaba

After the visit to Eldoret hub, I travelled the lane between Eldoret and Ugandan border at Malaba by road. The overall road condition and security levels of this lane are significantly better in comparison to the Lodwar-Kakuma segment, mainly because this road segment is part of the Northern Corridor, a route that connects Mombasa Port to landlocked countries such as Uganda, Burundi, Rwanda and Democratic Republic of Congo through Nairobi and Eldoret. These landlocked countries receive most of their imported goods via this network.

At the time of our visit, the crossing point of the border was considerably loaded with trucks. Number of trucks that crosses this border was 1000 per day as of 2012 (USAID, 2013), with the recent increases in import volumes of Mombasa Port and surrounding countries, this number further increased. In spite of the increased load, the recent efforts initiated by East African Trade Hub have improved the border crossing times. These efforts such as establishing joint border committees, decreasing the paperwork, computerizing the customs processes decreased the average crossing times from 24 hours in 2011 to 4 hours in 2012. Yet, during high periods as before Christmas or after the school season starts, the queue length of the trucks can go up to eight kilometers long and crossing times can be as high as ten hours.

3.2.2.3 Distribution Points

Kakuma Refugee Camp

Our initial plans included to visit Dadaab, the largest refugee camp in the world at the time, located in Garissa region. However, UN updated its security levels due to a terrorist attack near the camp with 152 casualties that took place a week prior to my arrival and banned the staff visits to the region until a second notice. Instead, we decided to visit Kakuma camp in Turkana region. The security in the region was also alarming. The UN staff are required to hire armed security escorts to travel this route. The road condition was also poor, the tarmac was seriously damaged that our vehicle had a flat tire. Some bridges were washed away due to rainfall, so we had to wait until the flood is cleared and the bridge is safe to travel again. Certain snapshots showing the road condition as well as the armed guards can be seen in Figure 3-5.

Figure 3-5 Snapshots representing the road conditions

Kakuma Refugee Camp is World's third largest and Kenya's second largest refugee camp, which is established in 1992 and hosting mostly South Sudanese refugees since then. Currently, the camp has over 180,000 occupants and each year 40,000 more refugees are joining the camp. Dadaab and Kakuma camps together receive more than 60% of the food aid distributions within Kenya. Consequently, almost all transporters which have a contract with WFP perform transportations to Dadaab and Kakuma. The roads to these camps are neither high quality nor safe. Low quality roads are not surprising because the governments usually choose underdeveloped and remote areas when they are asked to choose a land for refugee camps. Prior to the camp construction, usually these places have very few residents, if not completely deserted. The low level of security and quality of roads cause the transporters to ask higher transportation rates. Snapshots from Kakuma refugee camp, including a food distribution point, can be seen in Figure 3-6.

Figure 3-6 Snaphots from Kakuma Refugee Camp

There exists an EDP located right outside of the camp and three FDPs within the camp in different locations in order to cover the camp area. These FDPs have temporary storage capacity and shared with UNHCR (United Nations' High Commissionaire for Refugees) for non-food distributions. All distributions are made based on the records in the UN database and are handled on a household basis. Each household designates two to three people as food collectors and only designated people are entitled to receive that household's portion during the distribution. Designated people receive a card which shows the number of portions (people) in that household and the previous food distributions that the family attended. Food rations include pulses, grains, vegetable oil and salt. Food baskets are prepared based on the stocks in the EDPs and determined based on a single person's calorie needs. Overall, the in-kind food aid distribution operations are very similar in refugee and non-refugee settings.

One of the major logistical problems is that the transporters who bring the food to the Kakuma EDP refuse to carry the food to FDPs inside the camp. Although, the EDP and the camp are very close to each other (less than 2 kilometers), getting in and out of the refugee camp causes delays for the transporters due to non-tarmac roads within the camp usually occupied by pedestrians. The transporters decline to transport this extra mile, since they are contracted for the Kakuma EDP. WFP Kakuma officers have to find local transporters for the extra mile between the EDP and FDP and to load and unload these trucks one more time. All these operations increase the congestion and waiting times of transporters for unloading docks at the FDP.

Lodwar EDP and FDP

On the way back to Nairobi, I have also visited the Lodwar EDP as seen in Figure 3-7, which mostly serves to the Turkana County located in south-west of Kenya. It is one of the largest EDPs in the country and serves over 200 FDPs in the region. Its main responsibility, as other EDPs, is mainly maintaining the food received from the major hubs. The storage of the goods has to be handled carefully against thefts and spoilage as in the major hubs.

However, the secondary distribution (transportation from EDPs to FDPs) does not fall under their job description. Instead, partners (i.e., local NGOs) handle this transportation. Main partners that collaborate with the EDP in Lodwar are World Vision, Turkana Rehabilitation Program and ChildFund. During our trip to Lodwar, we also visited local World Vision branch, the main collaborator of WFP in the region. Main issues raised by WFP Lodwar team and World Vision officials were very similar and can be listed as follows:

Figure 3-7 A storage tent from Lodwar EDP

- First of all, number of transporters and trucks are inadequate to satisfy the demand in the region. To be specific, there are 19 transporters with mostly one or two trucks, and they are the only ones serving the whole region. These transporters operate within the region, but they also bring loads from larger cities as well. In total, there are 40 trucks.
- There is no RFQ mechanism employed by WFP for secondary transportation. As a result, transportation rates offered by WFP are fixed and also have not been increased in the past five years. On behalf of WFP, World Vision sends WFP's rates to the transporters, and the ones that accept the rates are awarded with a contract, the contract is also signed between World Vision and the transporter, yet the payment is installed by WFP. Besides the steady rates in the recent years, transporters are also complaining on the rating scheme provided by WFP. In the current scheme, if the destinations are located 10 km or farther than the origin than the rates are calculated as US \$0.28 (25 Kenya Shillings) per km/per tonne. However, if the destinations are within the 10 km range, then whatever the total distance traversed, WFP pays US \$6.83 (600 Kenya Shillings) per tonne and leaves distance out of the equation. Considering the fact that WFP combines multiple destinations in a single tour, this scheme is much less profitable compared to

destinations which are out of the 10 km range. Consequently, all transporters ask for further destinations and attempt to avoid the destinations within the range as much as possible.

- Another issue that complicates the operations in the region is the low security levels. There are many conflicts between the tribes located in this region and consequently incidents such as hijacks, thefts and attacks to the drivers and the vehicles are observed quite often. Trips to several destinations require paid escorts (cars with arm guards). WFP do not provide funding for security payments and so the profit margin for these destinations gets thinner.

3.2.3 Interviews with Transporters

Our site visits confirmed that the context that WFP operates is rather challenging in comparison to the North American transportation sector. The road infrastructure is broken or incomplete in many regions and periodically become obstructed by heavy rains. Certain regions that WFP delivers food aid have major security concerns; ambushes, hijacks and theft are common. Given these factors WFP was under the impression that the transporters may be inflating the bids in order to protect themselves from additional maintenance and security costs incurred by delivering cargo to the rural destinations of WFP. In order to understand the perspective of the transporters, we have conducted interviews with a group of transporters. In this subsection, I summarize the findings of these interviews.

Exploratory researches relying on quantitative techniques usually work with purposefully selected but small samples to avoid single informant bias. On the other hand, quantitative models are constructed over larger samples for statistically valid results. Accordingly, I have collected data from a small group of selected transporters by conducting interviews with open-ended questions. Among different interview modes, I had the chance to have face-to-face interviews with the informants while I was at the field. Face-to-face interviews, especially for the exploratory research phase, have certain advantages over telephone and computer-based interviews such as question clarification, use of non-verbal cues and richer data collection.

WFP Kenya has currently over 90 shortlisted transportation companies with varying profiles from very modest companies (with a fleet of 10 trucks) to international ones (with 400+ dry cargo trucks as well as numerous oil tankers, refrigerated and non-refrigerated container carriers). The transporters, especially the ones that serve multiple clients, have a solid understanding of the challenges and opportunities of the transportation market in Kenya. Also, they have the position to compare WFP with other shippers in the market in terms of performance, rates, and contracting schemes. Therefore, their input may help to figure out the market dynamics and WFP's position in the market. For our qualitative analysis, we have selected the interviewed companies using criterion sampling approach with the criteria:

- At least five years of previous business relationship with WFP,
- Have submitted a bid in the last RFQ season,
- Five companies each with a base in Mombasa or in Nairobi.

Considering the conflict of interest in revealing their perspectives on the market, I acknowledged the transporters that these interviews are performed solely from a research perspective and the transporters would also benefit from the possible outcomes. I designed an interview consisting of open-ended questions to convey an open discussion led by questions but not restricted to. I stated that we would like them to evaluate overall working process with WFP, especially after the recent changes in the RFQ and awarding processes. Although I put every effort to overcome the biases in the answers provided by the transporters due to the potential conflict of interest, whether or not they responded forwardly remain unknown to us. The transporters may doubt of us sharing their responses with other transporters and shippers, they may not share their true bidding scheme or cost structure in order to keep their profit margins high.

Our questions can be grouped under four main titles: Company profile, market perception, bidding and contracting practices, and information sharing behavior among the players. The list of transporters that we interviewed, the questionnaire and the tabulated responses are provided in Appendix A. Here, I present the common responses and the main issues raised under each title:

Company Profile: The visited transporters have at least five years of business relations with WFP, yet some of them have just lost the WFP's contracts after many years of business. Some transporters stated that WFP operations constitute 70% of their total workload whereas some others, mostly larger international companies, claimed that WFP's share is only 10%. This can be interpreted as smaller companies are more desperate to win a WFP contract since their business highly relies on the organization. On the contrary, larger companies can easily compensate the loss of the contracts from WFP and also save their fleet from the trouble of serving on long distance, low-security lanes. These larger companies have newer and well-maintained trucks and provide reliable, faster service. As a result, their rates might be slightly higher than smaller companies. This can be considered as a premium. However, as a non-profit organization, WFP and its donors do not welcome the idea of paying premiums. On the other hand, small companies with fewer and older trucks provide a less reliable service, so they do not ask for premiums. Given the two sides of this story and WFP's current awarding mechanism (i.e., awarding the lowest bidder), it is not hard to anticipate that WFP would end up signing contracts predominantly with small transporters providing unreliable service.

Market Perception & Seasonality: Almost all transporters that we interviewed view WFP as one of the largest shippers in the market. As a result, they believe WFP has the power of determining the market rates. Some of the transporters specifically stated that other shippers follow WFP's rates. The list of other shippers includes Government of Kenya, construction companies, farmers, and retailers. After the recent changes in the contract awarding mechanism, they claimed the new rates fell below the market average.

Other than fuel price and the distance, the major determinants of the rates that are commonly listed by the transporters are: road conditions, security levels, rainy seasons and border crossings.

Bidding & Contracting: The recent changes in the bidding and awarding scheme of WFP, (i.e., rewarding only at the lowest bid level) have created the impression of underpayment by WFP on the transporters. This may be true for some destinations such as refugee camps, for which the risks and maintenance costs yield higher rates. However, for overland destinations such as Juba and Kampala, it is highly unlikely that WFP is paying less than the market average since almost all transporters stated that those are their most profitable destinations. Albeit the changes in WFP's awarding scheme, transporters have not updated their bidding strategies. As a result, many of them lost contracts because either they could not provide the lowest bids, or they decline the unprofitable counter-offers. Many of the transporters complained about terminated long term business relationships during the last contracting period. Almost all of them prefer longer term contracts and they usually sign annual contracts with other shippers. Some of them mentioned that they can apply for bank loans if and only if they have contracts with effective terms longer than a year. WFP's current contracts last for only six months and this prevents transporters to invest more in their fleets through loans. During the recent years, WFP has extended the contracts several times without updating the rates. Unfortunately, extending a six-month contract for another six months does not comply with bank loan requirements. Instead of renewing the contracts without re-considering the market rates, a well-designed and presumably dynamic contract that lasts at least for one whole year would benefit both parties. This way, both the WFP and the transporters would be protected from unanticipated fluctuations in the market rates.

Communication Behavior: Small companies claimed that they do not share information with any other companies. Larger companies state that they develop partnerships with other shippers and share information on market projections. Also, the companies, especially the ones located in Mombasa follow the spot market rates closely. Almost all companies reflect their interest on more frequent information and feedback exchange with WFP. They believe such an exercise may improve the mutual trust and increase the quality of the service and may lower the rates to some extent.

Overall, the most common complaint raised by the transporters was that the new awarding mechanism of WFP, i.e. awarding the five lowest bidders, decreased the contract rates below the market averages. Although, WFP benefited from significant cuts in transportation costs in the short-term, the strained relations with the certain transporters and decreased levels of service can do more harm than good in the long term. In order to have clear understanding on where WFP's rates stand in the overall market, we needed further contract data from other shippers or transporters. We asked WFP logistics team to reach other NGOs in their network and to ask for their contract rates. Table 3-1 shows the collected rates from five NGOs for several O-Ds. Top of rows denote the destinations within the country (rates in Kenya Schillings), whereas the lower group of rows denote international destinations in neighboring countries (rates in US dollars). In addition to the rates per tonne for a given O-D, I have added the distance between each O-D pair to calculate the average rate per km per tonne.

Table 3-1 Comparison of WFP's transportation rates with five different NGOs operating in Kenya

	Origin	Destination	WFP	NGO 1+	NGO 2	NGO 3	NGO 4	NGO 5	Distance	NGO Rate Statistics: Avg. Rate/km-tonne	Mean	Min
Inland (KSh)	Mombasa	Nairobi	3300*	3053	3400	3700	3500	3571	485	7	3444.8	3052.7
	Mombasa	Kakuma	10450*	16979	14850		12500	13415	1314	11	14435.9	12500.0
	Mombasa	Dadaab	5700**	13393	5900		7500	10255	945	10	9261.9	5900.0
	Mombasa	Lodwar	10000*	13631	13000		10000	12128	1194	10	12189.8	10000.0
	Mombasa	Wajir	9000*	15783	9500			11553	850	14	12278.5	9500.0
	Mombasa	Mandera	12500**	18891	13100			15707	1236	13	15899.4	13100.0
	Mombasa	Garissa	4900**	7893	5500	9150	6500	9041	463	16	7616.7	5500.0
	Mombasa	Marsabit	12500	11718	13500	11250	7500	9983	1077	10	10790.2	7500.0
	Mombasa	Maralal	9450*	12674	11500	11250	7500	8633	833	12	10311.4	7500.0
	Mombasa	Eldoret	5760*	4544	5500	7100	6000	8298	815	8	6288.5	4544.1
	Nairobi	Garissa	3800*	12196	4500	6700	3000	4723	465	13	6223.8	3000.0
	Nairobi	Marsabit	8500*	16023	9500	8950	4500.00	4518	528	18	9747.6	4517.9
	Nairobi	Eldoret	2650**	4544	3200	4550	3000	3254	308	12	3709.7	3000.0
Outland (US $)	Mombasa	Kampala	105*		105	100	120	107	1155	0.09	108.0	100.0
	Mombasa	Tororo	90*		95	90	100		951	0.10	95.0	90.0
	Mombasa	Juba	220**		255	250	300	276	1965	0.14	270.2	250.0
	Nairobi	Kampala	71*	94	82	97	80		670	0.13	88.1	80.0
	Nairobi	Tororo	49**	77	75	85	70		466	0.16	76.8	70.0
	Nairobi	Juba	180**	226	204	230	275		1152	0.20	233.6	204.0

+ NGO names are not provided for confidentiality reasons.

* Denotes the WFP rates below the average rate

** Denotes the WFP rates below the minimum rate

The analysis presented in Table 3-1 provides two significant insights:

1. The new contracting mechanism of WFP, introduced in 2013 that became effective in 2014, yielded significant decreases in their transportation rates in comparison to the other NGOs. WFP's contracts are lower than the mean rate of other NGOs in all but one destination and even lower than the minimum rate for seven out of 19 O-D pairs. This data validates the comments of the transporters who claimed WFP is one of lowest paying NGOs in the market.
2. While in North America transport market the distance is the main driver of the rates, we observe that rates for two destinations within almost the same distance from the origin can be very different in Kenya. Consider the average rates for Mombasa-Nairobi (7 KSh/km-tonne) and Mombasa-Garissa (16 KSh/km-tonne) lanes. This means certain ***lane specific*** factors, other than the distance, (e.g., road conditions, security issues, etc.) have significant effects on the transportation rates. Another interesting point is that even for the same origin destination the variance among the NGO rates is notable. Depending on the ***contract specific*** factors, i.e., total load, length of the contract, etc. the rates may differ.

Although the data provided by the NGOs was insightful, it was not comprehensive enough to generate statistically valid results to explain the underlying factors that derive the market rates. During the last days of field trip, I presented the observations and interview responses that I gathered from the field, the recurring challenges and the NGO rate analysis with the administration of WFP. Finally, I presented a research agenda on how we can address these challenges.

3.3 Identified Challenges and the Research Design

In this section, I explain the major challenges identified regarding the two action items that WFP presented to us during our initial communications (as explained in

Section 3.1), and how the designed research agenda can respond to these challenges based on the findings of the field research.

Responding Item 1: Contracting Practices

Regarding the first agenda item related with the contracting practices, the first identified challenge is the fact that WFP's counter-bids are determined by the bids that they receive rather than the average market rates. This may be yielding unrealistically low rates, so that the transporters cannot make profit or even cover the incurred costs. WFP cargos often need to be delivered to rural destinations with rough roads and security problems. Transporters do not prefer such destinations and tend to request higher rates for these lanes. It is understandable that the WFP, an organization which solely relies on donations, would like to seek ways for minimizing its logistics costs. For the same reason, it is not a valid expectation that WFP pays premiums to receive high quality service. However, understanding how the transportation market determines these rates and implementing better contracting practices would benefit both WFP and the transporters. I devised a two-phase process to achieve this objective.

Phase 1: Building a model that estimates the market rates for different O-D pairs.

Our interviews with the transporters already revealed different factors that they take into account while determining their bids. On the other hand, none of the transporters provided a clear formula for their bid calculations. In order to achieve statistically valid results, we needed a sample of contracts from the transporters. By performing an econometric analysis on these contracts, one can determine the main drivers of the rates and design a tool that suggests reasonable counter-bids relying on the market rates, in place of the lowest bid received.

Phase 2: Designing a new contract that increases transporter compliance.

The model in phase 1 would improve the business relationships between the transporters and the WFP by generating more reasonable bids. But to take it one step further, we need a new contracting scheme that responds to other complaints of the transporters and increases the service quality. Fixing the rates throughout the contracting term without any updates for the fluctuations in the oil prices or exchange rates may cause problems for both parties. At the time of the field trip, the transporters were suffering from the rise of the USD currency rates in 2014, which is reflected in oil prices. Another drawback of the current short-term-contract approach is that the transporters have no job security. For such a short commitment that they can easily lose (they may not take place in the five lowest bidders during the next bidding season), they do not prioritize WFP LTIs. This is another reason why WFP receives low quality service. To respond all these challenges, I developed a framework that enables longer term and dynamic contracts that is updated as the market rates are changing. The details of this two-phase counter-bidding and contracting framework are presented in Chapter 4.

Responding Item 2: Delivering aid in alternative modalities

The operational challenges associated with WFPs in-kind food aid delivery activities are burdensome. These challenges can be summarized as follows:

- WFP Kenya Office needs to operate offices and warehouses, and also to allocate staff to many rural destinations for EDP/FDP management, aid distribution, and demand estimation operations.
- WFP Kenya Logistics Office issues RFQs, determining counter-bids, awarding contracts in every six months for more than 50 origin-destination pairs with more than 90 transportation companies. WFP Kenya Logistics Office issues more than 15,000 individual LTIs per year, if the transporters do not fulfill the LTI on time, this number increases proportionately with renewed LTIs provided to other transporters. These operations require significant human resources.
- Besides the storage, handling and staffing costs that perform these operations, annual transportation operations cost approximately US $50 million.

WFP Kenya office considers the possibility of gradually retracting its in-kind food aid operations and delivering the aid in other modalities such as cash or vouchers. WFP has certain guidelines (WFP, 2008, 2014a, 2014b; WFP Office of Evaluation, 2014) regarding cash and voucher operations, and these guidelines provide certain methodologies to evaluate the best fitting modality to a certain context. They list numerous factors to be considered during the evaluation process including beneficiaries' access to the financial systems, beneficiaries' nutritional requirements and the capacity of the local food markets. However, these documents fall short to provide a systematic approach for quantifying these factors and incorporating them into a decision-making mechanism. The lack of such mechanisms is not unique to WFP. We have examined guidelines of different NGOs, as well as the academic literature related with this problem and did not encounter a model that addresses the aid modality selection problem. Therefore, we decided to design a generic mathematical model that all NGOs can utilize for their modality selection activities. The current practices of these humanitarian organizations and the details of the proposed generic model are provided in Chapter 5. Furthermore, we tested this model in WFP Kenya context to show how the suggested approach can be used to design a real-life aid program. The required level of detail is tremendous to realistically model and incorporate the dynamics of different aid modalities and their effects on the stakeholders, i.e., the aid agency, the beneficiaries and the local community. This data estimation process and the subsequent results for WFP aid operations are provided in Chapter 6.

Chapter 4

Data-driven Contract Design for Food Aid Delivery

4.1 Introduction

WFP Kenya office (the UN headquarters in Africa) not only serves more than two million people facing food insecurity in the country but also plays a major role as a food aid entry point to the East Africa from Port of Mombasa. Each year this office carries more than 350,000 tonnes of food commodity. For these transportation operations within the region, WFP signs long-term contracts with local transporters instead of relying on a private fleet of trucks. They do so to reduce transportation costs as well as to support local markets. The transportation markets in Africa, however, are still not well developed; there is a considerable lack of information transparency. The economy of the region is negatively affected by high freight transportation costs and poor service quality (World Bank, 2016). To lower its costs, WFP awards fixed-term contracts to the carriers that offer the lowest bid through a request for quotation (RFQ) process. However, the transporters often fail to honor their contracts with WFP by channeling their trucks to more profitable business opportunities instead of prioritizing WFP's shipments at the time of a request. This leads to poor service including delivery delays and vehicle unavailability. On the other hand, transporters also have their own challenges. Although the contracts with WFP are initially signed for a six-month-period, WFP often extends the end-date because the RFQ process is resource consuming. As a result, transporters may suffer losses by offering their services to WFP at the contracted rate when they face cost increases due to volatile market conditions. This seems to fuel the poor service issues mentioned above. Difficult road conditions and security problems are other pressing challenges that the transporters need to face while carrying food aid in East Africa.

Designing an efficient transportation strategy is a critical logistics activity for delivering aid to people in need (Pedraza Martinez *et al.*, 2011). This is a common problem among the humanitarian agencies that distribute food aid via local transporters in long-term development context. The aim of this study is to provide a framework for designing more flexible contracts to overcome the operational challenges that both the transporters and the humanitarian agencies face. For this, we designed a two-phase methodological framework. WFP's contract rates are determined by the lowest bids that they receive during the RFQ period rather than the market dynamics. Thus, in the first phase we aim to develop an econometric model that estimates the market rates for different Origin – Destination (O-D) pairs. However, the literature and data sources that pertain to the dynamics of the transport market prices in East Africa are scarce. We have contacted the transporters in the shortlist of WFP and requested their most recent contracts signed with shippers other than WFP. This data set includes over 200 contracts from over 60 carriers operating in Kenya and it is rather unique given the scarcity of information in African transportation markets. Based on these contracts we built an econometric model to identify the factors that determine the market rates, especially the factors that tend to change during the contract such as oil prices. In the second phase, we incorporate the results of this econometric model in a real options scheme, which enables WFP to make adjustments in the contract rates based on the fluctuations of dynamic factors determining the rate. The contracts resulting from this approach let WFP to share the transporter's risk associated with the market volatility. By covering the transporters' risks, at least partially, caused by the price volatility of the transportation market, WFP can arguably incentivize the transporters to provide better service. The proposed methodology is applicable in a wide range of developing countries, where shippers are struggling with difficulties similar to those encountered by the WFP Kenya office.

A significant majority of the real options applications focus on the manufacturing sector. For the service sector, unlike the manufacturing context, selling, storage, and salvage costs are not relevant. Therefore, the models established for the manufacturing settings are not readily applicable to the area of service procurement. One of the differentiating features of the transportation contracts studied in this paper is the requirement of service under a fixed rate per tonne type of contract, where the total amount of the cargo to be shipped is unknown at the outset. Therefore, the transporters usually do not know how much capacity to allocate and fail to respond WFP's requests. In the literature, usually these types of behavior are targeted with either penalty or bonus mechanisms. Although the WFP's contracts indicate that the contracts shall not be renewed in case of failing to respond to the requests, in practice, WFP is unable to impose penalties since the transportation prices are already lower than their competitors' prices. By imposing penalties, WFP do not want to scare off the transporters. Providing bonuses for timely delivery is not an option for WFP, either. The organization runs on a tight budget provided by donors who question every expense report meticulously. The novelty of our study lies within the proposed framework that yields price flexible contracts. The designed contracts incentivize the transporters to provide a higher service level even if WFP's contracts do not contain penalty or bonus mechanisms.

The remainder of this chapter is organized as follows. Section 4.2 presents the description of the problem studied and the overview of the literature related to transportation procurement operations. The first phase of the study consisting of the econometric analyses and their insights is discussed in Section 4.3. Section 4.4 explains the overall framework of the new contract scheme as the second phase of the study. Section 4.5 provides numerical results for the highest volume lanes in our case and compares these results with current WFP contracts. Finally, Section 4.6 presents the conclusions.

4.2 Problem Definition and Related Literature

4.2.1 Problem Definition

The transportation market in Africa is not nearly as mature as in Europe or North America, where the rates are mostly dependent on the distance between origin and destination of the transportation and oil prices. However, the transportation rates in Africa can be very different for two destinations within almost the same distance due to varying infrastructure of roads. Also, estimating the actual value of the service poses a significant challenge for the inexperienced business owners. In addition, some transporters, who have a contract with WFP, often send their trucks to the spot market for other customers who pay better rates as revealed by our field research. Usually the transporters look for ways to delay the expiration time whenever they receive an LTI from WFP. There is no immediate consequence of this practice for the transporters since the contracts do not contain penalty or premium measures for that contract period.

Another problem with the WFP contracts is the fixed rates during the contract period, that is, there are no adjustments for the fluctuations in the spot market prices. Since WFP uses 6-month contracts, this may not appear as a significant problem. However, WFP tends to extend the duration of the contracts for another six months or even for a year. Fixed contracts may cause problems for both sides, the transporters are suffering from the rise of the USD against Kenya Schillings, since the fuel is imported as well as the trucks. On the other hand, the transportation spot market reacts to the price changes much faster than long-term contract holders. As a result, the transporters may choose to dedicate their trucks to the spot market or newer contracts and this causes a decline in the responsiveness of the transporters to WFP requests. It is also important to note that the WFP does not have the option to resort to the spot market when its contractors are not available. Even for a single lane, WFP's demand can only be handled by multiple contracts and the supply from the spot market, which is usually composed of smaller family companies, is not sufficient. In addition, collecting bids, preparing long-term contracts and assigning the demand to the contracted companies already require significant efforts. Dealing with the spot market contractors on a day-to-day basis would bring a tremendous operational burden. As a result, the decision for WFP is not the choice between spot market and the contract. Instead, WFP needs to provide more reasonable counter-bids and then adjust the contracts to reflect the fluctuations in the spot market for higher service rates. The need for a framework that calculates counter bids reflecting the market dynamics and the adjustments in the contracts are inevitable. In this chapter of the thesis, we aim to address these two issues relying on real data and novel mathematical approaches.

4.2.2 Related Literature

In this section, we focus on the two streams of literature that are directly relevant to our study: transportation markets in developing countries and real options contracts. This enables us to better position our paper with respect to the state-of-the-art literature and highlight its contributions. The fledgling literature on food aid distribution mostly focuses on the network design aspects (Stauffer *et al.* 2016). However, we study the food aid transport contracts presuming that the network structure is predetermined.

Concerning the transportation markets, the empirical literature on Africa is sparse due to the scarcity of accessible data. Arvis *et al.* (2010) have developed an analytical framework to interpret and model the constraints faced by logistics chains African trade corridors. They show that in East African countries on top of suffering from high costs, the delays and the unpredictability of transportation operations considerably hamper the development of the economy. Teravaninthorn and Raballand (2009) conduct a transporter survey to analyze the main international corridors. They observe that poor logistics infrastructures quality is a significant contributor to high transport prices lead and to low service quality. Rancourt *et al.* (2014) identify the main determinants of transportation rates in Ethiopia and quantify their relative importance by analyzing contracts between the WFP and private carriers. In our paper, we determine the factors that have a significant impact on the rates of the Kenyan domestic and international transportation market by using data from transporters that serve multiple shippers. Thus, we rely on a more diversified dataset to capture the market dynamics.

Transportation contracts are quite different from those between manufacturers and retailers, which is a broadly studied area. Cachon (2003) provides a comprehensive review of supply chain contracting literature. Although the primary focus has been on demand uncertainty, there is an increasing trend of including future price volatilities in the contracts. A sizeable number of authors, view real options as a means for introducing flexibility to the contracts in a wide range of applications including capacity of production (Miller & Park, 2005), investing to or divesting from R&D projects (Huchzermeier *et al.* 2001), and procuring energy (Secomandi & Kekre, 2014). In the supply chain management context, many researchers design real options contracts between a manufacturer and a retailer, where the demand of the retailer is uncertain (Barnes-Schuster *et al.* 2002; Pei *et al.* 2011). Option contracts are used for hedging this uncertainty by adjusting the quantity.

The most relevant paper is by Tsai *et al.* (2011) that focused on a long-term option contract for transportation procurement where the cargo-owner either choose to exercise the option by using the contract or else it can rely on spot market transporters. For this model, they collect the historical spot market prices in North American markets. According to the authors collecting such data is quite challenging, even in the North American setting. For each period the only available data is the previous month's maximum, minimum and average prices. In their study, they list the possible causes of the spot market fluctuations as threefold: (i) regional economic activities, (ii) backhaul cargo opportunities, and (iii) fuel prices. However, instead of exploring the links between these factors and the spot prices, they model the prices as a mean-reverting process by itself.

In addition, there are very few leasing applications of contract rate adjustments. Al sharif and Qin (2014) propose a flexible contract for vessel leases where both the lessor and the lessee have one rate adjustment opportunity during the contract period. They point out the risks of having a fixed rate contract in volatile markets. Contrary to all the papers listed so far, which use simple ***European*** or ***American*** options, Hendershott and Ward (2000) propose a ***barrier-type*** option, classified as an ***Exotic*** option, for adjusting store leases in shopping malls, where the lease is increased if the sales volume hits a certain barrier and remains the same if the selling quota is unfulfilled, so that both counterparts partially have protection against volatility.

In our paper, we also design a contract with a barrier-like option to solve WFP's problem. The challenge that WFP faces is the low service levels by the transporters, especially when the market prices surge. However, due to its regulations and operational constraints, WFP cannot employ penalty or bonus mechanisms in order to improve the service level. Thus, we first develop an econometric model to understand the fluctuations of the transport spot market prices. In this way, we can address and model the components of the underlying mechanism of the rate fluctuations, instead of treating the rates as a random process by itself. Then, we introduce flexibility by embedding a barrier-like option to the contracts, in order to respond the market rate volatilities and to increase the transporter compliance. Instead of simple European or American options, we choose the barrier options since the resulting contracts are easier to comprehend, to implement and to monitor by WFP. Barrier-type options provides a higher level of protection in comparison to simple European options, in which the contract update can be exercised once, i.e., at the pre-determined due date of the option. If the market rates increase but then decreases right before the due date, such contracts cannot respond to the downside risk of the transporters. Simple American options may provide higher levels of protection for the transporters. However, their inclusion to WFP's contracts comes with two set of problems. First of all, the transporter needs tools for accurate calculations for the value of the option, in order to decide the optimal time of exercising the option. Second of all, barrier type of options provides partial protection of volatility for both parties, whereas American type of options provides protection only for transporters.

Finally, the real options problems can be approached with three different methodologies: closed form formulations, binomial trees, and Monte Carlo simulation. In our paper, we used the binomial tree approach, since, as stated by Mun (2002), they are intuitional and easy to administer for potential users. This is crucial given that our counterparts are local transporters, which may not have access to computational resources required for closed form solutions or large simulation sets.

4.3 Phase I: Econometric Model

The development of a flexible contract scheme for risk sharing between the WFP and the transporters needs to be based on a solid understanding of the transportation market prices and the main determinants of their volatility. This section aims to fill the gap in the literature concerning the transportation spot market prices in East Africa. The analysis of the rates provided by five different NGOs showed that the variance of the rates is high both between the O-D couples (even with the same length) and between the NGOs, i.e., contracts. Thus, we developed a multiple linear regression model predicting the transportation spot market rates t as a function of two sets of independent variables: a set for lane specific factors $\mathcal{L}$ and a set for contract specific factors $\mathcal{C}$. We aimed to determine which factors have a significant impact on transportation rates and to use the results to design better contracting approaches. We stipulate that, T=$f(\mathcal{L}, \mathcal{C})+ \epsilon$ where ϵ stands for the random errors caused by unobservable factors.

4.3.1 Data Collection

As explained in the previous chapter, during the field trip to Kenya, I observed transportation-related activities and conducted interviews with logistics managers (clearance agents, warehouse and transport managers, etc.) working at the crucial nodes of the Kenyan humanitarian transportation network. I also interviewed with ten transportation companies at the two largest hubs, Mombasa and Nairobi. Finally, I collected the rates of five other NGOs to understand where WFP contracts stand in the market. The data obtained from the fieldwork was essential for this research in three ways. It ensured that all the important tangible variables provided by transporters were considered in our econometric models, the interpretation of our results is reliable, and our contracting recommendations are feasible from an implementation perspective. We requested contract data from all the transporters in WFP's short list (90 transporters) and inquired their transportation rates for cargo owners other than WFP, to develop a solid understanding of the transportation spot market in Kenya. We asked for the following information about their most important national and international corridors with their other clients: contracted rate, start, and end date of the contract, type of commodity transported, the total load carried during the contract, number of trucks used, anticipated road conditions, and the average traveling time. Out of 90 transporters, 61 of them responded to our request. This yielded a raw contract data set of 407 observations. Some observations were discarded due to incomplete or inaccurate information so that the final data set consisted of 213 observations summarized in Table 4-1. This is a rich dataset considering little empirical research has been conducted in East Africa (Teravaninthorn & Raballand, 2009).

Table 4-1 Summary statistics of the transportation rate data

	International corridor **(cross-border = 1)**	**National lane** **(cross-border = 0)**
Network	7 origins 19 destinations 29 corridors 29 transporters 96 contracts (observations)	12 origins 40 destinations 62 corridors 32 transporters 117 contracts (observations)
Statistics	Average rate (US $/tonne): 176.73 Average distance (km): 1,246.94 Average rate per km (US $/tonne-km): 0.14 STD of rate per km (US $/tonne-km): 0.05	Average rate (US $/tonne): 53.90 Average distance (km): 556.35 Average rate per km (US $/tonne-km): 0.11 STD of rate per km (US $/tonne-km): 0.09

Moreover, secondary data was obtained from online sources. The origin and destination population numbers were taken from the United Nations Statistics Division (2015) whereas historical data on fuel prices and exchange rates was collected online from the Energy Regulatory Commission (2016) and Exchange Rates UK (2016). Such factors can partly explain the transportation market dynamics and could be used as proxies for market predictors.

4.3.2 Variable Descriptions

In this section, we connect our data to the dependent and independent variables used in our econometric models. The dependent variable in our model is the transportation rates in USD per metric ton to carry merchandise from an origin to a destination (O-D) during a specified period of time, and the independent variables are the lane-specific factors pertaining to the O-D lane and the contract-specific factors. Below we provide a detailed discussion of each of these factors.

4.3.2.1 Lane Specific Factors

Distance (continuous): The distance is the length of the road between the origin and destination points measured in kilometers. The length of the lane is an important determinant of the transportation rates since it has a direct impact on the resources required to make the delivery.

Fuel price (continuous): We used the monthly pump price of diesel (US $/lt) published by the Kenyan Energy Regulatory Commission (2016). Fuel cost has a significant impact on overall transportation costs, as confirmed by many of the transporters interviewed for the present study. All the transporters and cargo owners closely monitor oil prices, which fluctuates over time.

Average perceived road conditions (continuous): Road safety is a major issue in most African countries. Only 34% of the land in rural Africa is accessible by road, whereas the figure is 90% in the rest of the world (African Development Bank, 2010). This factor leads to higher operating costs because it lowers vehicle utilization by limiting speed, and causes damage to vehicles, resulting in higher maintenance costs. Unfortunately, the shapefiles of the complete road network and the security levels are not readily available. To circumvent this, we asked transporters to score the road conditions using a five-point Likert scale, where one corresponds to the best possible conditions five to the worst. We believe that surveying transporters during the request for quotation process is a simple, effective, and low-cost assessment method. The perception of the transporters may be subjective, but the price they set for transportation service is based on their perception.

Large origin and destination population concentrations (indicator): In the transportation industry, the cost of serving a lane depends on backhaul opportunities that allow for economies of scope (Caplice, 2007). Imbalanced transportation networks increase connection costs for transporters because such networks involve empty hauls. The likelihood of finding return loads is greater in the major cities, where there is more economic activity. Prices also reflect the supply and demand of transportation services at origin, which are different in urban and rural areas. To capture the effects of these phenomena, we introduced two dummy variables that indicate whether the population at the origin and the destination is greater or equal to one million people, which is a commonly used threshold to distinguish large urban areas from small ones.

Border crossings and refugee camps (indicator): Transporters complained about long queues at borders that involve costly waiting times. To determine the effect of border crossings on transportation rates, we used a dummy variable to indicate whether a lane involves border crossing or not. Refugee camps are also critical nodes in humanitarian supply chains in East Africa. They are densely populated trading centers and labor markets, and this gives them urban features (Montclos & Kagwanja, 2000). Today Kenya hosts the largest (Dadaab) and the third largest (Kakuma) refugee camps in the world. Other refugee camps located in the neighboring countries (Sudan, Uganda, Ethiopia, etc.) are also served from the Port of Mombasa. We add a dummy variable for refugee camp destinations as well.

4.3.2.2 Contract Specific Factors

Total load (continuous): The total load is the total amount of cargo that is moved during the contract and is measured in metric tons.

Heavy cargo (indicator): There were 82 different commodity types in our dataset, and we grouped them into two distinct categories: heavy cargo (wind turbines, furniture, fuel tanks, etc.) and stackable cargo (cereals, vegetal oil, beverages, etc.).

Rainy seasons (indicator): During the rainy seasons (November to December and March to May), some roads are entirely or partially impassable. This disturbs the transportation services because transit times and costs increase due to waiting times. Thus, a variable that indicates whether or not the period of the contract covers a rainy season was introduced.

Short contract (indicator): Long-term relationships between shippers and transporters may lead to lower transaction costs and strengthen commitments. Thus, we introduced a dummy variable that indicates whether the rate has been agreed on for a short-term contract (shorter than six months) or not. The threshold was fixed at six months because it is the practice currently implemented by most UN agencies.

4.3.2.3 Descriptive Statistics

Table 4-2 contains descriptive statistics for the main variables of interest. It shows, for the lane and contract specific factors, information about the distribution of each continuous variable: the average, standard deviation, median, and the minimum and maximum values. For the indicator variables, note that out of 213 observations 96 of them have border crossings, 65 of them have a large origin population, 56 of them have a large destination population, 11 of them are destined to refugee camps, 35 of them are for heavy cargo transport, 118 of them covered rainy season and 148 of them had a length of less than six months.

Table 4-2 Descriptive statistics of continuous variables

Variable	Average	Standard Deviation	Median	Minimum	Maximum
Dependent variable					
rate (T) (US $/tonne)	109.25	88.28	83.00	0.33	400.00
Lane specific factors					
distance (km)	867.60	477.94	785.00	36.70	2,148.00
fuel price (US $)	0.99	0.16	0.97	0.73	1.25
average perceived road conditions	2.62	0.89	2.00	1.00	5.00
estimated travel time (h)	4.18	3.24	3.00	1.00	21.00
Contract factors					
total load (tonne)	856.43	3,144.31	144.00	15.00	31,000.00

4.3.3 Econometric Models

We now explain how the variables were selected in developing our final regression model. Table 4-3 shows the number of observations, the R-squared, the regression coefficients and their robust standard errors obtained for three different specifications. Note that we assumed heteroscedasticity and so used heteroscedasticity-robust standard errors as suggested by Stock and Watson (2003). We first regressed the rates (Model I) on the variables that stick out in the interviews with the transporters and in the trucking industry reports: distance, fuel price, and the interaction between these two variables, as the effect of fuel price is likely to vary as a function of the distance. The results obtained from Model I, which explains about 68% of the variability in transportation rates, showed that the interaction variable is significant at a level of $p < 0.05$. Model II considers all the explanatory variables.

To detect whether there was a specification error, we ran a link test (Pregibon, 1979). The results indicated that we had chosen meaningful predictors, but that there was a specification error. This means that either a relevant variable was omitted in Model II or that the dependent variable was not properly specified. After carefully examining the relations between all the variables and the interactions between all the independent variables, we added the square of the distance and ran another link test on this new model (Model 3), and we did not detect any specification errors. Model 3 explains about 80% of the variability in transportation rates. Therefore, we consider it as an efficient specification for predicting transportation rates in this context.

Table 4-3 Regression models

Variables	Model 1	Model 2	Model 3
Line-specific factors			
fuel price (US $/lt)	-12.68	-9.190	-30.48
	(30.16)	(32.74)	(31.53)
distance (km)	0.0633*	0.0620**	-0.0594
	(0.0359)	(0.0310)	(0.0414)
fuel price · distance (US $-km)	0.0831**	0.0544	0.0767**
	(0.0358)	(0.0339)	(0.0341)
distance^2 (km^2)			4.61e-05***
			(9.57e-06)
average perceived road conditions		11.13*	12.06*
		(6.070)	(6.180)
cross-border		42.33***	50.10***
		(10.69)	(10.99)
refugee camp		-35.55**	-31.27**
		(16.63)	(15.41)
destination population concentration		-17.88**	-20.40***
		(7.277)	(6.850)
origin population concentration		17.41***	15.02**
		(6.472)	(6.549)
Contract factors			
total load (tonne)		-0.000941	-0.000922
		(0.000978)	(0.000814)
rainy season		1.017	2.652
		(6.887)	(6.705)
short contract		-14.84*	-11.70
		(7.671)	(7.406)
heavy cargo		32.09***	29.99***
		(9.660)	(9.642)
Constant	-3.868	-23.72	30.88
	(30.20)	(40.08)	(40.07)
number of observations	213	213	213
R-squared	0.683	0.784	0.8002

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4.3.4 Analysis of the Results

In this section, we highlight the insights provided by Model 3, that is, the significant determinants of transportation rates and their impacts.

4.3.4.1 Insights from the results obtained for the lane specific factors

The most critical factor with a significant impact on the transportation rates is the interaction term between the fuel price and the distance. The coefficient of this interaction term, which is significant at a 95% level, can be interpreted as the average fuel consumption of a truck that is equal to 7.67 lt/100km. Multiplied with fuel price and distance, this component overall explains the fuel consumption costs within a trip. Note that, among all the ones considered, this is the only component of the transportation rate function that may fluctuate during the effective term of a contract. The squared distance is also significant with a positive coefficient. This implies that the effect on rates is stronger as the distance increases, which may be partially explained by the likelihood of encountering more road incidents and by the higher maintenance costs as the trucks drive further from the origin in a sparse and poor road network like in East Africa. As expected, the coefficients of the variables average perceived road conditions ($12.1/tonne), and border crossing ($50.1/tonne) are significant and positive. It implies that rates per trip are higher when road conditions worsen and that there is a minimum fixed cost for crossing a border probably due to the average wait time of eight hours.

The coefficient of the refugee camp indicator is significant with a negative value (-$20.4/tonne), which implies that the cost of transporting goods to a refugee camp is lower than transporting them to other destinations. Although refugee camps are located in remote areas, they are economically vibrant and densely populated zones. The roads to the refugee camps are well known to the drivers, and off-loading operations are usually more supervised in refugee camps compared to other EDPs in rural areas. The variable that indicates a large population concentration at the origin has a significant positive coefficient, whereas the variable that indicates a large population concentration at the destination has a significant negative coefficient. The results imply that delivering goods from larger cities is more expensive. This may be explained by traffic congestion and control points or by an imbalance between supply and demand for transportation services. On the other hand, delivering goods to larger cities seems to be less expensive, which may be because more backhaul opportunities generate extra profit for transporters.

4.3.4.2 Insights from the Results Obtained for the Contract Factors

Economies of scale did not appear to be significant in the Kenyan transportation sector based on our interviews. None of the transporters mentioned adopting such pricing schemes when they were explicitly asked questions about discounts for larger loads. In line with this idea, total load variable is not significant in Model 3. The rainy season and the short contract indicators are not, either. One reason for this may be that transporters do not differentiate between the rainy and the dry seasons when pricing their services, maintaining a uniform price throughout the year that compensates for the difficulties occurring during the rainy seasons or simply they do not accept jobs that require travelling to the regions affected by the rain. Moreover, contract duration does not seem to have a significant impact on the market rates. This means that the transporters myopically ask for the spot market rates at the beginning of the contract period regardless of the duration of the contract. The only significant variable related to the contract terms is heavy cargo. When the commodities to be transported belong to this category, our results show that the rate is expected to increase by about $30/tonne. This increase is justified because transporting heavy cargo requires special handling and may involve specific equipment. None of the other variables related to the contract terms have a significant impact on transportation rates. This is a positive finding since it suggests that simpler contracts are more preferable.

4.4 Phase II: A Barrier-Type Option for Transportation Risk Sharing

We use a real options approach in order to incorporate flexibility into the long-term fixed-rate contracts to allow the cargo owner to share the transporters' risk due to spot market volatility. In this context, the choice for the state variable is critical since the stakeholders determine their actions based on this variable. It should represent the real source of the volatility and should not be affected by the actions of the decision maker. In our case, as the regression analysis in Section 4 revealed, *fuel price* is the primary source of the uncertainty and its interaction with the distance is the only significant dynamic variable determining the spot market rates. Therefore, it constitutes our state variable. Having a state variable as a price of a commonly traded commodity comes with its advantages. One benefit is the ample amount of publicly available historical data that can be used for modeling the future behavior of the state variable. Furthermore, these prices enable us to exclude the subjective risk assessments of the decision maker since they already incorporate the risk expectations of the market. In our analysis, we use a barrier-type real option. Barrier options are widely used in finance theory, but their applications to the operations management problems are quite rare. The distinction between the simple real options and the barrier options is that the barrier options come into existence only when the state variable hits a pre-determined threshold or barrier. In our analysis, we adopt this approach to update contracts based on the fluctuations of the fuel price, so that the rate adjustment is possible only if the fuel price hits a certain threshold.

4.4.1 Proposed Framework for the Contract Design Process

The proposed framework presented in this section aims to incorporate flexibility in transport contracts so that they are responsive to the changes in the market rates. Without loss of generality, we use fuel price in explaining this framework, but the proposed framework is generic, and it can be utilized to capture other dynamic factors in different contexts. As depicted in Figure 4-1, a multivariable regression analysis (conducted in the previous section) constitutes the first step, where we aim at representing the transport spot market prices as a function of the statistically significant dynamic factors i.e., the fuel price in our case. Meanwhile, we represent the random fluctuations in the fuel price using the binomial tree approximation of the Ornstein-Uhlenbeck process. By estimating the spot market rates for each node of the fuel price binomial tree, we obtain a new tree that represents the fluctuations in the transportation market rates. Then, we use the transporter's downside risk as the value function and find the value of the contract using backward induction on the spot market prices tree for a given contract setting. By solving this problem for different rates and contract adjustment thresholds, we obtain an efficient frontier of the contract settings, which can be helpful for the negotiations between the shippers and the transporters.

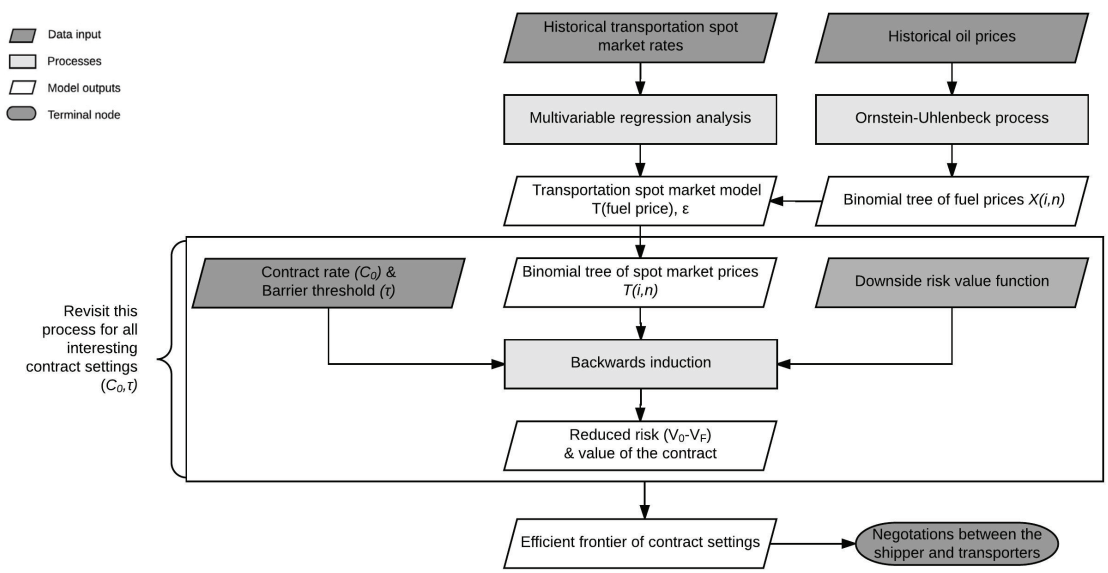


Figure 4-1 Proposed framework for flexible contract design

Now, we explain the second phase of the proposed framework in more detail. The common approach to solve the real options using a binomial tree of the state variable was first suggested by Cox, Ross and Rubinstein (1979). In this study, we adapted the approach presented in the book by Guthrie (2009). In our case, the state variable is the fuel prices and in the literature, there are two commonly used models for the fluctuations of fuel prices: (i) random walk with a drift and (ii) mean reverting process, specifically, one-period autoregressive process, i.e., AR(1). The variants of these models are studied and compared by Ederington *et al.* (2011). We adopted a data-driven approach, which is explained in Appendix B.1, to choose the best fit for the monthly Brent Crude Oil spot market prices of the last five years (U.S Energy Information Administration, 2016), which is widely used as a benchmark for the oil industry. Since both models work with the logarithm of the prices, we regressed the log-prices in period j (p_j) on the difference in log-prices ($p_{j+1} - p_j$) to see whether the coefficient of p_j were significant (hinting a mean reverting process) or not (hinting a random walk). We find that the coefficient is significant and hence we adopt an AR(1) process to represent the fuel price fluctuations. In a stationary AR(1) process, price shocks are not permanent, and the prices tend to return to their long-term averages, which is called a "mean-reverting" behavior.

4.4.1.1 Construction of the Binomial Tree for Fuel Price

Once we decide the AR(1) is a better fit to our data, we need to choose how to actually model the fuel prices. We can use a closed-form formulation, a binomial tree or a Monte-Carlo simulation. Among these we choose the binomial tree approach since it does not bring a significant computational burden to the end users within WFP and it is intuitional in the sense that non-expert end-users can easily implement it.

In the binomial tree of the fuel prices, the price can either go up or down at the end of each period with a certain probability. Let $X_{(i,n)}$ denote the fuel price after i down movements in n periods and π_u (π_d) denote the risk-free probability of going up (down) in the next period as illustrated in Figure 4-2. We estimate the $X_{(i,n)}$ values through an Ornstein-Uhlenbeck (O-U) stochastic process that generalizes AR(1).

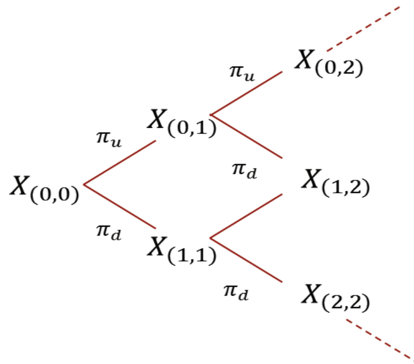


Figure 4-2 Binomial tree representation of fuel price fluctuations

In AR(1), the change in the price between two periods in AR(1) is determined by the price in the previous period as in Equation (4.1).

$$p_{j+1} - p_j = \alpha_0 + \alpha_1 p_j + \epsilon_{j+1}, \qquad \epsilon_{j+1} \sim N(0, \phi^2), \tag{4.1}$$

α_0, α_1 and ϕ are constants, and α_1 is negative, indicating the mean-reverting behavior. However, in O-U process if the prices are observed within *arbitrary time intervals* (Δt), this difference can be written as:

$$p_{t+\Delta t} - p_t \sim N\left((1 - e^{-\rho\Delta t})(\gamma - p_t), \frac{\sigma^2}{2\rho}(1 - e^{-2\rho\Delta t})\right) \tag{4.2}$$

Here γ, ρ and σ are constants, and they represent the mean, the mean-reversion rate and the volatility respectively. According to (4.1), the change in the log-prices from one period to the other, is normally distributed with mean $\alpha_0 + \alpha_1 p_j$ and variance ϕ^2. Therefore, the relation between the parameters of AR(1) process and those of O-U process is given by:

$$\alpha_0 = (1 - e^{-\rho\Delta t})\gamma, \quad \alpha_1 = -(1 - e^{-\rho\Delta t}), \quad \phi^2 = \frac{\sigma^2}{2\rho}(1 - e^{-2\rho\Delta t}). \tag{4.3}$$

Using these parameters derived the estimates for the O-U process can be written:

$$\hat{\rho} = \frac{-log\,(1 + \widehat{\alpha_1})}{\Delta t}, \qquad \hat{\gamma} = -\frac{\widehat{\alpha_0}}{\widehat{\alpha_1}}, \quad \widehat{\sigma^2} = \widehat{\phi^2}\frac{2log\,(1 + \widehat{\alpha_1})}{\widehat{\alpha_1}(2 + \widehat{\alpha_1})\Delta t} \tag{4.4}$$

As suggested by Nelson and Ramaswamy (1990), the above parameters are used for estimating the binomial approximation of the O-U process. As explained previously, at each period the fuel price can either go up or go down, where the proportions of the up and down movements are assumed to be the same. Therefore, given the last observed fuel price, $X_{(0,0)}$, and length of the period between two movements in the binomial tree, Δ_t, the log price will go up or down by the size of the volatility measure $(\hat{\sigma}\sqrt{\Delta t})$ for that period. Thus, after i down and $n - i$ up movements in n periods, the log of the fuel price will be:

$$log\, X_{(i,n)} = logX_{(0,0)} + (n - 2i)\hat{\sigma}\sqrt{\Delta t} \tag{4.5}$$

Then, the value for each node (i,n) in the fuel price tree can be estimated as:

$$X_{(i,n)} = X_{(0,0)}{}^{(n-2i)\hat{\sigma}\sqrt{\Delta t}} \tag{4.6}$$

Now, we need to calculate the risk-free probabilities of these up and down movements. Let $\pi_{(i,n)}$ denote the risk-free probability of the price going up after observing state $X_{(i,n)}$. Since, our state variable is a commodity price, the calculation of the risk-free probabilities should include market's risk expectation, as well as the supply and demand responses. The main assumption that is commonly relied on while calculating risk-free probabilities in the literature is the infamous "no-arbitrage" principle. In other words, the prices of two portfolios that generate the same cash flow should be the same. Therefore, we can use historical 1-period-ahead crude oil prices and pump prices to adjust our probabilities. The details of risk-free probability calculations are given in Appendix B.2, where we also show that there is almost a perfect linear relationship between the futures and the pump prices. Using that relationship, we can use the futures values of oil prices to estimate the pump prices after taking the exponentials of both sides as follows:

$$F_{(i,n)} = e^{a_0 + a_1 logX_{(i,n)}} \tag{4.7}$$

Since we have already derived the $X_{(i,n)}$ values on the tree and found the relationship between the pump and the futures prices, the risk-free probabilities for each node can be calculated as:

$$\pi_{u(i,n)} = \frac{F_{(i,n)} - X_{(i+1,n+1)}}{X_{(i,n+1)} - X_{(i+1,n+1)}} \tag{4.8}$$

With these risk-free probabilities, our binary tree is complete. Now, we need to determine the value function that represents the value of the flexibility added to the contract.

4.4.1.2 The Value Function

In order to represent the mindset of the transporters, we use the downside risk notion of the transporters as the basis of our value function. Although this model is inspired by the interviews conducted with transporters that also serves for WFP, we believe their mindset is a reasonable generalization of the transport market that works with large shippers using long-term fixed-rate contracts.

Downside risk under the current contract

The transportation spot market changes have no influence on WFP's long-term fixed-rate contracts. Obviously, if the spot market prices are below the fixed contract rate, transporters have no problem assigning their trucks to the contracted shipper. Yet, during elongated contracts resulting from an auction the shippers occasionally enjoy contract rates lower than spot market prices. If the contract rates are lower than the spot market rates, transporters are reluctant to send their trucks to the contracted shipper, in the hope of finding a better paying job in the market. It is reported by WFP that transporters delay their response to the shipping requests or LTIs by coming up with excuses. Once they are confident that they cannot find a better job, they aversely fulfill the transportation request of WFP for the sake of not keeping their trucks idle.

We derived the binomial tree for fuel prices in the previous sub-section, whereas the rate estimation model was developed in Section 4.3. For a given O-D, all the variables, except the transportation spot market prices $T_{(i,n)}$, are known at the beginning of a contract. For any node (i,n), all we need to do is to plug-in the estimated fuel prices, $X_{(i,n)}$ to the rate prediction function provided by the regression model and calculate $T_{(i,n)}$. Note that, our regression function uses diesel pump prices, where the calculations in this section use crude oil prices. The details related with the conversion of crude prices to pump prices can be found in Appendix B.3.

Let us consider an arbitrary realization of the fuel price changes and the corresponding transportation spot market values. Given that the signed contract rate is C_0, the transporter is highly motivated to respect the long-term contract when the spot market rate $T_{(i,n)}$ is below this value. On the contrary, transporters are seeking outside opportunities when prices go over the contract value.

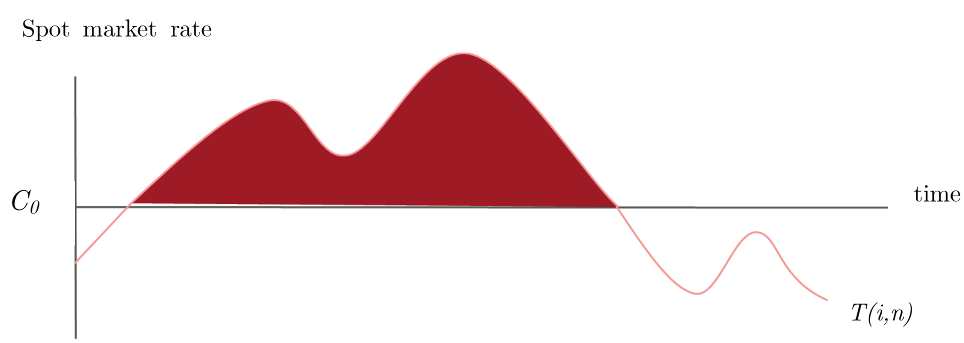


Figure 4-3 Downside risk under the original contract

In Figure 4-3, we can observe both situations, where the shaded area represents the loss of opportunity incurred by the transporter, i.e., the downside risk if they keep channeling their trucks to the shipper under the current contract. The associated value function, i.e, the downside risk of the transporter at any period is represented as the positive difference between $T_{(i,n)}$ and C_0 plus the expected risk in the next period, where r_f denotes 1-period-risk-free rate of return:

$$V_{C(i,n)} = \left[\left(T_{(i,n)} - C_0\right)\mathbf{1}_{\{T_{(i,n)}>C_0\}}\right] load_n + \frac{\pi_{u(i,n)}V_{C(i,n+1)} + \pi_{d(i,n)}V_{C(i+1,n+1)}}{1+r_f} \tag{4.9}$$

Downside risk under the proposed price-flexible contract

The main idea of introducing price-flexibility is to update the contract rate whenever the fuel price surpasses a certain percentage threshold of the fuel price at the time the contract is signed. For example, let $X_{(i,n)}$=\$1/lt at the beginning of the contract and let the threshold (τ) that both parties agreed on be 15%. If during the validity period of the contract, fuel price hits to the barrier \$1.15/lt then, the contract is updated accordingly as long as the price remains above this level. But, the increase in the contract rate is not 15%, instead, we use the fuel price elasticity (ε) dictated by the rate estimation model in Section 4.3. For each O-D, we can calculate the elasticity of the fuel price by observing the change in the market rate, as $\varepsilon = \frac{\%\ change\ in\ fuel\ price}{\%\ change\ in\ contract\ rate}$. Thus, while the spot market price remains above the barrier, the effective contract rate will be $C_0^\tau = C_0(1+\tau\varepsilon)$.

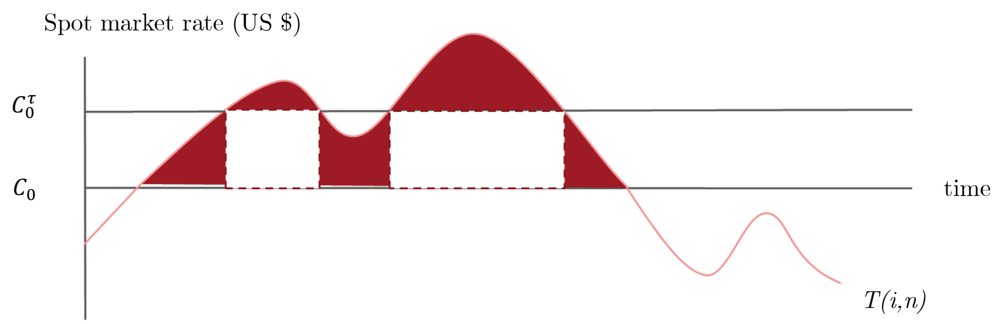


Figure 4-4 Downside risk under the flexible contract

As long as $T_{(i,n)}$ is greater than C_0, there is still a certain level of downside risk as depicted by the shaded area in Figure 4-4. Nonetheless, the downside risk for the transporter is reduced and, it is represented as:

$$\begin{aligned} V_{F(i,n)}(C_0,\tau) &= \left[\left(T_{(i,n)} - C_0\right)\mathbf{1}_{\{C_0^\tau > T_{(i,n)} > C_0\}} + \left(T_{(i,n)} - C_0^\tau\right)\mathbf{1}_{\{T_{(i,n)} > C_0^\tau\}}\right] load_n \\ &+ \frac{\pi_{u(i,n)}V_{F(i,n+1)} + \pi_{d(i,n)}V_{F(i+1,n+1)}}{1+r_f} \end{aligned} \tag{4.10}$$

One may question why the contract rates are updated only by a pre-determined margin, instead of exactly matching the prices beyond the barrier. Although such a practice may be fairer for the transporters, from an implementation point of view is has flaws. First of all, WFP would be assuming almost all the risk brought by fuel price increase while the transporters are not assuming WFP's risk brought by fuel price decreases. Secondly, calculating the new rates for more than 200 origin destination pairs and updating the contracts of more than 90 transporters each month brings a significant operational load for the WFP logistics office.

Value of introducing flexibility

We can calculate the total expected downside risk assumed by the transporters under both contracts using backward induction. First, we need to define the terminal conditions for both contracts. Since there is no guarantee that both parties will renew the contract, we set the downside risk at the end of the planning horizon, period N, is zero:

$$V_{C(i,N)} = V_{F(i,N)} = 0, \forall i. \tag{4.11}$$

Starting from these final nodes, we can calculate the downside risk values down to the very first node of the associated binomial trees, where $V_{C(0,0)}$ and $V_{F(0,0)}$ determine the expectations of the total expected downside risks under the corresponding contracts, given that the price fluctuations are determined by X and π. The difference between $V_{C(0,0)}$ and $V_{F(0,0)}$ constitutes the reduction in the expected downside risk of the transporter under the new contract. In other words, this difference signifies the value of introducing price-flexibility to the contracts.

What is in it for the shipper (WFP)?

The price-flexible contract, with the introduction of a barrier, amounts to a higher expense for the shipper in hope of receiving more reliable service from the transporters. The increase in the contract value is due to the new rate of $C_0^\tau > C_0$ when the fuel price exceeds the threshold. This higher contract rate aims to deter the transporters from sending their trucks to other jobs they can secure from the spot market.

For the transporter, the contracted rate C_0, may not be solely based on the true cost of doing business with the shipper. The transporters may inflate their bids to protect themselves from future surges on the spot market rates (or fuel prices). This downside risk is pronounced due to the current practice of WFP in often renewing the 6-month contracts with the same rate over longer periods. Since the proposed barriers protect them from these surges to some extent, transporters may agree to abandon such defensive bidding strategies and settle for lower contract rates, $C_L < C_0$. Thus, under the new contract design, when the fuel price barrier is surpassed, the updated contract will be $C_L^\tau = C_L(1 + \tau\varepsilon)$.

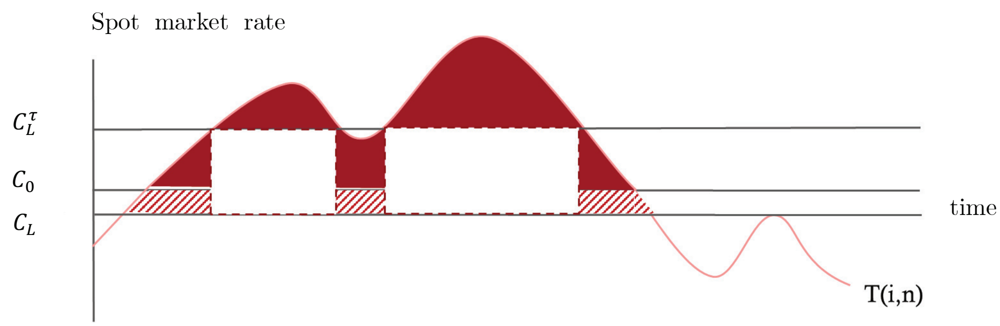


Figure 4-5 Downside risk after lower base rates

It is evident from Figure 4-5 that decreasing the contract rate from C_0 to C_L adds to the downside risk of the transporter (dashed area). We need to explore the alternative contract settings for lower base rates, where the downside risk reduction is positive (meaning that the sum of the white areas is larger than the dashed area) and the expected pay-off of the overall contract does not deviate much from what is effectively being paid under the current contracts.

4.5 Numerical Results

In this section, we test the performance of the suggested contracting scheme using the estimated spot market prices and compare them with current contracts of the WFP. We calculate the possible risk reductions and base rate discounts using the methodological framework explained in the previous section by focusing on the top five O-D pairs served by WFP via Port of Mombasa regarding their contract value. Since these are also the top five O-D pairs in terms of the total amount shipped, our analyses amount to 69% of the transport activities overseen by WFP Kenya office. In Table 4-4, we report the details pertaining to these O-D pairs using 2014 data. The same contract rates were in effect by the time we collected this data around mid-2015.

Table 4-4 Description of the top five origin-destination pairs

Origin	**Destination**	**Distance (km)**	**Rate, C_0 ($/tonne)**	**Load (tonne)**	**Contract Value ($)**
Mombasa	Juba	1634	197	81,694	15,720,130
Mombasa	Kampala	1147	90	46,690	4,104,627
Mombasa	Tororo	934	70	44,857	3,067,120
Mombasa	Dadaab	567	54.35	52,206	2,771,436
Mombasa	Kakuma	1278	93.87	24,955	2,288,294
Total				250,405	27,951,608

The Port of Mombasa is the common origin for all these five lanes. Juba is the capital city of the youngest nation in the world, South Sudan. Torn by years of civil war, in South Sudan, there are millions of internally displaced people, who are in urgent need of food aid. The two large cities in Uganda, Kampala and Tororo, have depots that serve both the country itself and the neighboring countries, including Rwanda and Burundi. Both cities are located on the route, called Northern Corridor that connects Mombasa port to landlocked countries surrounding Kenya. Finally, Dadaab and Kakuma, are the world's first and third largest refugee camps, respectively. Figure 4-6 depicts these locations on the map.

For each O-D pair, we calculated and compared the downside risks of transporters under the current and the proposed price-flexible contract values, then we developed the efficient frontier of the barriers and the alternative contract rates. WFP and the transporters can use this information during the bidding and counter-bidding negotiations to identify mutually acceptable contract terms.

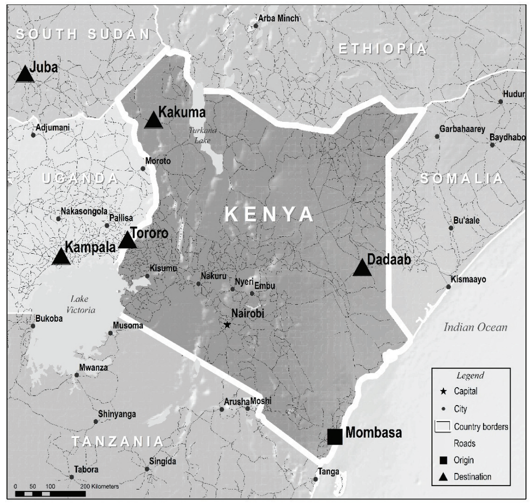


Figure 4-6 Port of Mombasa (origin) and top 5 Destinations

We start by providing the results for Mombasa – Juba shipments in detail. In our calculations, we assumed the transportation demand is distributed evenly throughout the year. July 2015 is the starting point for our analyses since WFP was collecting new bids for the next period at that time, and the planning horizon is 12 months. Our interviews revealed that yearly contracts are standard practice between the transporters and other shippers in the market. The time step that we choose in our binary tree is one-month.

For each O-D, we have explored a wide range of alternative contract values, $C_L \in [0.75C_0, C_0]$, and fuel price thresholds, $\tau \in [0,1]$, to develop our efficient frontier. For each (C_L, τ) pair, we have calculated the downside risk using the flexible contract model and compared that with the current fixed contract value:

$$Risk\ Reduction(C_L, \tau) = V_{F(0,0)}(C_L, \tau) - V_{C(0,0)} \tag{4.12}$$

Not all contract values and thresholds in our solution space yield a positive risk reduction. As C_L decreasing, the negative deviation from the spot market value increases, and no value of barrier can compensate the additional risk. On the other hand, the reduced risk responds concavely to the increase of the threshold. As the threshold (τ) increases, at the beginning, the risk reduction also increases since the updated contract rate is $C_L^\tau = C_L + C_L\tau\varepsilon$. However, if we keep increasing the threshold, the probability of the fuel price ever hitting the barrier decreases and as a result the contract rate remains not updated for longer periods. Figure 4-7 depicts that reduced downside risk (or the value of the contract) is monotonically decreasing in C_L and concave in τ. Note that, this graph does not include the points that yield non-positive risk reduction values.

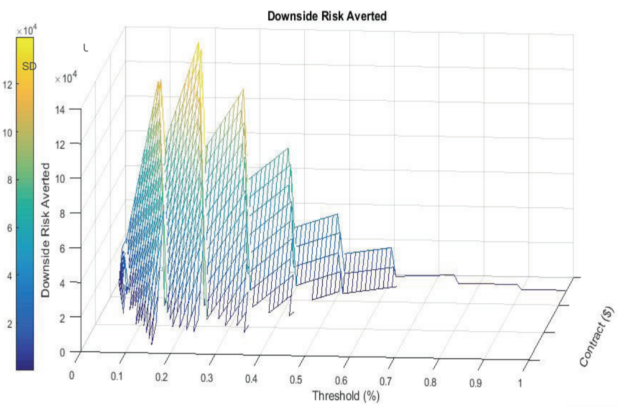


Figure 4-7 Downside Risk Averted as a function of different contract settings (rates and thresholds)

There can be multiple threshold values yielding a downside risk reduction for each contract rate. In order to facilitate a fair negotiation process, we assume WFP will offer the threshold that yields the highest risk aversion for a given contract rate. Table 4-5 shows the results for the Mombasa-Juba instance. The first two rows represent the contract setting in terms of the new rate and optimum threshold. Within our test space, there are 10 contract settings that generate positive downside risk reduction and the current contract is in the first column. The third and fourth rows represent the magnitude and percentage of the risk reduction obtained by these settings. The final row expresses the expected total discounted contract payments. The tenth setting is one extreme where we impose a flexible contract to the current rate. Clearly, this is a very desirable contract for the transporter, in which she receives the original rate (which may already be inflated for risk-protection) and on top of it, an updated rate if the fuel price increases 18% or more.

Table 4-5 Numerical results for Mombasa - Juba

	Instances										
	Original	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Contract Settings											
τ (%)	0	16	16	16	15	14	22	21	20	19	18
C_L ($/tonne)	197.0	192.5	193.0	193.5	194.0	194.5	195.0	195.5	196.0	196.5	197.0
C_L^τ ($/tonne)	197	201.1	201.6	202.1	202.1	202.1	206.9	206.9	206.9	206.9	206.9
Results											
Downside risk ($1,000)	281	268	239	211	204	197	189	177	165	153	142
Risk reduced ($1,000)	-	13	42	70	77	83	92	104	116	128	140
Risk reduced (%)	-	5	15	25	27	30	33	37	41	46	50
Contract value ($1,000)	15,720	15,564	15,604	15,645	15,673	15,700	15,729	15,762	15,795	15,827	15,860

On the other extreme i.e., in the first setting, the transporter expects to receive US$156,175 less, where her expected risk reduction accounts only for US $13,207. The instances in the middle seem more plausible for both parties. For example, in instance 6, we see with correct contract parameters significant risk reductions (33%) can be achieved for the transporters while WFP's total expected payment remains almost equal to the current contract. In fact, by only manipulating the contract settings, with no additional costs incurred by either of the stakeholders, a significant risk reduction is achievable. Although, a risk reduction of US $92,488 may not seem substantial for a contract valued at almost US $15.7 million, it actually corresponds to a 6% increase in the net profits, given that the transporters report a 10% profit margin in the overall contract value.

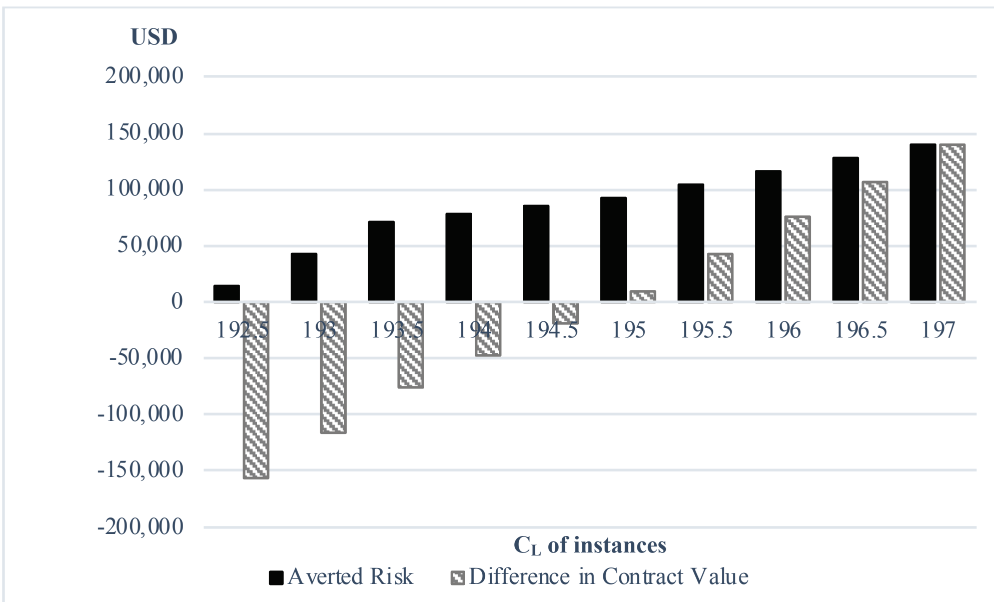


Figure 4-8 Efficient frontier of risk reduction and total payment for Mombasa – Juba lane

Figure 4-8 depicts the efficient frontier of the risk reduction (solid bars) and change in the contract value (dashed bars) generated for the shipment on Mombasa – Juba lane. The first setting (i.e., contract rate $192.5) is not very appealing to the transporters due to the negligible risk reduction for a lower gain compared to the original contract. Similarly, the last setting is not agreeable for WFP since the expected cost of the new contract is raised by almost US $150,000. On the other hand, there is a number of other settings that seem to be agreeable for both stakeholders. Having a base rate of \$195/tonne seems reasonable for a risk neutral transporter, whereas rates of \$194.5/tonne or even \$194/tonne can be plausible for a risk-averse transporter.

Our methodology yields significant risk reductions for the Mombasa – Juba contract. However, this result is not completely generalizable to other contracts. In Table 4-6, we report the maximum risk reduction that can be obtained from the new contract for the five O-D pairs. The third column represents the original contract rate, where the fourth column shows the spot market prices estimated by our regression function given the fuel price in July 2015. The fifth column gives the deviation among these two rates and, finally, the last column represents the maximum risk reduction that can be achieved using our model.

Table 4-6 An overall performance of flexible contracts on selected OD pairs

Origin	**Destination**	**Actual Contract, C_0 (\$)**	**Spot price at T(0,0) (\$)**	**Percentage Deviation (%)**	**Risk Reduction (%)**
Mombasa	Juba	197	193	2.1	49
Mombasa	Kampala	90	108	-16.7	6
Mombasa	Tororo	70	112	-28.6	1.5
Mombasa	Dadaab	54	35	54.3	47
Mombasa	Kakuma	93	86	8.1	45

As it is apparent from the table, the model can provide risk reductions only if the original contract is significantly greater than the spot market prices. If WFP manages to receive a better deal than those on the spot market, our method does not produce a sizeable reduction in risk as for Kampala and Tororo, since the main risk is caused by the low contract rates, and not by the fluctuations in the spot market prices. Interestingly, these two cities are linked to Mombasa by the Northern Corridor, which is a high traffic intercountry lane. Almost all transporters, from small family businesses to transportation companies with large fleets have experience of operating on these routes. In other words, since the competition is already high on these lanes, the market rates are regulated by the competition including WFP's rates. This high level of supply on these two routes may justify why transporters are willing to accept contracts of lower rates from a shipper with ample cargo, and thus have a job guarantee. On the other hand, the other three destinations are refugee camps with insecure roads. The demand on these lanes are mostly coming from WFP and due to rough road conditions the supply for transportation is not ample either. As a result, WFP cannot enjoy lower rates, and in addition have to deal with service unreliability. The results for those instances show that, as the motivation of our paper, our model generates higher risk reductions and ultimately, better service levels.

4.6 Concluding Remarks

Sustainable food aid transportation is an essential component of providing food security in the regions that suffer from hunger and malnutrition. Many of the leading aid organizations, including WFP, outsource their ground transportation rather than owning and managing a truck fleet. The transportation markets in developing regions, however, are characterized by a lack of transparency and structure. In this environment, the transport companies are less loyal to honoring their contracts, and often seek alternative business opportunities at the spot market – primarily due to the fuel price fluctuations and the inability of aid organizations to impose penalties when a contract is breached. The unreliability of the transporters, in turn, jeopardizes the sustainability of food aid transportation. Motivated by the challenges faced by the WFP Kenya Office, we propose a new transport contract mechanism that can provide (i) the transporters with some protection from the market fluctuations, and (ii) provide the aid organization with higher service levels than the current practice. The novelty of the proposed data-driven methodology is the adoption of barrier type options in incorporating flexibility in the transportation contracts. We calibrate the contract parameters by using real transportation spot market prices. Our numerical experiments reveal that, for high volume transport corridors, the transporters' downside risk can be reduced significantly without a sizeable increase in the associated cost incurred by the aid organization. This also undermines the need for the transporters to inflate their rate bids as a protection from price volatility.

The framework we propose in this paper is not without its limitations. Firstly, although the binomial tree we developed for the fuel prices can be easily implemented in a spreadsheet, its parameters need to be updated if there is a huge drift in the global oil market (e.g., 2008 oil crisis). Secondly, the monthly steps we use in tracking the fuel prices can be considered rough-cut, since daily or weekly tracking would certainly increase the accuracy of the binomial tree representation. Keeping the tractability in mind, however, we chose a step size that is short enough to model the prices effectively, but also long enough that yields an applicable contract-reviewing regimen for the aid organization.

Chapter 5

Food Aid Modality Selection (FAIMS) Problem

5.1 From Food Aid towards Food Assistance

Physical, or in-kind, food aid to the developing world started with the United States President Eisenhower's Food Surplus Utilization Programme in 1960. The main goal was to create a destination for the food surplus accumulated as a result of the subsidies given to the American farmers (Barrett & Maxwell, 2004). Later in 1961, a US delegation under the Kennedy administration proposed a multilateral program to share the burden of humanitarian development efforts. Since then, numerous aid agencies deliver millions of tonnes of food aid commodities to developing countries to alleviate hunger each year. Yet, there are still 815 million people who are facing hunger on a daily basis, and even more people (one third of the world population) suffers from malnutrition, as of 2018 (WFP, 2018b).

One of the major reasons of persisting hunger is that the development projects receive significantly less donations compared to disaster response efforts. Moreover, 40% to 70% of the food aid budget is spent on logistics operations (WFP, 2015). I discussed the challenges associated with WFP's food aid transportation operations in detail in the two previous chapters. These challenges are typical to the supply chain operations of other aid organizations as well given that food aid is often delivered to the most remote regions of developing countries. These logistics costs significantly drain the limited monetary resources that the aid agencies have. Another criticism towards the in-kind food aid is that it creates a dependency to the aid programs by de-incentivizing local production and further impoverishing the local producers (Moyo, 2009). All these disadvantages of in-kind food aid led to debates on better ways of providing aid. As a result, the idea of distributing aid using different modalities, other than in-kind, namely, cash and vouchers, became the center of attention in humanitarian community in the last decade.

Vouchers are coupons that are redeemable for food items at selected retailers. Instead of delivering food commodities procured internationally, vouchers are predominantly distributed in the regions, where the food is available in the local markets, but poor households do not have the resources to buy them. Aid agencies sign contracts with a selection of local retailers and the beneficiaries purchase items in these selected stores in exchange of their vouchers. There are two types of vouchers: commodity vouchers and value vouchers. Commodity vouchers indicate which types of food can be redeemed and in which quantities. Value vouchers indicate the total amount of money that can be spent in the store, but do not identify the quantities. In that case, the choice belongs to the beneficiaries. Since, the items and quantities are not determined, this second type of vouchers highly resembles the cash modality. Thus, in this chapter, I will use the term 'voucher' to signify the commodity vouchers.

Cash modality signifies the practice of distributing the local currency to the beneficiaries. Cash can be distributed in the form of banknotes, but other applications also include pre-paid bank cards, and mobile money transfers. As for the voucher distribution, food has to be available in the local markets for cash distribution to be applicable. Cash programs, however, do not require a retailer selection process since cash can be spent anywhere and in any way the beneficiary choses.

There are major advantages and disadvantages of each modality as summarized in Table 5-1 and Table 5-2. These advantages and disadvantages are established through numerous pilot studies and collective experience of humanitarian agents. Think-tanks, governments, NGOs still do not agree on the golden standards of the aid modality selection. There are numerous guidelines, decision-trees and discussion papers on this subject. Each organization prepares its own guidelines for the same problem. Pilot studies provide valuable empirical results and create credible evidence for the consequences of each modality, however, they do not provide a decision making tool for the problem of designing aid programs in different contexts with different parameters (Gentilini, 2016). The need for a mathematical model that assists decision makers during the modality selection phase of food aid programs is clear. However, this is not a trivial task. Appropriateness of either modality is extremely difficult to determine since the decision makers should take into account many factors including the program objectives, the economics of food consumption, the characteristics of the local markets, and the beneficiary preferences.

In this chapter, I incorporate all these factors and define a new problem called Food Aid Modality Selection (FAIMS)[2]. The question we address is that whether it is worthwhile to switch from the current in-kind aid distribution practices to cash or voucher-based programs for certain geographic or demographic groups, or not. To choose among different program designs, I assess the solutions of this problem not only by their incurred program costs but also their effects on the nutritional improvements of the beneficiaries and the economic contribution to the local economy. In addition, I incorporate a lower level model in the problem to realistically capture the beneficiaries' undesirable use of cash on non-nutritious items. The resulting decision-making framework is a bi-level optimization model, where the aid agency decides the amount and the modality of the aid to be distributed in the upper-level whereas the beneficiaries decide how to use the aid in the lower-level model.

[2] This abbreviation is a reference to the French word "faim", which means "hunger."

Table 5-1 Advantages of aid modalities

In-kind	**Voucher**	**Cash**
• In-kind food is usually procured from abroad, so it is applicable even if food is not available in local markets or the markets are not well functioning (i.e., delays and disruptions in the value chain, inflated market prices due to lack of competitors.) • It is the only applicable mode for drought or famine related emergency interventions. • Distributed grains are fortified with minerals and vitamins, so the nutritional values are significantly better compared to its equivalents in the local markets.	• Vouchers provide a certain level of dietary diversity by enabling beneficiaries purchase fresh food. • Since vouchers are spent in local markets, wealth is transferred to the local retailers and producers. With this modality other low-income groups (i.e., farmers, retailers) are also supported alongside the beneficiaries. • No logistics costs associated with this modality since it does not involve physical commodity distribution. • It allows verifiable data on household expenditures.	• Cash provides the ultimate freedom of choice to the beneficiaries. More popular among the receivers. • Since cash is spent in local markets, wealth is transferred to the local retailers and producers. With this modality other low-income groups (i.e., farmers, retailers) are also supported alongside the beneficiaries. • No logistics costs associated with this modality since it does not involve physical commodity distribution. • There is no need for contracting activities with local retailers unlike voucher administration.

Table 5-2 Disadvantages of aid modalities

In-kind	Voucher	Cash
• Requires effective management of complex supply chains. Overhead costs are much higher than cash or voucher distribution. • May disincentivize local food producers. • Although in-kind food is fortified, it cannot completely satisfy all nutritional needs. It should be supported with other products. • In-kind is the least preferred modality of aid by the beneficiaries.	• There should be a well-functioning market near to the beneficiaries. If there is no food available in the region, vouchers are useless. • Vouchers may put pressure on the value chains of certain commodities since beneficiaries can only spend the vouchers on certain commodities on selected markets. The availability of food distributed via vouchers may decrease, or their prices may increase. This can adversely affect both the beneficiaries and the non-beneficiaries. • Vouchers need extensive levels of vendor management. Periodic shop selection and contracting periods incur high operational costs.	• There should be a well-functioning market near to the beneficiaries. If there is no food available in the region, cash is useless. • Cash may compromise food security and nutrition related objectives due to misuse of the distributed budget on non-food or non-nutritious items. • High fixed costs and initial operational burden. Cash distribution requires financial infrastructure for effective cash distribution especially in rural areas.

Cash and vouchers can be distributed for different purposes (improving nutritional, educational outcomes, shelter, etc.) and in different contexts (poverty alleviation, disaster response, refugee settlements, etc.) and each of these settings require further considerations to be modeled. Since no other study has ever been modeled the aid selection mechanism in the operations management domain, this study serves as a first step to mathematically model the complex mechanisms associated with cash and voucher distribution and shows implications of the model in a chronic hunger response context.

The rest of this chapter is organized as follows: in Section 5.2, I provide related streams of literature. In Section 5.3, I provide a formal problem definition and its mathematical formulation. I begin by describing the beneficiary's consumption model, and then describe the aid agency's modality selection consumption problem. Together these two models constitute a bi-level optimization model. Finally, I propose a solution methodology for this problem.

5.2 Related Literature

The literature on aid modality selection can be examined within two streams: the current practices and guidelines of humanitarian agencies, and the field studies on the effectiveness of different modalities conducted by economists. To this date, there is no study published in the field of operations management that tackles with aid modality selection problem. At the end of this subsection, I also briefly refer to the multi-objective and the bi-level optimization problems in resource allocation settings at the end of this section since these streams of research are relevant to the methodology that I used.

5.2.1 Background of the Modalities

WFP, the world's first food aid humanitarian agency, was founded in early 1960s. Since then, the organization provides food aid with respect to four major aid principles: (i) food aid must be granted for the promotion of the economic and social development, (ii) agenda of development must be decided by the aid-receiving country, (iii) food aid needs to be integrated in national development programs, and (iv) use of food surplus should not endanger the balance of the national economy (FAO, 1961). Although significant efforts are performed to achieve and maintain these principles, in-kind food aid also faced many obstacles and criticisms.

Starting from the early days of WFP, contributions from donor countries can be made in the form of commodity or cash, where the latter is for covering the program operation costs. However, most of the donor countries preferred to donate food commodities rather than cash and thus, monetization of the food aid became more and more prevalent. Monetization is the sale of the in-kind food aid commodities in the local markets by the aid organizations in order to provide the needed cash for operations if the cash donations are not sufficient. Also, the cash received for the commodities was not compensating the cost of aid shipment and caused tremendous loss of efficiency (Barrett & Maxwell, 2006).

This practice generated issues such as harming the local producers by creating an influx of international commodities. For example, Del Ninno, Dorosh and Subbarao (2007) compares four food aid programs, two from Africa (Zambia and Ethiopia) and two from South Asia (India and Bangladesh). Unlike Asian countries, they observe that a disincentive to local production due to food aid is realized in African countries. The authors conclude that the countries ruled by weaker administrations who do not prioritize agricultural investments are more prone to side effects of foreign food aid.

Providing aid in the form of cash and vouchers, as an alternative to in-kind aid, received increasing attention starting from the 1990s. Earlier examples of cash and voucher distributions include consumer food subsidy programs executed by the World Bank in developing countries. Based on their experience and strengths, almost each humanitarian agency came up with their own guidelines and methods to assess the demand for aid, to investigate the situation, and to decide the most fitting modality. In the next section, we examine these practices.

5.2.2 Guidelines and Decision Trees of Aid Agencies

Initially developed for emergency responses, almost all these guidelines are based on decision trees, which are yes/no questionnaires. By answering such questions, depending on the collected data, the agency decides *the* modality that will be used in the aid program. The interested reader can view the following representative examples: European Commission (2013), Humanitarian Policy Group (Levine & Bailey, 2015), OXFAM (Cretì & Jaspers, 2006), and Market Information and Food Insecurity Response Analysis (MIFIRA) (Barrett, *et al.* 2009). WFP distinguishes the emergency (WFP, 2009) and developmental contexts (WFP, 2014a) and has two separate guidelines. Based on its own experience, WFP concluded that cash and voucher would be more efficient in transition and development contexts rather than emergency response (WFP, 2008). Indeed, the dynamics of both contexts are significantly different from each other. Here, instead of explaining them individually, we summarize the shared characteristics of the guidelines belonging to different organizations.

First of all, the decision trees are designed in a simplistic way to ease the administration and to promote effective communication between the stakeholders. Answering a number of yes/no questions certainly ensures a swift disaster response planning. Yet, for communities suffering from chronic hunger, well-planned and stable solutions are more critical. Secondly, a decision tree tends to yield a single modality solution. Figure 5-1 depicts the European Commission's decision tree as an example. Starting from the in-kind, the modality that is least dependent on the local market structure, to the most dependent one, i.e., cash, the decision tree explores whether each of the modalities are applicable or not.

If all the market conditions are viable for cash, i.e., if the decision maker can reach the bottom of the tree without ending up on another modality, cash distribution is selected. The main logic behind this approach relies on prior pilot studies, which reveal that cash interventions are more-cost effective compared to voucher and in-kind ones. Cost-effectiveness is indeed critical for NGOs who rely on modest budgets. However, this myopic approach may lead to unwanted consequences, including cash distribution even if it is not cost efficient in that specific context or it may compromise the food security of the beneficiaries due to misuse of cash.

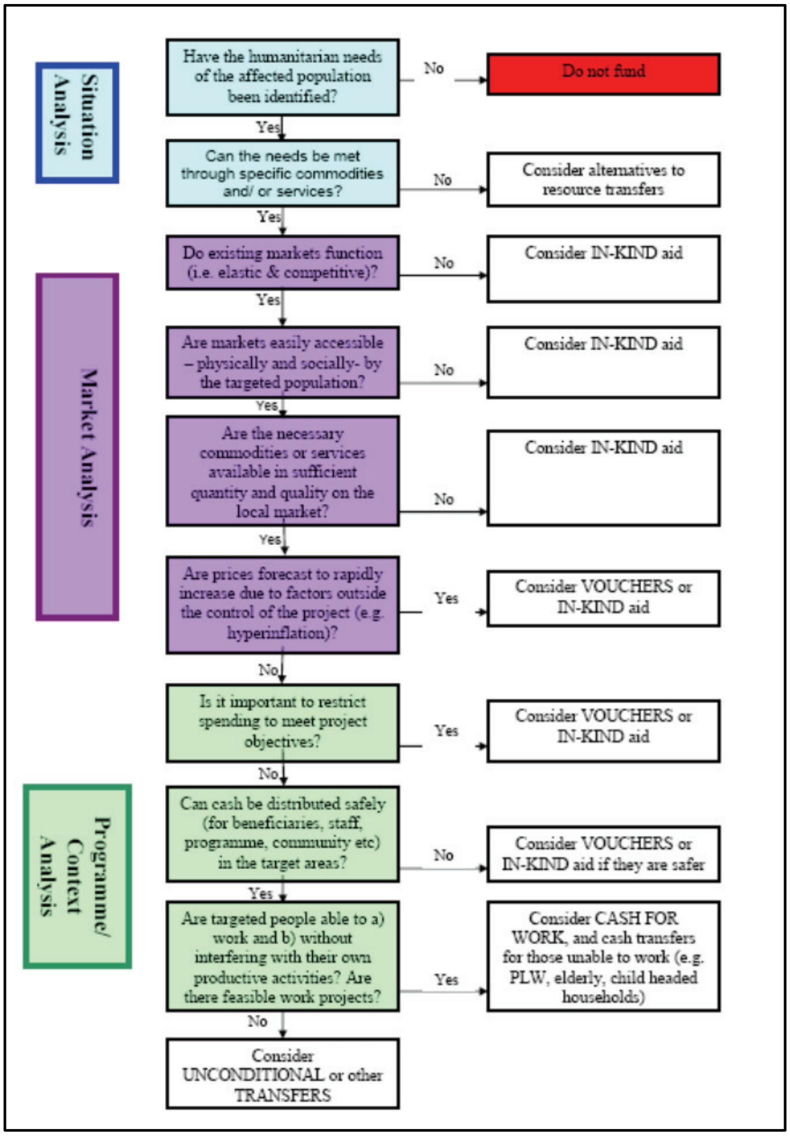


Figure 5-1 European Commission's modality selection tree
Source: (European Commission, 2013)

Emergency response efforts are usually short-term, administering multiple modalities simultaneously may not be feasible due to the required infrastructure investments (e.g., a secure cash distribution system). On the other hand, developmental aid efforts are continuing for the last four decades in certain regions of the world. Better solutions can be achieved by expanding the possible solutions with the combination of different modalities, which cannot be attained using decision trees. Another downside of such trees is that they cannot be used for *ex-ante* comparison of the modalities. In the event of a change in the surrounding environment of the program (i.e., price changes, retail market collapse, etc.), expected financial and nutritional outcomes cannot be assessed by trees. However, well-structured mathematical models can be used for such scenario analyses and complement food insecurity response plans. Referring to the discussion in Chapter 2, the resources and donations are much more restrained in development contexts in comparison to emergency response, and the development aid planning is not required to be as rapid as a sudden-onset disaster case. Thus, the decision makers can afford the time to achieve the most efficient program design over a rapid one.

5.2.3 Field Studies on Effectiveness of Cash and Vouchers

The prioritization of cash and vouchers in decision trees, as illustrated in Figure 5-1, is in line with numerous field studies conducted by economists that examine the effects of cash transfers compared to the other modalities. Save the Children (2005) lists the cash programs administered by several NGOs in different Sub-Saharan Africa countries including Kenya, South Africa, and Burundi. The study also compares four case studies conducted in Ethiopia, Lesotho, Mozambique, and Zambia. This comparative analysis reveals that cash distribution enables families to purchase more expensive, but more nutritious food such as meat. It also shows that beneficiaries prefer cash over in-kind. Das (2005) compares 13 different conditional cash transfer programs incentivizing certain outcomes such as increasing school attendance of children and decreasing child labor.

There are also single-country field studies that aim to answer the modality selection problem by randomized controlled trials. In these studies, while treatment groups receive one type of modality, the control groups receive another one, so that the outcomes of these programs can be compared. The studies in Malawi (Harnett, 2008) and Congo (Aker, 2014) favor cash distribution over the other two. They conclude that people spend the cash rationally. In addition, cash is a more favorable modality for the aid agency, given that the distribution costs are lower. According to Hidrobo *et al.* (2014), vouchers are the most cost-effective modality in terms of costs and nutritional outcomes. However, it is the least preferred modality by the beneficiaries due to the restrictions it imposes.

Despite the studies favoring cash distribution, there are also other studies that highlight the downsides of this modality. Skoufias *et al.* (2011) find that cash-only policies are not sufficient for nutritional purposes, especially in terms of micronutrients. Basu (1999) states that people are impatient and unwilling to make certain sacrifices for outcomes in distant future such as saving for children's education instead of spending the cash on non-urgent items. This study sets a scientific foundation for the belief of cash misuse, by concluding that many people lack self-control on their expenditure behaviors and tend to misuse the family assets.

5.2.4 Literature on Modelling

In this chapter, we develop an optimization model to effectively analyze the outcomes of each modality, while taking into account the pitfalls highlighted by the field studies in the previous subsection. In particular, our model includes the beneficiaries' spending priorities and their possibility of misusing the cash-based aid. The beneficiaries have freedom of choice while deciding how to utilize the cash aid since the aid agency has no control over how the beneficiaries will spend the cash, in practice. Therefore, the proposed model incorporates the beneficiary consumption behavior while planning the modalities. This sequential nature of the events can be modeled using a bi-level optimization approach, where the aid agency decides the amount and modality of the aid and then the beneficiary spend the received aid, where both the aid agency and the beneficiaries optimize their own objectives. To this extent, one study that is similar to ours is by Wang and Lootsma (1994). In that study, the authors build a resource allocation model for multiple departments, where each department maximizes their claimed gains, while the decision maker maximizes total profits.

Although bi-level optimization problems have a wide domain of applications including congestion management, energy production, and hazmat transportation, its applications are rather limited in humanitarian logistics domain. Only a recent paper by Camacho-Vallejo *et al.* (2015), address the international aid planning problem in a post disaster setting, where the international community minimizes the response time and the local government minimizes the cost of delivering the aid to the affected communities. We believe that humanitarian logistics can be a fruitful application sector for bi-level problems since the aid efforts almost always fall under a similar hierarchical structure, i.e., the coordinating body being the leader and the coordinated actors (e.g., beneficiaries and other organizations) being the followers. One concern about this approach can be the challenging nature of optimally solving bi-level problems. Yet, there are numerous exact and heuristic algorithms proposed as solution methodologies (Bard, 1998; Dempe, 2002).

Bi-level problems are successful at addressing problems among two parties with conflicting objectives. In this case, it is straightforward to establish the objective of the beneficiaries. As human beings, our spending choices are determined by the utility that we derive from consumption of certain items. Conversely, the objective of the aid agency is not always obvious. Although the cost minimization is a common objective among all humanitarian players who are funded by the donations exclusively, Holguín-Veras *et al.* (2013) argue that addressing complex humanitarian logistics problems without comprehensive objective functions is unproductive. Efficient allocation of limited resources in the existence of conflicting goals of different stakeholders can be achieved with the adoption of social welfare cost functions rather than solely focusing on cost-effectiveness. In this sense, the dynamic aid allocation model among multiple receiving countries by Carter *et al.* (2015) is a good example of weighted social welfare functions. In this problem, I will also consider the welfare of involved stakeholders: the aid agency (cost objective), the beneficiaries (nutritional objective), and the non-beneficiaries (economical contribution) living in the same community with beneficiaries. As a result, Food Aid Modality Selection Problem is modeled as a bi-level, multi-objective optimization problem.

5.3 Food Aid Modality Selection (FAIMS) Problem

In this section, I summarize the concepts used to build the beneficiaries' household expenditure model and provide the decision model of the beneficiaries in Section 5.3.1. In Section 5.3.2, I describe the aid agency's problem by discussing the different components of the model: constraints, objective function and parameters. Finally, in Section 5.3.3, I formulate the Food Aid Modality Selection (FAIMS) Problem as a bi-level optimization problem where the aid agency is the leader and the beneficiaries are the followers.

5.3.1 Incorporating Beneficiary Behavior in the FAIMS model

The problem presented in this chapter is the strategic decision of determining the aid modality and amount of the aid that should be provided to different beneficiary groups during the aid program. Once the modalities are decided and provided to the beneficiaries, the beneficiaries need to decide how to use the received aid. If the beneficiary receives only in-kind or voucher aid, this problem becomes trivial, since it has no other choice but to consume them. In the case of cash distribution, however, beneficiaries decide on which commodities they spend their cash and the aid organization has no power to alter that decision. Thus, the organization has to consider the beneficiaries' expenditure patterns while choosing the modalities. We formulate this sequential nature of the events with a bi-level optimization model: leader's (upper level) model for the aid agency and follower's (lower level) model for beneficiaries.

Modelling geographically and demographically dispersed beneficiaries with preferential differences is not a trivial task. One of the major concerns related with cash distribution within the humanitarian community is the possibility of misuse of cash by beneficiaries (Heaslip, Haavisto, & Kovács, 2016). Distributing cash provides an ultimate freedom to the beneficiaries, so that the cash can be spent for non-nutritious food items (e.g., beverages and sweet pastries), non-food needs (e.g., clothing and shelter), and even for leisure purposes (e.g., celebrations and visits). Although some of these spending patterns may be perceived as more beneficial for the community then certain others, from the aid organization's perspective, every dollar that is not spent on nutritious food is a waste. Therefore, the aid organization should be cautious about the risk of misuse before opting for the cash modality.

Defining the exact expenditure pattern of beneficiaries *a priori* is a challenging task. Nevertheless, consumer theory models can be very helpful to provide insights on such patterns. Neoclassical consumer theory assumes that households' objective is to maximize their utility. The utility is realized by the consumption of the purchased items and services subject to the budget at hand. The main assumption at the heart of this theory is that the individuals are rational and fully capable of understanding their utility and maximize it with respect to their budget (Felder, 1988). Most of the household utility models consider the cases where the households already have sufficient budgets to satisfy all of their basic needs (food, shelter, etc.). However, extremely poor households have not even reached to the first step of Maslow's hierarchy, i.e., physiological need for food. Thus, in their decision model, the beneficiaries seek for satiation as observed in the field study by Jensen and Miller (2010). They study the consumption patterns of the extremely poor households in China and found that the beneficiaries consume sufficient number of calories in order to achieve a certain subsistence level. In their study, the subjects maximize their utility subject to this subsistence calorie constraints. I incorporate this idea in our beneficiary model.

Including each commodity available in the market to the beneficiary problem may lead an intractable model. Yet, we can group these commodities based on the observed commonalities in beneficiary diets. Firstly, extremely poor households under strict budget constraints highly rely on diets that consist of staple foods or ***basic foods*** such as bread, potato, maize, rice, etc., (Food and Agriculture Organization (FAO), 1995). Basic foods are usually rich in carbohydrates that supply plenty of calories to survive, but also cheaper than other nutrition sources such as meat and dairy. The basic food itself may depend on the availability and geography, but the existence and significance of it in the households' diets remain unchanged. Common basic food examples are: rice in Asia, maize in Africa wheat in middle east. Unfortunately, basic foods lack many micronutrients and they should be supported with other food groups such as vegetables and meat in an adequate diet. These more nutritious food groups are also perceived tastier by the consumers. This brings us to the second observation: when poor households observe an increase in their incomes, they do not put their whole budget in staple food to get more calories. Instead, they favor better-tasting but more expensive options keeping their overall calorie intake constant (Subramanian & Deaton, 1996), indicating a higher utility is associated with such ***tasty food***. Finally, we introduce a third group to the item set, namely ***temptation food***, to model possible beneficiary expenditure on non-nutritious items that provide high levels of taste such as coffee, tea, soda, and desserts. Ignoring such expenditures in a model that involves cash distribution will fall short in capturing the spending patterns. Many studies specifically look into the cash donation expenditures on alcohol or tobacco and many successfully rule out those two items as a major source of expenditure. Yet, there is still a vast literature on how extremely poor beneficiaries spend significant shares of the household income on weddings, religious celebrations, or other social activities that make life more enjoyable for themselves (Banerjee & Duflo, 2012). Even among the food options, one may be tempted to purchase unhealthy, non-nutritious goods. As George Orwell (1958) pinpointed in his autobiography:

> *"[…] when you are underfed, harassed, bored and miserable, you don't want to eat dull wholesome food, you want something a little bit tasty. There is always some cheaply pleasant thing to tempt you"* (95-96).

Larsen (2015) provides further information on the sociological mechanisms behind the consumption of unhealthy food in low socioeconomic classes. From a social point of view, the expenditure on weddings or sugary pastries may be more acceptable compared to alcohol or tobacco consumption. However, from the aid agency's point of view, any amount of cash that is spent on a non-nutritious item is undesired since it brings extra cost without contributing to the program's objective.

5.3.2 Beneficiary's Perspective (lower level model)

The beneficiary's problem can be defined as the allocation of the household budget among these three groups of food in order to maximize their utility while respecting the calorie consumption constraint. In the sequence of events, the beneficiary's problem (follower) takes place after the aid agency's decision (leader). However, the agency needs to take into account beneficiary's perspective while choosing the modality to administer. This is why the beneficiary's model appear as a lower level problem in aid agency's model. In other words, the aid agency decides the amount of in-kind, voucher and cash to be distributed, while the beneficiary is the one who decides the consumption levels for the three food types.

I have already mentioned that tasty food provides higher utility to the beneficiaries. However, such a relationship is not as clear for the temptation food. Some households tend to spend their budget on these items, while others may prefer tasty food over temptation food. We model the households by distinguishing them based on their preferences (or utility functions). Let $h \in \{1, \dots, |H|\}$ be different household types, which have different preference relationships over the food items $I = \{1{:}\, basic\, food,\ 2{:}\, tasty\, food\,, 3{:}\, temptation\, food\}$. These preferences may be affected by spatial factors (e.g., living near a water body or in an arid land, local culture etc.) or the gender of the household leader (female headed vs male headed) (Gentilini, 2007). Beneficiaries are also geographically dispersed. Each beneficiary settlement region $r \in \{1, \dots, |R|\}$, may differ in terms of the cost of delivering the aid, the availability of food, the prices of the food types in the adjacent food markets, etc. In a region *r,* we assume that all the beneficiaries living in a household type *h,* which have a total population of π_{hr}, receive the same type of modality.

Typically, in-kind food aid consists of basic food (i.e., grains) since it is high in calories and durable. Unlike in-kind aid, cash and vouchers can be distributed for all three types of commodities. Therefore, in the FAIMS model there is a decision variable for each modality representing the amount of modality distributed to all households of type *h,* residing in region r; x_{hr}, for in-kind basic food aid, y_{hri}, for voucher aid for commodity $i \in I$; and z_{hr} for cash aid. These three vectors are decision variables in the bi-level FAIMS model; however, they are parameters to the lower-level beneficiary model. Given a certain amount of aid (x_{hr}, y_{hri}, z_{hr}), the households h living in region r will choose their consumption levels of each food type i, q_{hri}. They will directly consume the in-kind and voucher aid to satisfy their calorie constraint, and purchase and consume items of price p_{ri} with the cash aid. At the end they will derive a utility ϕ_{hri} for each unit of consumption of item i.

The model below represents the beneficiaries' problem, where the aid distribution amounts are given as parameters by the program:

Sets

H	Set of household types (differentiated by their taste vectors)
I	Set of food types
R	Set of regions

Parameters

x_{hr}	Amount of distributed food aid in-kind to household h in region r
y_{hri}	Amount of distributed food aid voucher of item i to household h in region r
z_{hr}	Amount of cash distributed to household h in region r
ϕ_{hri}	Taste acquired by unit consumption of item i by household h in region r
Θ	Minimum calorie intake that a person needs to maintain a healthy life
θ_i	Calories acquired by unit consumption of item i
π_{hr}	Total population in household h in region r
p_{ri}	Price of item i in the adjacent market to region r

Decision variable

q_{hri}	Consumption of item i by household h residing in region r

Model 1: Beneficiary's Consumption Problem

$$max\, f(q_{hri}) = \sum_{i\in I}\sum_{h\in H}\sum_{r\in R} \phi_{hri} q_{hri} \tag{5.1}$$

s.t.

$$\sum_{i\in I} \theta_i q_{hri} \geq \Theta \pi_{hr} \qquad \forall h \in H, \forall r \in R \tag{5.2}$$

$$q_{hr1} \geq y_{hr1} + x_{hr} \qquad \forall h \in H, \forall r \in R \tag{5.3}$$

$$q_{hr2} \geq y_{hr2} \qquad \forall h \in H, \forall r \in R \tag{5.4}$$

$$q_{hr3} \geq y_{hr3} \qquad \forall h \in H, \forall r \in R \tag{5.5}$$

$$p_{r1}(q_{hr1} - y_{hr1} - x_{hr}) + p_{r2}(q_{hr2} - y_{hr2}) + p_{r3}(q_{hr3} - y_{hr3}) \leq z_{hr} \quad \forall h \in H, \forall r \in R \tag{5.6}$$

$$q_{hri} \geq 0 \qquad \forall i \in I, \forall h \in H, \forall r \in R \tag{5.7}$$

The optimal solution of Model 1 represents the consumption bundles of food commodities that maximize the total utility derived by each household type in every region. Once the beneficiaries receive the aid, their first priority is to achieve sufficient calorie intake level[3] to maintain daily activities. This intake level is denoted by Θ and is defined per person. Constraints (5.2) ensure that the total calories acquired by the consumed food items are sufficient for the total calorie requirement of the households. Constraints (5.3) ensure that basic food provided in the form of voucher and in-kind is consumed by the household. Similarly, constraints (5.4) and (5.5) ensure that tasty and temptation food provided by vouchers is consumed. Note that, these two types of food cannot be provided in-kind. Constraints (5.6) ensure that the consumption levels of beneficiaries cannot exceed the amount of aid provided. Constraints (5.7) are non-negativity constraints.

[3] Although expecting the beneficiaries to know the exact calorie amounts of the goods that they consume in order to satisfy the calorie subsistence constraint may seem unrealistic, human beings can understand if they have consumed sufficient calories or not. Unless a person consumes sufficient calories, their blood sugar will not increase to a level that triggers a hormonal feedback mechanism, and they will experience the feeling of hunger (Douglas & Peggy W., 2006).

5.3.3 Aid Agency Perspective (upper level model)

The previous model formulates the integration of the beneficiary's perspective to the FAIMS model. In that lower-level model, the aid program modalities and their amounts (i.e., x, y, and z vectors) appears as parameters. However, these are the decision variables of the aid agency's upper-level model. In this subsection, I explain the aid agency's constraints and objective functions to decide these aid program modalities and provide the formulation of the overall bi-level FAIMS model.

5.3.3.1 Assumptions and Constraints

In a food aid program, the agency's main goal is to provide sufficient food to each household for them to sustain a healthy lifestyle. Sufficiency of the food aid is determined by the contained calories in the food aid commodities. Regardless of the modality, the first constraint of the agency is to provide the aid that is sufficient to satisfy the caloric intake needs.

Another consideration is related with voucher distribution in relatively isolated markets. Vouchers are valid only for a selected group of items in selected stores. As a result, there can be disruptions on the value chain of voucher-admissible commodities. When the beneficiaries use the vouchers, the prices can spike due to limited supply and harm the non-beneficiaries or even worse, these commodities may stock-out and harm both groups. To prevent this, vouchers redeemed from a single market should be limited so that the market prices or availabilities are not affected adversely (Gentilini, 2007).

5.3.3.2 Social Welfare Function

As suggested by Holguín-Veras *et al.* (2013), humanitarian logistics problems provide more inclusive solutions if they choose to integrate a social welfare objective instead of a simplistic cost minimization one. Indeed, this holistic approach is one of the major factors that distinguish humanitarian agents from the private sector. All donation-based food agencies aim to minimize their costs; however, they also need to incorporate the benefits of the other stakeholders affected directly and indirectly: the beneficiaries and the actors in the local markets (non-beneficiaries). As a result, the agency has to consider three objective functions: minimizing program costs, maximizing the nutritional state of the beneficiaries, and maximizing the economic contribution of the program to the local economies for continuing development.

Total program costs include fixed costs required to build or maintain the infrastructure needed for the modality distribution, and variable costs (i.e., operational costs and commodity costs). In addition, the agency needs to design an aid program that eventually leads to adequate nutritional outcomes. The beneficiaries may not aim to achieve the best nutritional conditions for themselves, mostly due to lack of knowledge. However, a thorough food aid design should deliver not only sufficient calories but also certain vital micronutrients (i.e. vitamins and minerals). Lack of certain micronutrients, i.e., micronutrient deficiencies, cause serious illnesses and deaths that lead to additional malnutrition treatment costs on local governments and international humanitarian community. With the help of a well-designed food aid program these micronutrients can be provided before the malnutrition related illnesses emerge. Therefore, ***improved nutrition of the beneficiaries*** due to the aid program signifies the contribution of the program to the overall social welfare from beneficiary's well-being perspective. The third component of the social welfare function captures the ***contribution of the aid program to the local economy,*** i.e., to the food producers and retailers residing in the same region with beneficiaries. Internationally procured in-kind aid has been long criticized for de-incentivizing the local producers and making countries dependent on further aid and resulting in a vicious cycle (Moyo, 2009). Implementation of cash and voucher programs can effectively overcome this handicap since provided money will be spent on the commodities harvested and distributed by the local agents (Taylor *et al.*, 2016). Such programs help the aid recipient country, not only by alleviating the beneficiaries from hunger, but also by empowering the low-income local producers with an influx of income. Our model incorporates all these three perspectives by means of a multi-criteria objective function.

5.3.3.3 Additional Parameters and Decision Variables

Parameters

In the previous two subsections we have conceptually explained the constraints and the objective function of the FAIMS model. Now, we explain the parameters needed to formulate this problem.

Cost Parameters

Let G be the set of modalities, $g \in G = \{$*1: in-kind, 2: voucher, 3: cash*$\}$. There are two cost components associated with each type of modality g: fixed costs (C_{0g}) and variable costs (C_{rg}). The fixed costs represent the initial investments required for implementation in the program country. Thus, the fixed costs are paid if there exists at least one household being served by the program with that modality. For in-kind (C_{01}), fixed costs include warehouse rents, staff costs, etc. For vouchers (C_{02}), this component includes the staff costs incurred while finding reliable retailers in the markets, signing contracts and performing regular visits in order to prevent disruptions and fraud. For cash (C_{03}), these costs are incurred by the contracts signed between the cash delivery provider (mobile money operators, banks, government safety net programs, etc.) and the aid agency.

Variable costs are required for each unit of aid to be distributed and may depend on the region. Variable costs associated with in-kind aid are the procurement, storage, handling and transportation operations costs (C_{r1}). Voucher variable costs include printing and distribution costs to households (C_{r2}). But, the major part of voucher-related costs come from the actual payments made to the retailers in exchange of redeemed vouchers. For the cash modality, a commission (C_{r3}) is paid to the cash provider per transaction.

Market Parameters

In rural contexts, the food markets are not geographically widespread. Usually, they are located near major roads or population center and there is not always a market in each region r. However, for cash and vouchers are to be distributed, there should be a market that is close enough to the beneficiaries. Usually, beneficiaries need to travel to the nearest market, $m \in \{1, \dots, |M|\}$.

Cash and voucher distribution costs may differ, especially if the commodity prices are fluctuating across markets. As a result, our model tracks the commodity costs by market (p_{mi}). Let β_{rm} be a binary parameter that denotes whether the market m is the closest one to the beneficiaries in region r or not. Using a data preprocessing procedure, one can define the commodity prices in a region as $p_{ri} = \beta_{rm}\, p_{mi}$. As explained previously, one of the major drawbacks of voucher distribution is the extra pressure they put on certain supply chains. Since the aid organizations contract with limited number of retailers for a limited number of items in each region, the demand of these commodities spike in such markets and cause food shortages threatening the overall population (κ_m) receiving service from that market (both beneficiaries and non-beneficiaries). To avoid this, a cap over the proportion of beneficiaries within the total population receiving service from a single market (Π) should be introduced. The final parameter associated with the markets is the economic contribution generated as a spill-over effect (Λ) of the money spent in the local markets via cash and vouchers.

Nutrition Parameters

Nutrition parameters are integrated to our model to measure the nutritional benefits of the program. The beneficiary's model already takes into account the calorie intake requirement of the beneficiaries. However, consumption of certain vitamins and minerals on a regular basis are also required for adequate nutrition. Absence of these nutrients has serious effects on physical well-being of the beneficiaries, including retardation of physical and mental development, chronic illnesses, reduced productivity, and eventually death. If malnutrition is not prevented or treated early, the burden of the health system increases disproportionately. Considering that countries experiencing prevalent malnutrition are already dealing with impoverishment, this response efforts may eventually be escalated to the international humanitarian community's attention and may require more costly interventions. By keeping track of the nutrient deficiency alleviated with the help of a food aid program, one can estimate the future savings from costs of the malnutrition treatment via supplements, medicines, and eventually hospitalization or loss of human capital caused by death (Shaw, 2011).

Let $k \in \{1, \ldots, |K|\}$ be the set of micronutrients. If a person ingests sufficient amount of a certain micronutrient ($\boldsymbol{\Theta}_k$) from consuming food commodities (i.e., $\sum_{i \in I} \theta_{ik}$) through the aid program, that nutrient related malnutrition is prevented, and provides future savings from supplement programs, medical costs or human capital losses (τ_k).

Decision Variables

The quantity of each modality distributed, which appear as a parameter in the beneficiary's (lower-level) problem, is a decision variable in the aid agency's (upper-level) problem. Recall that, for in-kind (x_{hr}) and voucher (y_{hri}) distribution, we define continuous variables that represent the tonnage of the food aid distributed to household type h in region r. Similarly, cash distribution variable (z_{hr}) represents the money distributed to the beneficiaries. The quantity of each food item consumed by households (q_{hri}) is defined in the beneficiary's problem as well. In addition, we define a binary variable (s_{hrk}) signaling whether a nutrient k is adequately consumed by each household in each region or not. Finally, binary variables for modality g (o_g) are defined to account the fixed cost components in the objective function.

5.3.3.4 Aid Agency's model

In this subsection, I present the bi-level mixed integer model formulation of FAIMS, that includes both levels. For the ease of exposition, I provide the full notation below.

Sets

H	Set of household types, H={1, ..., $\|H\|$}
I	Set of food types, I={1:basic, 2: tasty, 3: temptation}
R	Set of regions, R={1, ..., $\|R\|$}
M	Set of markets, M={1, ..., $\|M\|$}
K	Set of micronutrients K={1:calories, ..., $\|K\|$}

G	Set of modalities, G={1: in-kind, 2: commodity voucher, 3: cash}

Parameters

Cost Parameters

C_{0g}	Annual fixed costs associated with modality g
C_{rg}	Variable costs associated with modality g distribution in region r

Market Parameters

p_{mi}	Price of item i in market m
β_{rm}	1, if market m is the closest market to region r; 0, otherwise.
p_{ri}	Price of item i in region r
κ_m	Total population that receives service from market m
Π	Percent of beneficiaries to the total population that can receive service from a single market
Λ	Additional spill-over effect in the community that one dollar spent in the local economy

Nutrition Parameters

θ_{ik}	Level of nutrient k in one unit of item i
Θ_k	Daily consumption requirement of nutrient k intake
τ_k	Nutrient k deficiency related cost savings per person

Other Parameters

T	Planning horizon in days
L	Sufficiently large number
α,β,γ	Weights of objective function components, $\alpha+\beta+\gamma = 1$

Decision Variables

Continuous Variables

x_{hr}	In-kind food-aid distributed to all households of type h in region r
y_{hri}	Voucher of item i distributed to all households of type h in region r
z_{hr}	Cash aid distributed to all households of type h in region r
q_{hri}	Total consumption of item i by all households of type h in region r

Binary Variables

s_{hrk}	1, if households of type h in region r satisfied nutrient requirement k; 0, otherwise.

v_{hr} 1, if vouchers are distributed to the households type h in region r; 0, otherwise.

o_g 1, if modality g is distributed within the aid program; 0, otherwise.

Model 2: FAIMS model: the aid agency's problem

Upper Level:

$$\begin{aligned}\max \quad & \alpha\left(\sum_{h\in H}\sum_{r\in R}\sum_{k\in K}\pi_{hr}\tau_k s_{hrk}\right)+\\ & \beta\left((1+\Lambda)\left(\sum_{h\in H}\sum_{r\in R}\sum_{i\in I}y_{hri}p_{ri}+\sum_{h\in H}\sum_{r\in R}z_{hr}\right)\right)-\\ & \gamma\left(\sum_{g\in G}C_{0g}o_g+\left(\sum_{r\in R}\sum_{h\in H}C_{r1}x_{hr}+C_{r2}\left(\sum_{i\epsilon I}y_{hri}\right)+C_{r3}z_{hr}\right)\right)\end{aligned} \tag{5.8}$$

s.t.

$$\theta_{11}\left(x_{hr}+\frac{z_{hr}}{p_{r1}}\right)+\sum_{i\in I}\theta_{i1}y_{hr1} \geq T\,\Theta_1\pi_{hr} \qquad \forall h\in H,\forall r\in R \tag{5.9}$$

$$\sum_{i\in I}\theta_{ik}q_{hri}-T\,\Theta_{\mathrm{k}}\,\pi_{hr}\leq L\,s_{hrk} \qquad \forall h\in H,\forall r\in R,\forall k\in K \tag{5.10}$$

$$T\,\Theta_{\mathrm{k}}\,\pi_{hr}-\sum_{i\in I}\theta_{ik}q_{hri}\leq L(1-s_{hrk}) \qquad \forall h\in H,\forall r\in R,\forall k\in K \tag{5.11}$$

$$x_{hr}\leq L\,o_1 \qquad \forall h\in H,\forall r\in R \tag{5.12}$$

$$y_{hri}\leq L\,o_2 \qquad \forall i\in I,\forall h\in H,\forall r\in R \tag{5.13}$$

$$z_{hr}\leq L\,o_3 \qquad \forall h\in H,\forall r\in R \tag{5.14}$$

$$\sum_{i\in I}y_{hri}\leq L\,v_{hr} \qquad \forall h\in H,\forall r\in R \tag{5.15}$$

$$\sum_{h\in H}\sum_{r\in R}\beta_{rm}\pi_{hr}v_{hr}\leq \Pi\kappa_m \qquad \forall m\in M \tag{5.16}$$

$$x_{hr},y_{hri},z_{hr}\geq 0 \qquad \forall i\in I,\forall h\in H,\forall r\in R \tag{5.17}$$

$$s_{hrk},o_g,v_{hr}\in\{0,1\} \qquad \forall h\in H,\forall r\in R,\forall g\in G,\forall k\in K \tag{5.18}$$

Lower Level:

(5.1), (5.2), (5.3), (5.4), (5.5), (5.6), (5.7)

The first component of the objective function measures the improvements in the nutrition of the population in terms of the averted future losses due to increased health care burden and human capital loss (henceforth, objective 1). If a household type *h,* residing in region *r*, consumes sufficient amount of nutrient *k* ($s_{irk}=1$), then the malnutrition that may arise in the future will be averted by the population of that household. The second component measures the total contribution of the aid program to the local economy (henceforth, objective 2). Contrary to the in-kind distribution, the aid distributed in the form of cash and vouchers are spent in local markets. This helps to improve the livelihoods of local farmers and retailers with a factor of ($1+\Lambda$), since one dollar spent in the local economy may create a spill-over effect in the market and the actual effect can be greater than one dollar (FAO, 2016). Finally, the third component measures the total fixed and variable costs of the aid program (henceforth, objective 3). First two components of the objective function are maximized whereas the cost component is minimized.

Constraints (5.9) ensure that each household receives sufficient aid, regardless of the modality, to be able to satisfy their calorie consumption constraints (5.2) in the lower level model. In other words, this constraint reinforces the mandate of the aid agency, and also prevents the lower-level model from being infeasible. Constraints (5.10) and (5.11) together count if the households are consuming sufficient micronutrients or not. Constraints (5.12), (5.13), and (5.14) trigger the fixed costs associated with in-kind, voucher and cash distribution, respectively. Constraints (5.15) and (5.16) limit the number of people that can receive service via vouchers from a single market. Constraints (5.17) and (5.18) define the domain of the variables.

The lower-level beneficiary model (i.e., constraints (5.1) - (5.7)) is a part of the upper-level model constraints, however it is a standalone optimization model by itself with an objective function (equation (5.1)). Therefore, every feasible upper-level solution is required to be an optimal solution for the lower-level model. Solving bi-level problems are often difficult and require special algorithms such as double penalty function methods, rectangular partitioning and sub-gradient decent methods (Bard, 1998). However, in many cases, exploiting the special features of the problem can enable a simpler solution strategy. In our problem, the lower level beneficiary problem is a linear problem. As described by Bard (1998), we can construct Karush-Kuhn-Tucker (KKT) optimality conditions of this lower level problem and add these new conditions to the upper-level problem. With these optimality conditions, any feasible solution to the bi-level model will be optimal for the lower level model. Thus, we do not need to write the objective function of the lower level model. As a result, this transformation yields a new single-level problem that is equivalent to the original one.

One can transform the lower-level model to its optimality KKT conditions, namely primal feasibility, dual feasibility and complementary slackness conditions. Let $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$ be the dual variable vectors for constraints (5.2) and (5.6), respectively. Also let, $\boldsymbol{\gamma}_i$ be the dual vector of consumption constraints (5.3), (5.4), and (5.5) of each item in $i \in \{1,2,3\}$, respectively. Then, the complementary slackness conditions of these constraints in Model 1 are as follows:

$$\lambda_{hr}\left(\Theta\pi_{hr} - \sum_{i\in I}\theta_i q_{hri}\right) = 0 \qquad \forall h \in H, \forall r \in R \tag{5.19}$$

$$\gamma_{hr1}(y_{hr1} + x_{hr} - q_{hr1}) = 0 \qquad \forall h \in H, \forall r \in R \tag{5.20}$$

$$\gamma_{hr2}(y_{hr2} - q_{hr2}) = 0 \qquad \forall h \in H, \forall r \in R \tag{5.21}$$

$$\gamma_{hr3}(y_{hr3} - q_{hr3}) = 0 \qquad \forall h \in H, \forall r \in R \tag{5.22}$$

$$\mu_{hr}\Big(z_{hr} - \big(p_{r1}(q_{hr1} - y_{hr1} - x_{hr}) + p_{r2}(q_{hr2} - y_{hr2}) + p_{r3}(q_{hr3} - y_{hr3})\big)\Big) = 0 \qquad \forall h \in H, \forall r \in R \tag{5.23}$$

And the dual feasibility condition is as follows:

$$\lambda_{hr}\theta_{i1} - \mu_{hr}p_{ri} + \gamma_{hri} + \phi_{hri} = 0 \qquad \forall h \in H, \forall r \in R, \forall i \in I \tag{5.24}$$

Note that, the complementary slackness conditions (equations (5.19) - (5.23)) are non-linear. However, as suggested by Fortuny-Amat and McCarl (1981), a constraint in the form of $ab = 0$ can be linearized by replacing them with the following two expressions: $a \leq$

$Lw, b \leq L(1-w)$, where L is a sufficiently large number and w is a binary variable. Let us define such binary variable vectors $w_{hr}^1, w_{hr}^2, w_{hr}^3, w_{hr}^4, w_{hr}^5$ for these five constraints ((5.19) - (5.23)), respectively. The linearization procedure generates two linear inequalities per for each non-linear constraint. As an example, the linear inequalities for constraint (5.19) is as follows.

$$\lambda_{hr} \leq L\, w_{hr}^1 \qquad \forall h \in H, \forall r \in R \tag{5.19'}$$

$$\Theta\pi_{hr} - \sum_{i \in I} \theta_i q_{hri} \leq L(1 - w_{hr}^1) \qquad \forall h \in H, \forall r \in R \tag{5.19''}$$

Given that w_{hr}^1 is a vector of binary variables, the left-hand side of at least one of the inequalities above should be equal to zero with this linearization, as intended by the non-linear equation (5.19). If we apply this procedure on the remaining complementary slackness equations ((5.20) - (5.23)), we again obtain two linear inequalities per one non-linear equation: (5.20'), (5.20''), (5.21'), (5.21''), (5.22'), (5.22''), (5.23'), and (5.23''). Now we can express the bi-level FAIMS model as a single-level mixed integer problem.

Model 3: Single-level representation of the FAIMS problem

max (5.8)

s.t.

(5.9) – (5.18)

(5.1) – (5.7)

(5.24)

(5.19'), (5.19''), (5.20'), (5.20''), (5.21'), (5.21''), (5.22'), (5.22''), (5.23'), (5.23'')

Chapter 6

Modality Selection for WFP: Program and Policy Evaluation

In this chapter, I demonstrate the potential use of the FAIMS model for both food aid program design and policy evaluation purposes using the actual program data from WFP Kenya. In Section 6.1, I summarize food aid operations in the world and in Kenya. In Section 6.2, I describe the data set that belongs to Garissa region. In Section 6.3, I demonstrate how the FAIMS model can be used for program design purposes and compare the results with WFPs current operations. In Section 6.4, I evaluate food aid program improvement policies using FAIMS model.

6.1 Cash and Voucher Operations of WFP

Starting from its earlier days of foundation, WFP built expertise in food aid transportation and logistics practices, so that it can move large amounts of in-kind food aid in short period of times efficiently. As a result, WFP can provide food in the most remote regions of the world within a short time span. Each year WFP reaches 80 million people in 80 countries with food assistance in emergencies and working with communities to improve nutrition and fight against chronic hunger. WFP distributes 12.6 billion rations which require more than 2 million metric tons of food purchased annually (WFP, n.d.-c).

The discussion over cash and voucher use in humanitarian assistance gained momentum in the mid-1990s. On the other hand, WFP Board approved the policy named "Vouchers and

Cash Transfers as Food Assistance Instruments: Opportunities and Challenges" in October 2008. Since then, WFP's use of cash and vouchers has increased considerably. Over the period 2008–2013 implementation of these modalities increased steadily; by 2013 actual expenditure on cash and vouchers totaled US $507 million, implemented in 52 countries (WFP Office of Evaluation, 2014, p.7). While the Syrian regional response accounts for a significant portion of recent growth of cash and voucher use (61% of the total cash and voucher budget), even without this operation the overall growth is significant, as shown in Figure 6-1. The trend continues steadily in 2017, WFP provided US $1.3 billion in cash transfers worldwide, up from US $880 million the previous year (WFP, n.d.-a).

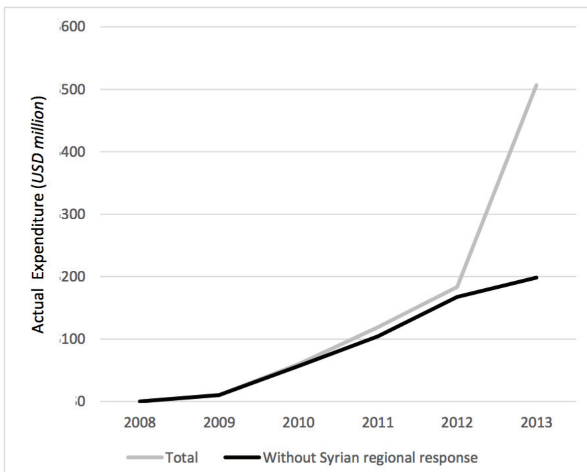


Figure 6-1 Total cash aid expenditure of WFP between 2008 - 2013

However, WFP's transition to cash and voucher programs in East and Central Africa region lagged behind the other regions. In Kenya, where WFP's ECA headquarters are located, poverty and hunger are ever-lasting problems: 47% of the population lives below the poverty line. A quarter of the children are stunted, meaning they are short and underweight for their ages. If untreated at early ages, this condition leads to disabilities for the rest their lives. 80% of the country lands is either arid or semi-arid and not quite suitable for farming and agriculture. The population residing in these regions is especially prone to food insecurity. Working with Kenyan government, WFP provides aid to the food insecure households under three different programs: Country Program, General Food Distribution Program, Food Assistance for Refugees. WFP Kenya office ships more than 350,000 tonnes of food commodities per year, among which 200,000 tonnes are distributed within the General Food Distribution Program (WFP, 2015). WFP Kenya office would like to shift from in-kind food distribution to cash-based assistance and eventually graduate the beneficiaries from these programs (WFP, n.d.-b). According to their strategic plans, Kenya Office aims to distribute 9% of the food aid distribution through cash modality by the end of the 2018 (WFP, 2015).

Increased amounts of cash and voucher distribution within WFP programs let the organization to gain knowledge on better implementation of these modalities. In a recent report by the internal evaluation office of WFP, it is recommended (WFP Office of Evaluation, 2014, pp 52-56):

- To further develop WFP's critical cash and voucher tools and supporting systems to better enable effective and efficient project implementation.
- To develop robust monitoring and evaluation and financial accounting platforms to systematically track cash and voucher specific costs, inputs, outputs, outcomes and implications within a framework that facilitates comparison among all modalities over time, across countries and across project/activity types.
- To continue to invest in the cash and voucher policy framework – directives, guidance and tools – with emphasis on communicating practical implementation guidance that clarifies expected outcomes, indicators and benchmarks.

The FAIMS model that we developed would be beneficial in addressing these recommendations. In the phase of scaling up the cash and voucher practices, this model would save substantial amount of planning time as well as resources by preventing cash and voucher implementation in regions where such programs would not be efficient. We believe our model fits WFP's current aid delivery practices seamlessly. In particular, Figure 6-2 shows the current modality selection process of WFP. In this figure, it is shown that in Stage

1, the total need for food assistance is determined by the needs assessment process. Then, each aid modality is assessed in terms of management, programme, supply chain, finance and IT and security perspectives in Stage 2. Finally, in stage 3, the aid modality is chosen among the modalities that are found to be eligible in the previous stage based on internal and external consultations. Our model complements this process impeccably by constructing a methodological bridge between the determination of the feasible modalities and the selection of the transfer modality.

In this chapter, we demonstrate how the FAIMS model can be used by WFP both for program design and for policy evaluation purposes. For this, we select the Garissa county of Kenya as a pilot for three reasons. First, WFP already initiated a cash program in Dadaab refugee camp, which is in this region. This allows us to estimate cash and voucher costs more realistically. Second, Garissa destinations are one of the least favorite ones among the transporters due to security and road quality concerns. As a result, retracting the in-kind operations would be beneficial for WFP. And finally, in this county, there are numerous markets within an acceptable distance to the beneficiary settlements making Garissa a good candidate for cash and voucher distribution. The rest of this chapter is organized as follows. In Section 6.2, we explain how we estimate the parameters used in the model in detail. In Section 6.3, and 6.4 we demonstrate how the model can be used for food aid program design and policy evaluation purposes.

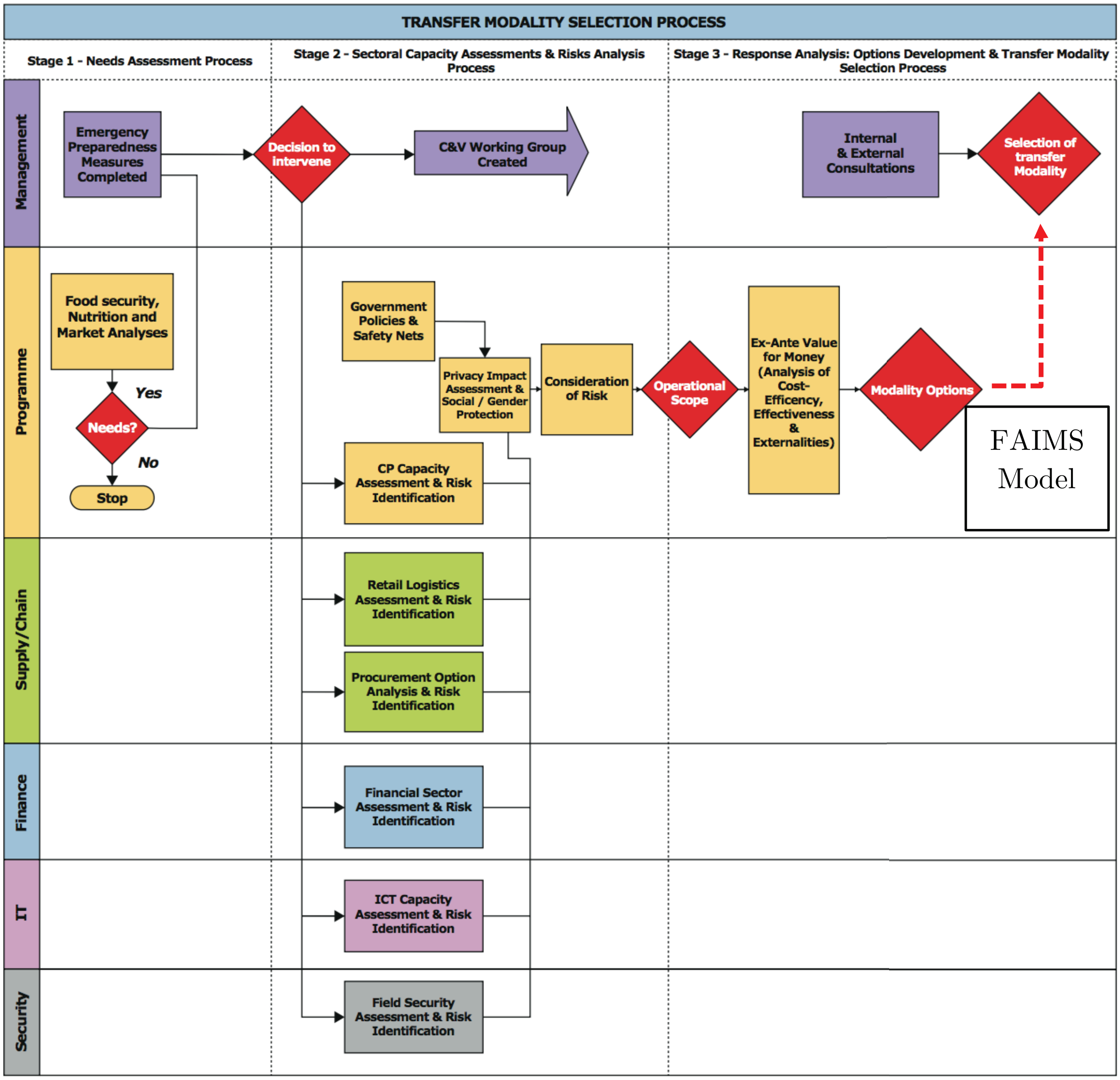


Figure 6-2 Food Aid Modality Selection Process of WFP (WFP, 2014a)

6.2 Data Description

In this section, I explain the data set used to validate our model and to conduct further experiments to demonstrate the use of our model. Data is gathered directly from WFP Kenya logistics office as well as other reports that are available online in WFP's database. I start with the parameters needed in the lower-level beneficiary model, then I explain the market network in Garissa and provide relevant parameters with economic contribution objective.

Finally, I explain in detail the measures used in nutrition and cost objectives of the model. The amount and the complexity required in the parameter estimation process for a realistic program design is tremendous; I explain this process in detail in the subsequent chapter.

6.2.1 Beneficiary Data

Garissa is one of the Kenya counties that WFP operates large scale operations. This county not only hosts the world's second largest refugee camp (Dadaab Camp, Population: 245,000), but also is the home of 623,000 people, 47.2% of which live below poverty line (Commission on Revenue Allocation, 2011). As a result, WFP provides food aid to these poor households under different aid programs. Figure 6-3 shows the location of the Garissa county on the map of Kenya.

Figure 6-3 Garissa county on the map of Kenya

As explained in Chapter 3, WFP delivers food to the beneficiaries through final delivery points (FDPs) that are temporary structures built in the rural lands, close to beneficiaries' villages. These structures are only active on the day of the aid distribution. On that day beneficiaries walk to the FDPs, and collect their rations. Since these FDP locations were initially chosen in a way that is close to the beneficiaries (Rancourt *et al.*, 2015), I clustered the beneficiaries around these FDPs, and divided the county into regions accordingly ($r \in R$). For this I used the data provided by WFP: the coordinates and the number of beneficiaries receiving service of each FDP. In Figure 6-4, grey dots mark the locations of

FDPs, thus the center of the regions. WFP has $|R| = 82$ such FDPs in Garissa county, serving a total number of beneficiaries equal to 138,097.

Other than dividing the regions, I also need to group the beneficiaries by their household types, $h \in H$. Introducing the types of households allows us to differentiate the taste functions of the households so that the cash spending behaviors of beneficiaries can be modeled realistically. In a study, which is conducted as a feasibility analysis for cash and voucher-based interventions, WFP determines the types and the prevalence of households in arid parts of Kenya (WFP, 2013). Table 6-1 shows the types of households in Garissa region, their composition and the average number of people residing in each type of household.

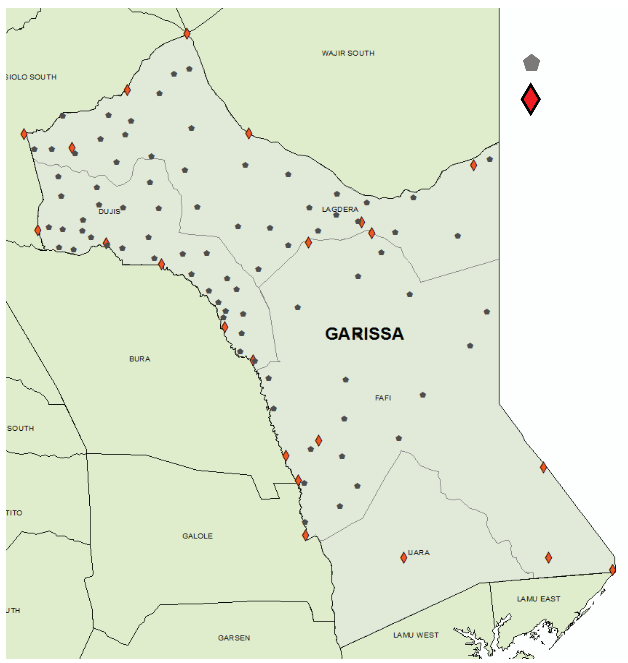


Figure 6-4 FDP locations and markets of Garissa

According to this data, there are three household types (i.e, $H = \{$1: male-headed polygamous households, 2: male-headed monogamous households, 3: female headed households$\}$) that people reside in. WFP's beneficiary data already provides how many beneficiaries are living in a region. With these percentages, we can distribute the beneficiaries to the household types and estimate how many people are living in that region, r, within a certain type of household, h, i.e., π_{hr}.

Table 6-1 Household statistics of the Garissa county

Household Types	Percentage	Average Population
Male headed polygamous HH	40	15
Male headed monogamous HH	35	8
Female/orphan headed HH	24	7

Once the household types and regions are established, we can define utility functions for each group. In the lower-level beneficiary model, the beneficiaries need to choose among three types of items $i \in \{1\text{: basic food, 2: tasty food, 3: temptation food}\}$ based on the utility that they derive ϕ_{ihr} by those items. As previously explained in Section 5.3.1, it is established in the literature that tasty food provides higher utility than basic food, so $\phi_{1hr} < \phi_{2hr}$, for all h and r values. On the other hand, temptation good can be different from household to household so as the utility derived by its consumption. Therefore, estimating the preference relationship between the temptation items over the tasty food is rather challenging.

In order to determine the taste values regarding the temptation item, we benefit the same cash and voucher feasibility report. In that study, WFP investigates the expenditure preferences of different types of households. Figure 6-5 shows how female and males would spend a hypothetical cash assistance. It is important to note that, this study includes both beneficiaries and non-beneficiaries. Thus, there is a number of non-food items in the list. But, we can still derive conclusions about the taste vectors of the beneficiaries. First of all, the break-down of the preferences is not by the household type, but by the gender of the household leader. A general rule confirmed by a large number of focus groups is that, in principle, men can decide to purchase goods without consulting their partner(s), while women have to consult their husband, even if the cash assistance is provided to the female in a male headed household. With this regard, in our model I assume the decision maker are men in male-headed households (both polygamous and monogamous) and women in the female-headed households. Both for men and women, food is the highest priority, however, food is much more important for women than men. Almost all female headed households below poverty line reported that food is their priority. It is however noteworthy that men, unlike women, have a number of “unproductive” spending priorities. Alcohol or miraa (a type of plant-based drug), is a priority for men in this region that is only exceeded by food.

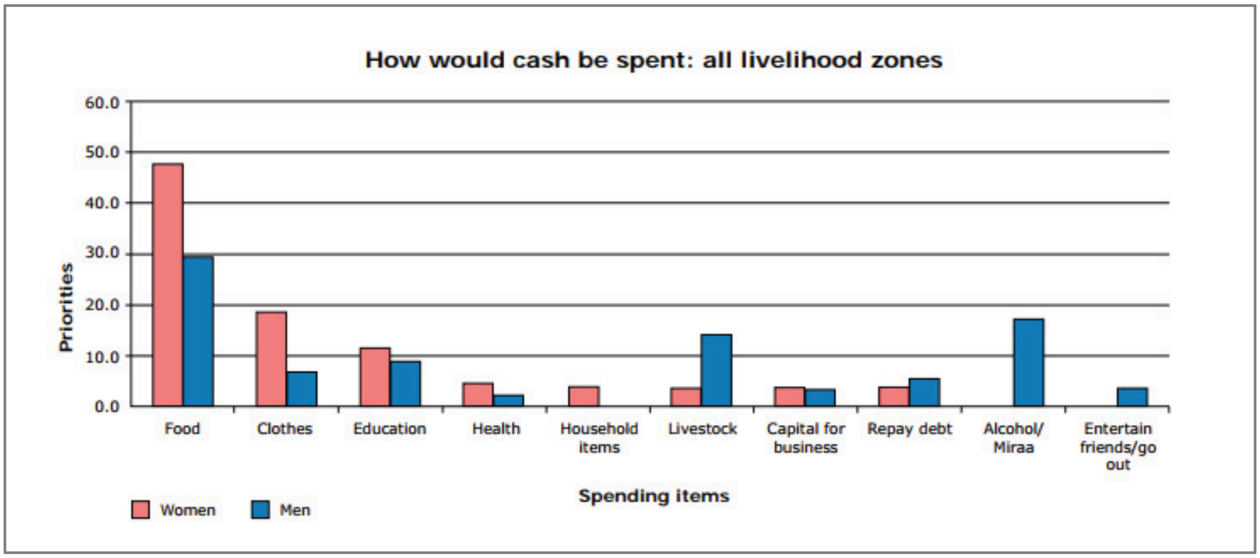


Figure 6-5 Spending priorities of female and male headed households after a hypothetical cash assistance

Note that, this expenditure preferences is quite similar to the model suggested by Jensen and Miller (2010), which we base our model on. Extremely poor households spend their money on cheap food commodities until they reach a subsistence level, then they spend the rest of their money over other items. Therefore, prioritization of the basic food items by both male and female headed households is reflected with the calorie requirement constraint. If we increase the cash aid slightly over the subsistence level, as Subramanian and Deaton (1996) established, beneficiaries consume tastier but more expensive calorie resources (i.e, tasty food), while their calorie consumption levels remain the same. On the other hand, there is a risk of spending the cash on a temptation item such as alcohol or miraa by male headed households, as these items are their second priority and can be accessed easily in food retailers at the time of shopping. It is important to note that we are not claiming all male households would spend the rest of their money unproductively once they receive a cash increase. However, from a modelling perspective we believe it is important to design a program conservatively by taking into account the risk of unproductive spending as this already concerns the donors and aid agencies, especially if there is evidence for such a behavior. It is also important to note that, due to desirability bias the survey responders may not have reflected their true spending intentions transparently. In fact, the actual tendency of misspending can be even higher. Based on these arguments, we model the preference relationship between items for male-headed households (h= 1 or 2) as: $\phi_{3hr} > \phi_{2hr} > \phi_{1hr}$, and for female-headed households (h=3) $\phi_{2hr} > \phi_{3hr} > \phi_{1hr}$.

So far, we have only established the ordinal utilities of each item using their cash spending priorities. Determining ordinal utilities is not sufficient since we need the cardinal values of ϕ_{ihr} in order to solve the lower level model. Luckily, in this case the lower level model has a linear knapsack problem type of structure, that is, the beneficiary wants to maximize their profit subject to budget. It is well established in the literature that; the optimal solution of such problems is purchasing the item with the one that has the highest taste over unit price ratio (ϕ_{ihr} / p_{ir}). As long as we choose taste values that yield ratios reflecting the household's preference rankings, the actual values need not to be precisely determined. Yet, we still need to choose ϕ_{ihr} values that matches the taste over price ratios with the ordinal values of the taste vectors. For this we first need to estimate the p_{ir} parameters, which are provided in the next subsection.

6.2.2 Market Parameters

As we explained in the previous chapter, not all beneficiary regions, r, coincide with a food market. Food markets are mostly located alongside the transportation corridors, yet, there exists a few of them in remote regions as well. Figure 6-4 shows the location of 22 markets on the Garissa map. Their coordinates are provided by WFP. In their cash and voucher feasibility analysis, WFP has established that the maximum distance that should be traveled by beneficiaries for market shopping is 30 kilometers. The beneficiaries living outside of this range should not be considered for cash or voucher distribution. As a result, we have excluded the beneficiary regions which are not within a 30 km radius of any market. This yielded a set of 68 beneficiary regions that are eligible for cash and voucher. Then, we assigned each region, r, to its closest market, m, using the geographical information system (GIS) data, so that we can define the parameter, β_{rm} is equal to 1, if region r is assigned to market m. After these assignments we have established the following summary statistics shown in Table 6-2 Summary statistics of the Garissa instance:

Table 6-2 Summary statistics of the Garissa instance

Total # of beneficiaries		112,402
# of beneficiaries per region	Min	100
	Avg	1,653
	Max	5,629
Total # of eligible regions		68
Total # of markets		22
Region distance to market (km)	Min	0.73
	Avg	14.67
	Max	28.96

Depending on their connectedness to the transportation network, the market prices of the commodities (p_{rm}) are changing. WFP divides the markets into five categories depending on their closeness to the transport corridors (on corridor, off corridor) and to the center of the county (main, remote), which also hosts WFP's headquarters. Table 6-3 shows the breakdown of the 22 markets in our data set in these categories.

Table 6-3 Breakdown on markets located in Garissa

Market Categories	Number
District Headquarter (HQ)	1
Main market on transport corridor (TC)	3
Main market off transport corridor	1
Remote market on transport corridor	3
Remote market off transport corridor	14
TOTAL	22
Total population served by these markets	623,600

Figure 6-6 shows two examples of such markets:

Figure 6-6 Two example markets: Remote market off TC (left), Main market on TC (right)

In the cash and voucher feasibility report WFP lists the market prices of certain commodities in these different types of markets. These commodities include: Maize flour, beans, rice, potatoes, tomatoes, goat meat, sugary products. Among these we chose representative items for each type of commodity represented in our model. As the basic food (i=1), maize flour is chosen since it is also distributed by WFP in their in-kind donations. For the tasty food (i=2), we have chosen goat meat, as it is the major source of animal protein in this region. For the temptation good (i=3), the alcohol prices are not listed in the market analysis, as a substitute we have chosen sugary products. They are also listed as temptation goods in other contexts since such products do not contribute to the nutrition of the household. The listed prices of the commodities, p_{im} are listed in Table 6-4:

Table 6-4 Commodity prices of three representative items for each food group in different markets

Market Type	Maize (US $)	Meat (US $)	Sugar (US $)
District HQ	0.88	4.82	1.41
Main Market on TC	0.85	4.29	1.47
Main Market off TC	0.90	3.85	1.50
Remote Market on TC	0.95	4.33	1.54
Remote Market off TC	1.04	3.90	1.70

Now, we can estimate the p_{ir} values as the multiplication of p_{im} and β_{rm}. In addition, we can also estimate the taste vectors ϕ_{ihr} of beneficiaries. Any taste vector that would satisfy $\frac{\phi_{3hr}}{p_{3r}} > \frac{\phi_{2hr}}{p_{2r}} > \frac{\phi_{1hr}}{p_{1r}}$ for male-headed households (h=1 or 2) and $\frac{\phi_{2hr}}{p_{2r}} > \frac{\phi_{3hr}}{p_{3r}} > \frac{\phi_{1hr}}{p_{1r}}$ for female-headed households (h=3) would yield the same results, so we arbitrarily choose the following weights shown in Table 6-5.

Table 6-5 Utilities of each representative commodity for different household types

Household type	Basic (i=1)	Tasty (i=2)	Temptation(i=3)
Male-headed (h=1,2)	1	10	20
Female-headed (h=3)	1	10	5

Another market-related parameter is the proportion (Π) of the population that can be served with vouchers through each market (κ_m), as modeled in Constraint (5.16). For this, we have gathered the sub-county populations from the GIS online database, this sub-county borders can be seen in Figure 6-4. Then, assuming the population is evenly distributed around the markets, we divided the population of the sub-county to the number of markets located in there to roughly estimate the population receiving service from that market (κ_m). The proportion of the population that can be served via vouchers may change depending on how strongly connected the markets to the food commodity supply chain. As a rule of thumb in a cash and voucher guideline developed collaboratively by a number of food assistance organizations including USAID, CARE, Mercy Corps and World Vision, it is suggested that maximum number of beneficiaries receiving voucher support should not exceed 20% of the total population in the market service zone (Barrett *et al.*, 2009). In our analyses, we used this benchmark as the Π value.

Finally, we need to estimate the contribution of the cash and vouchers to the local economy (Λ). Cash and vouchers create a spill-over effect mostly on non-beneficiaries especially on food producers and retailers. In other words, this effect measures how much the food aid program indirectly contributes to the non-beneficiaries who also have low or middle income. These spill-overs emanate from the general-equilibrium effects of such aid programs on geographically isolated rural economies. Due to this isolation, it is tractable how much contribution is generated for each dollar spent in the local market through cash or vouchers. In a study by FAO (2016), which examines the economic impact of cash transfer on the local economy, data belong to previous cash aid programs is collected from seven African countries and the additional spill-over effect generated by these programs are estimated. Figure 6-7 shows the results of this study. According to these results, each dollar spend in the local market creates and additional \$0.23 (Λ) of impact in the local economy in Garissa region.

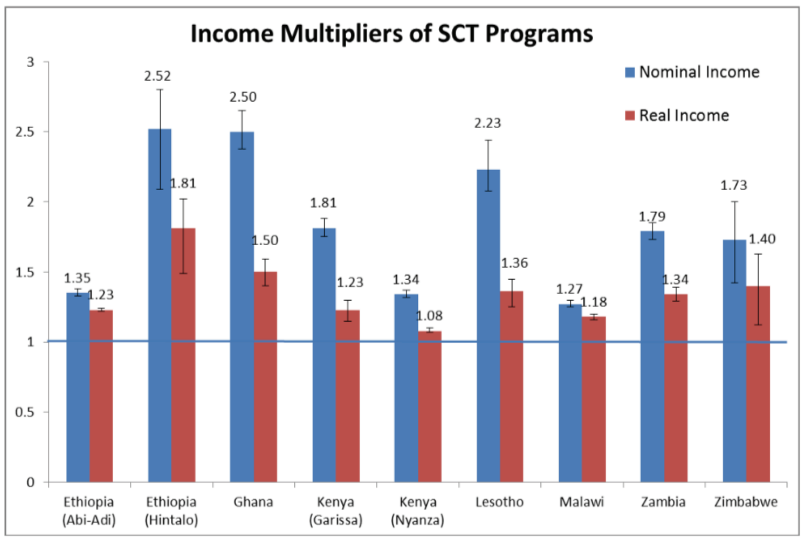


Figure 6-7 Economic impact of cash transfers on the local economy for each dollar transferred

6.2.3 Nutrition Parameters

In this section, I explain how we estimate nutrition related parameters θ_{ik}, Θ_k and τ_k. These parameters help our model to measure the nutritional outcome of the designed food aid program. By consuming different food items, beneficiaries ingest different nutrients $k \in K$. When the nutrient intake satisfies the suggested level in health guidelines Θ_k, the beneficiaries achieve a well-being state and the effects of malnutrition on country's economy through healthcare expenditures and human capital loss is alleviated, τ_k.

WFP aims to prevent malnutrition via fortified food distribution. The commodities distributed via WFP are treated to contain higher level of vitamins and minerals. If beneficiaries become malnourished acutely due to inadequate food intake, then they can be supported via nutrient supplements. However, nutrient supplements are less cost effective compared to fortified food consumption. Eventually, if disabilities cannot be avoided by the food aid program or the supplements, the country has to pay treatment costs (τ_k) as well as indirect costs associated with productivity losses due to nutrient deficiencies (Horton, 2006).

There are two major types of malnutrition: macronutrient (protein-calorie) deficiencies, and micronutrient deficiencies. The most common micronutrient deficiencies in Sub-Saharan Africa (SSA) are vitamin A, Iron, Iodine and Zinc deficiencies. Micronutrient deficiencies constitute a disproportionate disease burden on health care systems of low-income countries. SSA with 11% of the world's population accounts for more than half of the deaths due to deficiencies of vitamin A, iron, zinc, and iodine (Caulfield, *et al.* 2006; Ezzati *et al.*, 2006).

Health risk statistics for each condition and for each country are available via Global Burden of Disease (GBD) Database[4]. In Kenya, child wasting, a child development problem caused by malnutrition is the second highest ranking health risk as shown in Figure 6-8. Iron deficiency and vitamin A deficiency is also among the highest 20 risk factors for the population. A closer look at nutritional risks reveals that the main challenge remains as the simplest form of malnutrition: insufficient calorie intake causing child wasting, stunting, or simply being underweight. Iron deficiency ranks second with a steep increase in the last two decades. Vitamin A and zinc deficiencies are also contributing to nutrition-related risk factors. In our analysis, we exclude the remaining two factors: non-exclusive breastfeeding of infants and discontinued breastfeeding. Although malnutrition may indirectly affect these two behaviors, the direct link is not clear.

[4] GBD Data is available to the researchers and can be downloaded from the Institute of Health Metrics and Evaluation`s Global Health Data Exchange Platform (GHDx). This platform not only provides the Disability Adjusted Life Years (DALYs) but also mortality, life expectancy rates and risk factor estimates for global, regional and country-levels. (Institute for Health Metrics and Evaluation (IHME), 2016).

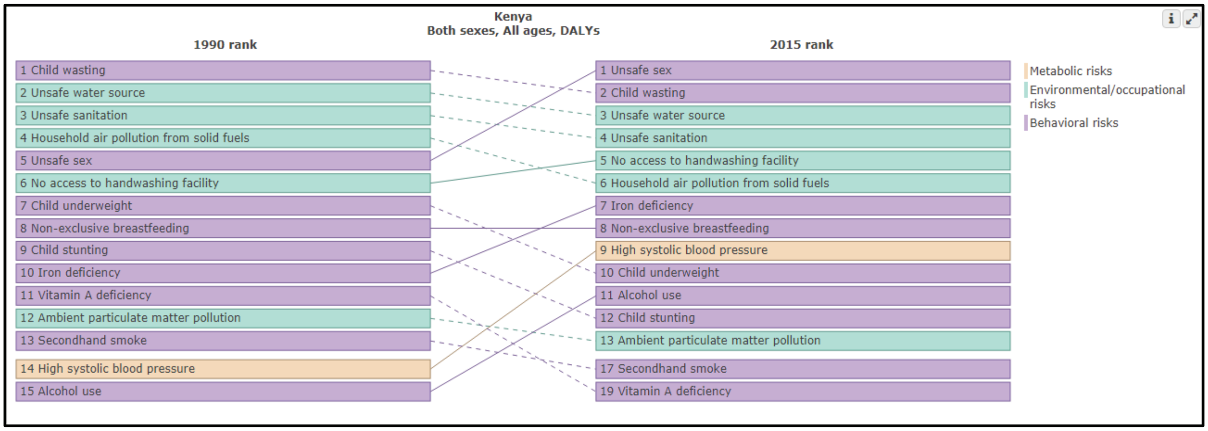


Figure 6-8 Major health risk factors in Kenya ranked by total DALYs

While a minimum calorie intake requirement covers wasting, underweight and stunting; the iron, vitamin A, and zinc deficiencies need to be modeled separately. In FAIMS model these nutrients are represented as $K = \{1\text{: calories, 2: vitamin A, 3: iron, 4: zinc}\}$ and daily nutrient requirements are modeled as Θ_k. In addition, the nutrient k level in food i, is represented as θ_{ik}. These two parameters are estimated in accordance to a food aid nutrition calculator developed by University of London Institute for Child Health for WFP. This tool named NutVal (NutVal 4.1 Ration Calculator, 2014) is used to calculate and compare nutrition values of different rations for different household compositions. The nutritional values (θ_{ik}) of the food items used in our model and daily requirements are listed Table 6-6. We have listed both WFP's fortified maize flour and the most common form of maize available in the local markets since the beneficiaries would consume the latter if they purchase the basic food via cash or voucher.

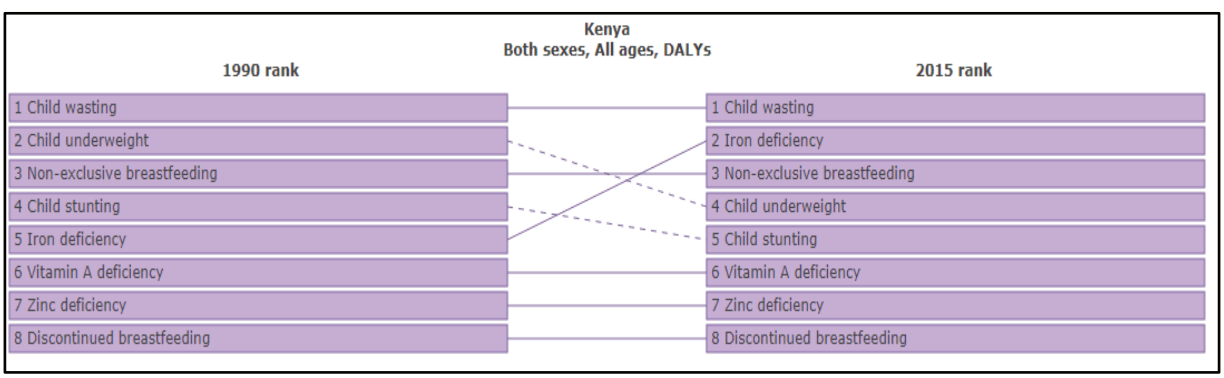


Figure 6-9 Major nutritional risk factors in Kenya

Table 6-6 Nutrient values (θ_{ik}) of fortified and regular maize meal and goat meat in 1000g and daily requirements for the nutrients (Θ_k)

Source: (NutVal 4.1 Ration Calculator, 2014)

Nutrients (in 1000 g)	Maize meal (WFP)	Maize meal (regular)	Goat meat[5]	Daily Requirement
Calories (kcal)	3700	3700	1116	2100
Vitamin A (µg)	1648	110	4968	550
Iron (mg)	26	11	30.4	32
Zinc (mg)	37.2	6.6	40	12.4

Note that constraints (5.10) and (5.11) in the FAIMS model account the nutrient satisfaction via the binary variable, s_{hrk}. Given that the nutritional values of the WFP's maize and the local maize is different these constraints need to be updated as follows, where θ_{0k} represents the nutritional values of WFP's fortified maize flour:

$$\sum_{i \in I} \theta_{ik} q_{hri} + x_{hr}(\theta_{0k} - \theta_{1k}) - T\,\Theta_k\,\pi_{hr} \leq L\,s_{hrk} \qquad \forall h \in H, \forall r \in R, \forall k \in K \qquad (5.10)$$

$$T\,\Theta_k\,\pi_{hr} - \sum_{i \in I} \theta_{ik} q_{hri} + x_{hr}(\theta_{0k} - \theta_{1k}) \leq L\,(1 - s_{hrk}) \qquad \forall h \in H, \forall r \in R, \forall k \in K \qquad (5.11)$$

Now, we need to estimate the avoided malnutrition treatment costs as a result of WFP's aid program (τ_k) using the current malnutrition statistics of Kenya. One way to accurately reflect the effect of a food aid program on nutrition is accounting the disability adjusted life-years (DALYs) caused by nutrition deficiency. DALY is a concept developed by World Health Organization (WHO) and is widely used in cost-effectiveness analyses of different treatments (Edejer, 2003). One DALY is considered as one lost year of a healthy life. The DALY caused by a condition is calculated as the summation of the years of life lost due to premature mortality and the years lost due to disability. In other words, this metric counts the extra years could have been lived (depending on the country`s life expectancy) and the

[5] For the goat meat calculations, we used a composition of 900 g. of raw meat and 100 g. of raw goat liver as they are commonly sold together in butcheries.

years could have been lived without the disability in the absence of that condition. Each condition has a different weight between 0 (healthy) and 1 (dead). For example, caloric deficiencies have a disability weight of 0.053, whereas diabetes has 0.015. Multiplying these weights with the life expectancy gives the years with disability.

The DALY contribution of the nutrition related risk factors and their shares in Kenya's total risk factors are as shown in Table 6-7:

Table 6-7 DALY contribution of each risk factor in Kenya

Risk Factor	Total Daly Loss ($DALY_k$)	Share
Wasting	1564108	7.96%
Underweight	466505.9	2.38%
Stunting	313613.9	1.60%
Iron Deficiency	677243.8	3.43%
Vitamin A Deficiency	144568.3	0.74%
Zinc Deficiency	78670.85	0.40%

As explained previously, the first three groups of deficiency are linked to the calorie deficiency, so we have combined the DALY losses of these three conditions. The latter three, the micronutrient deficiencies, are modeled on their own. In the existence of the subnational or regional data, WFP can directly use the number of nutrient-deficient population. In our case, I have access to nation-level aggregated DALY data only. So, here is how we estimated the total DALYs saved per household. Given that the people who are victims of malnutrition are the extreme poor, we divide the total number of DALYs of caused by a certain nutrient, k, deficiency, represented as $DALY_k$ to the number of people living in the bottom 20% of the wealth group who are classified as extreme poor ($pop_{<20}$) to figure out the DALY burden of an individual. Then, we multiply this number with the cost of treating that deficiency (tr_k). This is an intuitive definition since the treatment costs are usually reported as the money spent per DALYs saved in cost effectiveness analyses of different treatments in the literature. The resulting figure provides an estimate of τ_k, the avoided malnutrition treatment cost for nutrient k per person. Treatment costs, $tr_{k,}$ are highly dependent to the local context and the available treatments. Different cost-effectiveness analyses on malnutrition treatment in Sub-Saharan Africa provides a wide range of cost saving of $26 to $1344 per DALY averted (Bachmann, 2010; Puett *et al.*, 2013). Instead, I used a benchmark approach. According to a World Bank report (1993), a treatment in low and middle income countries is considered as "attractive" in terms of cost-effectiveness, if it costs less than $150/DALY averted. Shillcutt *et al.* (2009) suggests that this figure needs to be adjusted by inflation frequently. In our analysis, I have converted $150 of 1993 to 2016 dollars and obtained $250/DALY and used this value for all nutrient treatments.

$$\tau_k = \frac{DALY_k tr_k}{pop_{<20}} \tag{6.1}$$

6.2.4 Cost Parameters

In this subsection, I explain which cost structures emanated from a possible cash and voucher program for general food distribution in Garissa as well as the current cost structure for in-kind distribution. For cash, I based my analysis on current cash interventions of WFP for refugees. For vouchers, Iused the data from a voucher distribution program in Garissa operated by Action Against Hunger.

6.2.4.1 In-kind

WFP Kenya office operates in the region for the last couple of decades and mainly focuses on in-kind distribution. Thus, the infrastructure required for in-kind distribution is already operational and the costs associated with the initial investments can be considered as sunk costs. As explained in Chapter 4, WFP pays transportation costs per metric tonne, and no other fixed costs are associated with these operations. Similarly, WFP dynamically arranges its storage capacity numerous times throughout the year and achieves almost a pay-per-tonnage cost for this component as well. As a result, I can calculate an overall cost estimate per metric tonne in-kind aid distributed.

A brief summary of the in-kind food aid operations until it reaches its beneficiary and the costs associated with each step is as follows: WFP procures food commodities or receives donations and packages them mostly outside of the donor country (procurement costs), then transport the food to the Mombasa port (external transportation). The food is stored in this hub, or in other hubs (storage and handling costs). Finally, it is transported to the Garissa EDP (primary transport costs) and then to the FDPs (secondary transport costs). Meanwhile, the staff overseeing these operations incur operational costs. These cost components derived from WFP's reports and logistics office are listed in Table 6-8:

Table 6-8 Cost components of in-kind aid distribution by WFP in Garissa, Kenya

Cost component	
Procurement cost	\$323.1/tonne
External transportation cost	\$75.4/tonne
Storage and handling cost	\$177/tonne
Operational costs	\$142.6/tonne
Primary transportation	\$48.4/tonne
Secondary transportation	\$6.83/tonne if distance <10km
	\$0.28/tonne/km if distance >10km

6.2.4.2 Cash

Cash can be distributed via different mechanisms, however in Kenya the main cash transfer medium is M-Pesa, a mobile money transfer system. It allows users to deposit, withdraw and transfer money in exchange of goods and services through a mobile device with SMS (Saylor, 2012). The user does not need a cell-phone for a payment, but just a SIM card, as long as the retailer owns a cell-phone to complete the transaction. Although the Western World is getting accustomed to mobile payment with the development of smart phones, Kenya's M-Pesa is initiated in 2007 via Safaricom, country's largest mobile provider. As of 2014, M-Pesa transactions accounted for KSh 2.1 trillion, half of the Kenya's GDP (Safaricom, 2016). In short, M-Pesa is a branchless banking device, which gives an opportunity to people for the inclusion in financial service who do not have a bank account. A study examining the long-term effects of the system find that M-Pesa lifted 2% of extremely poor households out of poverty just by including them in financial services (Suri & Jack, 2016). The effects are more drastic among female-headed households: their food consumption levels increased more in comparison to the male-headed households and 185,000 women are transferred from farming activities to better-paying business occupations, mostly retailing the goods of their own production.

Existence of M-Pesa enables WFP to operate cash distribution in a substantially cheaper manner in comparison to other developing countries lacking a cash distribution infrastructure. WFP already started to distribute cash aid in cooperation with M-Pesa starting from 2015 in Kakuma and Dadaab refugee camps under the program called Bamba Chakula[6]. Beneficiaries in the refugee camps started to receive 10% worth of their in-kind rations as cash via M-Pesa accounts, in 2016 it is increased to 50% of the aid packages (WFP, 2016). Follow-up reports revealed that 97% of the beneficiaries redeemed their cash accounts regularly. SIM cards to access these services are provided by Safaricom to the beneficiaries, other than that the transactions cost 1%-3% of the cash transfer values (The Complementarity Initiative & World Food Programme, 2015). In our analysis, we assumed a similar program design is possible for the beneficiaries, with no fixed costs (SIM cards are provided by the Safaricom) and the transaction variable cost of cash aid is on average 2%.

6.2.4.3 Voucher

Cash and voucher programs of WFP Kenya office mostly refers to the mobile money distributions within refugee camps, however, WFP does not currently have a commodity voucher program *per se* operated in Kenya. As a result, I used cost data belonging to Action Against Hunger, another NGO that operates voucher programs in Garissa region assuming the cost structure would be similar to WFP's potential voucher program.

Voucher fixed costs incurred by program employees that are dispatched to the field. The employees need to find reliable retailers, sign contracts with them and perform frequent visits in order to make sure the program carries on smoothly. Unlike cash or in-kind distribution, if problems arise with contracted-retailers, the beneficiaries remain hungry. Also, it is possible

[6] Bamba Chakula means "Get your food" in Swahili.

that retailers may provide lower quantities than the face-value of vouchers, or exchange vouchers with unauthorized items (WFP, 2014a). This practice is forbidden in the contracts of WFP and the beneficiaries are warned against such practices. However, prevention of these behaviors requires meticulous monitoring efforts involving frequent retailer visits, thus higher operational costs.

On the other hand, variable costs associated with vouchers are less straight-forward compared to cash distribution. First of all, vouchers should be printed and distributed to each household. Then, each retailer accepting vouchers receives payments from WFP at the end of each month. Therefore, vouchers incur printing costs per household and payment transaction costs per market. Table 6-9 shows these costs reported in an external evaluation of the voucher program by Action Against Hunger (Dunn, 2009):

Table 6-9 Cost components of voucher distribution by Action Against Hunger in Garissa, Kenya

Cost component	
Operational costs (contracting & monitoring)	\$124138/market/year
Voucher printing cost	\$0.23/voucher
Market payment transaction cost	\$6.30/market/month

6.3 Program Design

As we described in Section 5.3.3.2, the model takes into account three different objectives: maximizing ***avoided malnutrition treatment costs*** (beneficiaries' perspective, objective 1 with weight α), maximizing ***contribution of the aid program to the local economy*** (non-beneficiaries' perspective, objective 2 with weight β), and minimizing ***program costs*** (WFP's perspective, objective 3 with weight γ). The first two represent the overall ***contribution of the program to the community*** within the host country, and the combination of all three objectives represents the ***total social welfare*** generated by the program. The FAIMS model with accurate weights for each objective would enable WFP to design an aid program that considers all three objectives. However, we have prioritized

WFP's perspective, i.e., cost minimization, to generate an accurate representation of the current context as for the base case.

In Section 6.3.1, we solve FAIMS model only with minimizing ***program cost*** objective using Garissa data ($\alpha=0$, $\beta=0$, $\gamma=1$) as the base case. This solution enables us to evaluate the current operations of WFP. Then, we run sensitivity analyses on selected cost parameters: local market prices (in Section 6.3.2), voucher fixed costs (in Section 6.3.3), and in-kind distribution costs (in Section 6.3.4) to evaluate the robustness of the results found in the base case.

6.3.1 Base Case

Currently, in the Garissa county, WFP solely distributes in-kind food aid under the general food distribution program. In this subsection, I investigate whether distributing aid with in-kind modality is the least costly program design or not by solving the FAIMS model for the parameter estimates of this region with the minimizing cost objective. In this experiment and all the future ones, I solve the models using CPLEX 12.7.1. The results in Table 6-10 demonstrate the optimal program design provided by the model. First three rows represent amount of aid distributed using each modality to deliver sufficient aid to all beneficiaries residing in the region. I only considered minimizing cost objective in this case, however the effect of this optimal design on other two objectives can also be calculated. Last two rows represent the values of the other two objective functions take under the base case.

Table 6-10 Optimal program design for the base case

	CHARACTERISTICS	SOLUTIONS
MODALITIES	Cash ($)	0
	Voucher (tonne)	0
	In-kind(tonne)	22,960
OBJECTIVES ($)	Program Cost	18,177,208
	Avoided Malnutrition Cost	7,289,100
	Contribution to the Economy	0

In the optimal solution, no cash or voucher is distributed to the beneficiaries, implying that the current in-kind aid program of WFP is optimal as is. In other words, the current context of the region is not viable for cash or voucher distribution. Given that WFP's in-kind distribution expenses to the beneficiaries (maximum $0.79/kg maize) are cheaper than the local market retailing prices (minimum $0.84/kg maize), these results are expected. Under these conditions, it is not advantageous for WFP to modify its current program; all 68 regions should continue to receive in-kind food aid.

It is important to note that WFP's in-kind distribution costs include procurement costs, international and in-land transportation costs, storage and handling costs. Furthermore, the retailing market prices of commodities do not contain fixed or variable costs related with cash and voucher programs. Therefore, with additional operational costs, distribution of cash and voucher would be even more expensive. One question worth answering is; however, how robust these base case results are to the local retailing market price fluctuations.

6.3.2 Local Market Prices

The results obtained from the base case revealed that providing in-kind food distribution is the least costly option in achieving the calorie requirements under the current commodity retail prices in local markets. These prices, however, are prone to significant variations over time mainly due to seasonal droughts and local supply chain disruptions. In this subsection, we analyze the effect of the local price changes on the optimal program design.

Before we start our analysis, we would like to demonstrate how these prices fluctuate over time. Figure 6-10 shows the price index fluctuation of maize in different market types (as explained in Section 6.2) located in northeastern corridor of Kenya, which also traverses the Garissa county. These price changes do not follow a clear pattern, nor correlated with each other. Still, tremendous changes within short periods of time can be observed. For example, a 120% price index change in six months is observed in main markets off main corridors (as depicted by the yellow line, between January - July 2009). This data illustrates that significant commodity price fluctuations, which can influence the optimal program design often occur in this region.

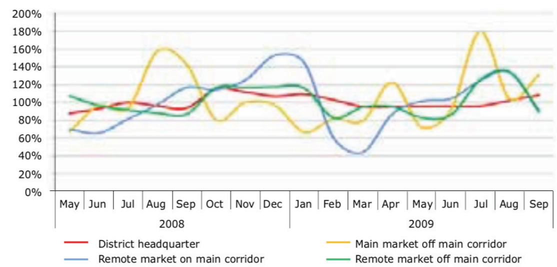


Figure 6-10 Seasonal Index, maize retail prices northeastern corridor
Source: (WFP, 2013)

In order to understand the robustness of the base case solution to such price fluctuations, I decreased the local commodity prices in our data set gradually with 10% increments and reported the optimal program design under each price level. A 90% decrease may seem unlikely, but it is within the observed fluctuation range of the Figure 6-10. Note that, the price surges have not been considered since any commodity price above the current level would also yield an "in-kind-distribution-only" design. Figure 6-11 shows the results of this sensitivity analysis on prices.

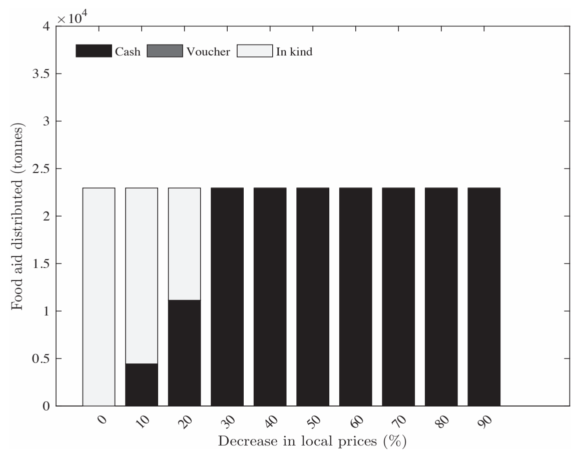


Figure 6-11 Tonnage and modality of basic food aid distributed as the local commodity prices decrease

In this graph, each column represents the total tonnage and the modality of the basic food aid distributed to the beneficiaries as its retailing price decreases in the local markets. For a direct comparison between tonnage-based modalities (in-kind and voucher) and cash distribution, I reported the distributed tonnage for in-kind and voucher distribution and the consumed tonnage of food consumed for cash distribution.

The first column, representing a 0% decrease, marks the base case, where all aid distribution is provided in the form of in-kind. However, even a slight 10% decrease in the local commodity prices, induces the cash distribution. Since the maize costs are cheapest in *main markets on transport corridors,* cash distribution is first realized in regions receiving service from those markets. As prices continue to decrease, other markets also start to receive cash aid instead of in-kind. Finally, at 30% mark, all beneficiaries start to receive aid in cash form. No voucher distribution is observed for different price values.

As the prices decrease, not only the aid modalities but also the objective function values change. Throughout this analysis, the model decides the amount of food aid distributed based on the calorie requirements while minimizing the program cost. As a result, same amount of basic food aid distributed regardless of the price level and modality, consequently, the calorie consumption is also stable throughout the price scale. No tasty food distribution or consumption is observed since its retail price per calorie is much higher than the basic food. Although the tonnage of distributed food remains constant, the modality switch from in-kind to cash affects the values of three objectives as in Figure 6-12.

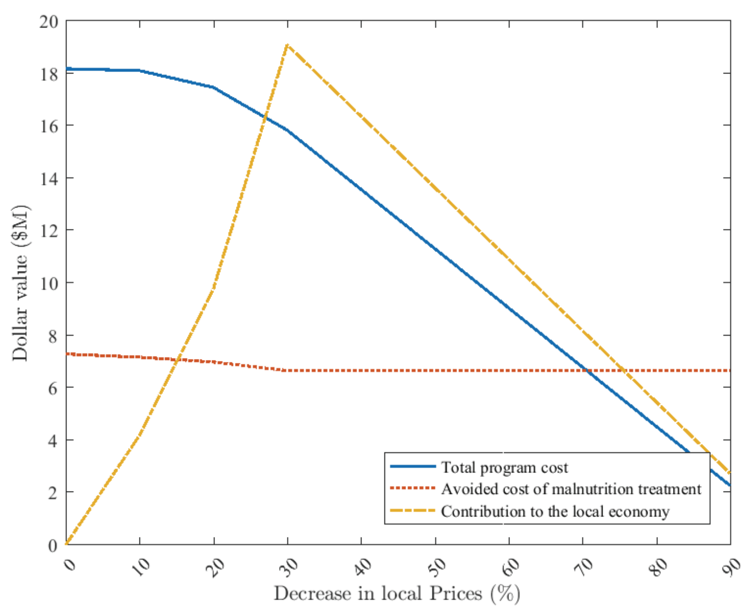


Figure 6-12 Changes in three objective function values as the local commodity prices decrease

Figure 6-12 shows that the ***total program costs*** decrease slightly when the in-kind modality is replaced with the cash as the local prices decrease. Once the aid is started to be distributed completely as cash (seen as 30% local price decrease in Figure 6-11), program cost decreases linearly as the local prices also decrease linearly in our test set. However, ***avoided cost of malnutrition*** also decreases as WFP switches to cash modality from in-kind aid. Although same type of food is consumed in the exact same amounts, maize provided by WFP is fortified with vitamins and minerals, thus it contributes towards malnutrition prevention better than maize (see Table 6-6) in the local markets. Finally, ***contribution to the local economy*** first increases as WFP switches to cash, but then decrease linearly as the amount of cash distributed decreases. This graph shows that a %10-%20 decrease in local prices, improves the total cost and economic contributions significantly, while it does not harm the nutrition objective significantly.

6.3.3 Voucher Fixed Costs and Market Capacity

In the previous subsection, as the local prices decrease, FAIMS model proposed a transformation from in-kind to a cash-based intervention, whereas vouchers are not distributed at all. In this subsection, I investigate the factors that prevent voucher distribution. The main reason behind this can be the high fixed costs associated with voucher operations compared to cash operations as explained in Section 6.2. To confirm if the fixed costs are the main obstacle for the voucher distribution, I removed the voucher fixed costs from the model while keeping voucher printing and transaction costs. Then, I solve the instances again decreasing the local commodity prices gradually. Figure 6-13 shows the results.

The amount of food is distributed remained unchanged. Yet, more aid is provided in voucher form as expected in the absence of voucher fixed costs. While this reduction in the fixed costs make the vouchers more favorable, total program cost decreases on average only 1%, and malnutrition treatment and economic contributions remain unchanged.

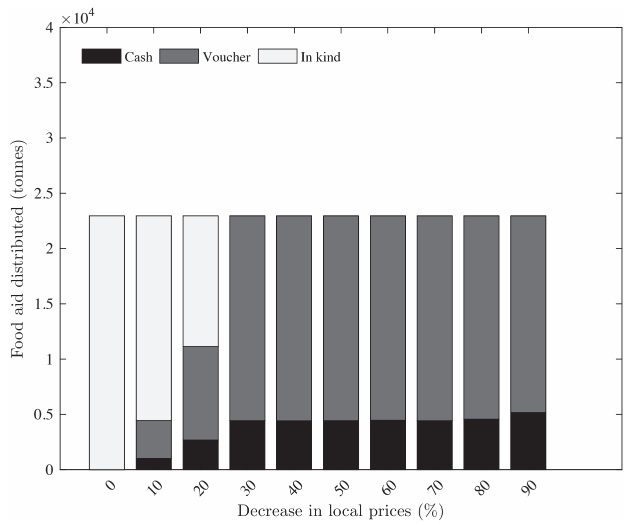


Figure 6-13 Tonnage and modality of basic food aid when no fixed cost associated with vouchers

As these results suggest, the effect of eliminating voucher fixed costs are not significant, neither this elimination is easy to attain. Voucher fixed costs are due to large groups of program employees should be dispatched to the field. The employees need to find reliable retailers, sign contracts with them and perform frequent visits in order to make sure the program carries on smoothly. This nature of voucher operations prevents the complete elimination of the fixed costs. I run further tests to find the voucher fixed cost break-even points, which are represented in Table 6-11.

Table 6-11 Break-even points for voucher fixed costs

Decrease in local prices (%)	10	20	30	40	50	60	70	80	90
Fixed cost break-even (%)	85	84	84	86	89	92	94	97	99

Although a complete elimination is not necessary for voucher distribution, the required cuts are quite substantial, and as the local prices decrease the required cut approaches to 100%. If a slight decrease in fixed costs would have yield a cost-efficient program with voucher distribution, certain strategies could have been employed to realize these reductions. For example, long-term contracts with renewals could have cut down the retailer searching costs, whereas improved field worker schedules for monthly visits would reduce the monitoring costs. However, decreasing the fixed costs by at least 85% seem neither feasible, nor extremely fruitful, given that the resulting program cost reduction is 1% on average.

One final observation before concluding the discussion on voucher fixed costs is that Figure 6-13 shows that the voucher distribution does not completely replace the cash distribution. Even if there are no fixed costs to be paid for the voucher distribution, cash is still provided in certain regions. This is due to the market capacity constraint imposed on vouchers (Constraints (5.15) and (5.16)). Indeed, a complete switch from in-kind to vouchers is observed when that constraint has been relaxed.

6.3.4 WFP's Efficient In-kind Distribution

In our data set, WFP costs are lower compared to the local market prices, and the local commodities cannot compete with these prices. However, as explained in Section 5.2, there is an ample body of literature claiming cash and vouchers are highly cost effective. This fact leads us to the following question: What if WFP is an exception and provide the in-kind aid in the most efficient way? WFP receives commodities from participating donors for free. For additional demand, the organization continuously follows the global commodity prices, and whenever there is decrease in food prices, WFP makes abundant purchases. Another advantage of WFP over other organizations is their expertise in the logistics operations in remote parts of the world. WFP not only has the one of the most connected and efficient supply chains among the humanitarian actors, but also provides logistics support to other organizations. For example, in Kenya, WFP continues its operations for decades and it holds long term relationships with service suppliers within the country longer than many other actors. Since it ships substantial volumes of cargo each year, it receives better contract deals than

On the other hand, there are many other aid organizations operating in Kenya including USAID, World Vision, Action Against Hunger and a Canadian Religious Agency, ERDO. Let us take the USAID as an example to compare its operational costs with WFP's. In their 2018 fact sheet, USAID report a \$64.3M budget for Kenyan food aid operations, 70% of which is spent for 51,150 tonnes of in-kind distribution (USAID, 2018). Adjusting these numbers to 2014 dollars gives a rough estimate of $868/tonne, whereas for WFP the same operation costs $794/tonne. Here, it is important to note that USAID partners with WFP in its operations and benefits from WFP's infrastructure. So, it is not unreasonable to assume that the costs would be even higher for a non-partner organization. Thus, for other organizations, especially for the smaller ones, cash or voucher could be more efficient as stated in certain studies in the literature.

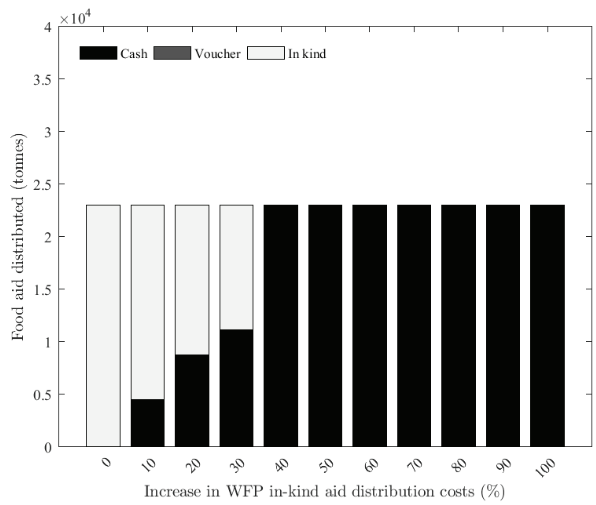


Figure 6-14 Amount and modality of basic food aid when WFP costs increase

Figure 6-14 shows how modality distribution changes, as the total cost of in-kind distribution increases. As expected, we get a very similar picture to the local market sensitivity analysis results depicted in Figure 6-11 . Even a 10% increase similar to USAID's costs, would make other modalities, in this case, cash, more cost efficient. The first group of beneficiaries receive cash resides near markets closer to the transport corridors. Smaller aid agencies are more likely to operate in these regions since their capacity may not be sufficient to locate and to bring help to the most scattered households in remote regions. If the aforementioned field studies are conducted in more central households, it is likely that they conclude the cash is more cost efficient. However, our experiments in this section and in the previous one show that for cash to be distributed in remote regions, either the market commodity prices should decrease significantly or the distribution costs of in-kind should be substantially higher than WFP's.

6.4 Policy Evaluation

The FAIMS model aims to support the aid organizations while designing their food assistance programs. Furthermore, it can also be used to evaluate certain policies that are proposed to improve the outcomes of a food aid program. Different aid organizations or local governments are involved in such policies to improve the effectiveness of aid programs, and eventually the well-being of the beneficiaries. The list of such policies is extensive, but in this chapter, I examine three of them: Increasing the program budget, educating beneficiaries on nutrition, and centralized fortification of the basic food.

6.4.1 Increasing Program Budget

Under the cost minimization objective (objective 3, γ), what WFP can attain is limited in terms of other two objectives. When WFP distributes only in-kind food aid as in the base case, the program achieves a limited level of nutritional contributions (objective 1, α), and there is no contribution to the local economy (objective 2, β). It is apparent that under the current market prices, if WFP wants to achieve better results on the latter objectives, it needs to increase the program budget. In this section, I investigate how these two objectives can improve as the budget increases. To do so, I add a budget constraint to Model 2 and obtain a new model, Model 3. Then, I start with the optimal value is obtained in the base case, i.e. current budget (B = \$18,177,208), increase it up to 100%, by 10% gradients ($\varsigma \in \{0, 10, ..., 100\}$), and then, solve Model 3 for each gradient.

Model 3: FAIMS with budget constraint

$max \quad \alpha$ Objective 1 + β Objective 2

$s.t.$

Objective 3 $\leq B\,(1+\varsigma\%)$

(5.1) – (5.7) , (5.9) – (5.18), (5.24)

(5.19'), (5.19''), (5.20'), (5.20''), (5.21'), (5.21''), (5.22'), (5.22''), (5.23'), (5.23'')

The two objectives of the Model 3 together represent the contribution of the program to both the beneficiaries and the non-beneficiaries residing in the aid-receiving country. Depending on the program's design purpose, or local government's agenda, either of the objectives can be the focus of the attention. Instead of prioritizing one over the other, I pursue a multi-criteria optimization approach to combine the Objectives 1 and 2. To do so, I adapt the reference point method, suggested by Clímaco *et al.* (2006) for generic multi-criteria problems. In this method, for each objective function component, *i,* i.e. Objective 2 and Objective 3, upper and lower bounds (UB_i, LB_i) have to be calculated, if not known by the decision maker *a priori.* Then, each criterion is normalized with a scaling factor equal to $\frac{1}{UB_i - LB_i}$. The objective is to maximize (minimize) the distance from the least (most) desired solution, that is $O_i - LB_i$ ($UB_i - O_i$). Finally, each criterion is multiplied with their weights, $0 \leq \alpha, \beta \leq 1$, $\alpha + \beta = 1$. By altering the values of these weights, the decision maker can explore the solution space, where either one of the criterion is dominating the other. As a result, the new objective function of Model 3 is as follows:

$$\alpha \frac{Objective\ 1 - LB_1}{UB_1 - LB_1} + \beta\ \frac{Objective\ 2 - LB_2}{UB_2 - LB_2} \tag{6.2}$$

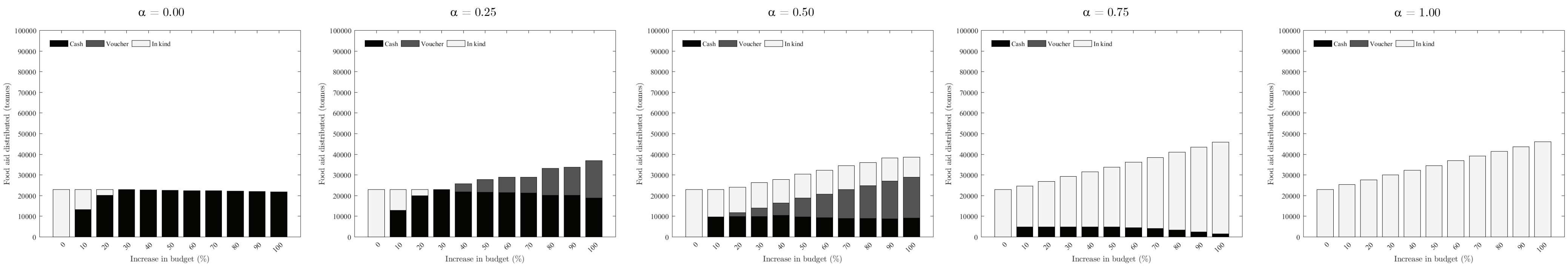
I calculated the upper and lower bounds of these objectives as follows: For the avoided malnutrition costs, the lower bound can be determined a priori by the constraint (5.9). All feasible solutions of the FAIMS model always satisfy the calorie constraint for all beneficiaries, i.e., $s_{hr1} = 1, \forall h \in H, \forall r \in R$. Calculating the treatment cost of caloric deficiency by (6.1), τ_1 = \$59.22 per beneficiary, one can calculate the lower bound of the avoided malnutrition objective by multiplying this value with the beneficiary population. This objective is bounded from above as well: if the beneficiaries consume bundles that satiate all four of the micronutrient requirements, the achieved malnutrition treatment savings in such a solution gives us the upper bound of the objective 1. Note that, this value is not attainable even with a 100% budget increase in Garissa case. To be precise, the budget has to be increased by ς=108% to fulfill the overall nutrition requirements.

Objective 2, the contribution to the local economy, also has a pre-defined lower bound, and that is zero. This value corresponds the case where WFP distribute all aid in-kind. Whereas, the upper bound is not that straight-forward. The spending on cash and voucher programs can continue to increase as the budget increases. Assume that there is no friction, i.e. no operational costs, and assume WFP can provide all the aid with cash distribution, the total amount of aid will be equal to the total budget. Note that, this is a feasible solution because cash has no market capacity constraint imposed on it. In such a case, the economic contribution to the local economy would be equal to the contribution factor $(1+\Lambda)$ times the total budget $(B(1+\varsigma\%))$. As mentioned earlier, we increase the budget B, up to ς=100% and the contribution factor is estimated as 1.23 as explained in Section 6.2 thus, we can estimate the upper bound on the economic contribution accordingly. Table 6-12 summarizes the calculated upper and lower bounds for Objectives 1 and 2.

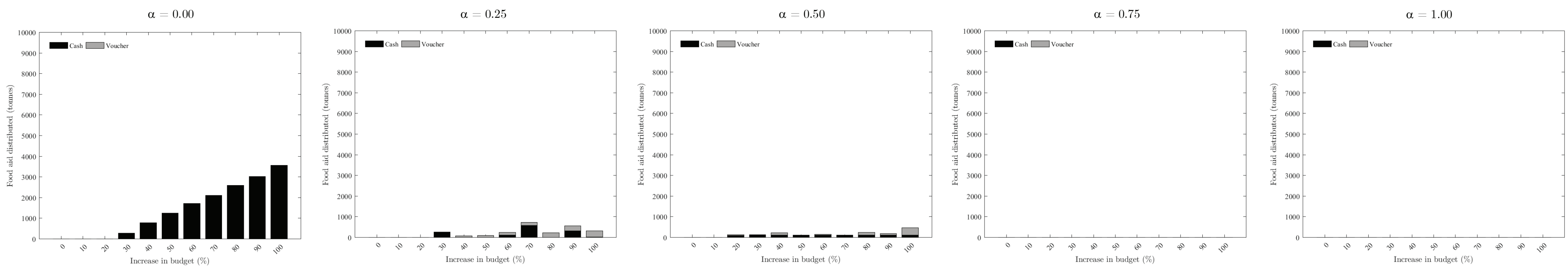
Table 6-12 Calculated bounds of Objectives 1 and 2 for Garissa Instance

	Lower Bound	**Upper Bound**
Objective 1	$6,655,319	$9,211,811
Objective 2	$0	$48,483,207

Using these bounds to normalize the multi-criteria objective function, I generate alternative optimal program designs by altering the budget (ς) and weight (α, β=1-α) parameters. For these experiments, I chose $\alpha = \{0, 0.25, 0.5, 0.75, 1\}$. Figure 6-15a and Figure 6-15b shows the basic and the tasty food consumptions of beneficiaries and the modalities that they are received in the optimal solutions for these parameter settings.



(a) Basic food aid



(b) Tasty food aid

Figure 6-15 Amount and modality of food aid distributed as the program budget increases

The leftmost two graphs in Figure 6-15a and Figure 6-15b belong to the scenario with $\alpha=0$, $\beta=1$, which represents the case where all emphasis is on economic impact. Conversely, the rightmost two graphs with $\alpha=1$, $\beta=0$, represent the case where all emphasis is on avoided malnutrition cost objective. The first column of each graph corresponds to the optimal solution for the original budget, and the remaining columns corresponds to the solutions for incrementally increased budgets.

In the first scenario, $\alpha = 0$, the basic food is completely sourced by cash after a 30% increase in the budget, but after that point the amount remains almost stable, whereas the amount of tasty food consumed starts to increase steadily after this point. It is important to note that, the demonstrated cash-only distribution is just one of the many alternative optimal solutions. As long as same amount of money is spent within the local markets through cash or voucher distribution, it will generate equal economic contribution regardless of the modality or the food type. Indeed, some alternative optimal solutions with same economic impact are provided in Appendix C.1.

As α increases, and the nutrition is emphasized more, we observe a significant increase in basic food consumption and a decline in tasty food consumption. Note that, there is one order of magnitude difference between the basic and tasty food graphs. In terms of modalities, we observe higher more in-kind aid distribution amounts as α increases. Although, the program shifts towards more cash and voucher distribution for $\alpha=0$, and 0.25 as the budget increases, this behavior is not observed for higher α values. Interestingly, for $\alpha=0.5$ value, all three modalities are distributed at the same time. None of the households receive cash and vouchers at the same time; however, many households receive in-kind distribution as a supplement to the other modality. In other words, there is a hybrid distribution of modalities.

Once α reaches the value 0.75, in-kind aid starts to dominate other modalities. As we slightly increase the budget by 10%, cash distribution increases significantly compared to the base case, but then decreases again as the budget expands. This distribution pattern can be explained as follows: With a slight increase in budget, achieving significant malnutrition gains is not possible, especially due to binary nature of malnutrition. On the other hand, distributing some of the calories using cash yields a notable jump from level zero in the economic impact component of the objective function.

Finally, for α=1.00, the nutrition objective is the main focus of attention, and the optimal solution indicates a single-modality program, i.e., in-kind distribution throughout the budget scale. The most important conclusion of these graphs lies in this final scenario. The rightmost two graphs prove that carrying an in-kind only program is optimum, not only from a minimizing cost perspective as seen in the base case but also from a nutritional outcome perspective. In other words, in-kind food aid is not only the least costly option but also the most cost effective one, in terms of nutrition for Garissa county.

These previous graphs give us an idea about how budget and WFP's preferences over objectives affect the aid program. It is also worth mentioning how the two objectives respond to these factors. As the budget and α increases, the values of avoided malnutrition treatment cost (Objective 1) and contribution to the local economy (Objective 2) corresponding to the aid distribution results to Model 3 are shown in Figure 6-16a and Figure 6-16b, respectively. The parallel lines to the x-axis indicate upper and lower bounds of the objectives calculated previously. In Figure 6-16a, we observe that, when WFP puts a higher emphasis on nutrition (α=0.75, 1.00), the objective value escalates almost linearly with budget. Even if WFP values both objectives equally (α=0.50), nutrition still increases slightly. For lower α values (α=0, 0.25), the nutrition objective decreases with budget increase since WFP transforms its operations from in-kind to cash as seen in Figure 6-15a, and beneficiaries start to consume local maize instead of the fortified alternative. After a cash-only modality is started to be distributed starting from 30% budget increase, and the consumption amounts starts to rise, the nutrition also increases slowly. Yet, even a 100% increase in budget cannot restore the base case nutrition levels.

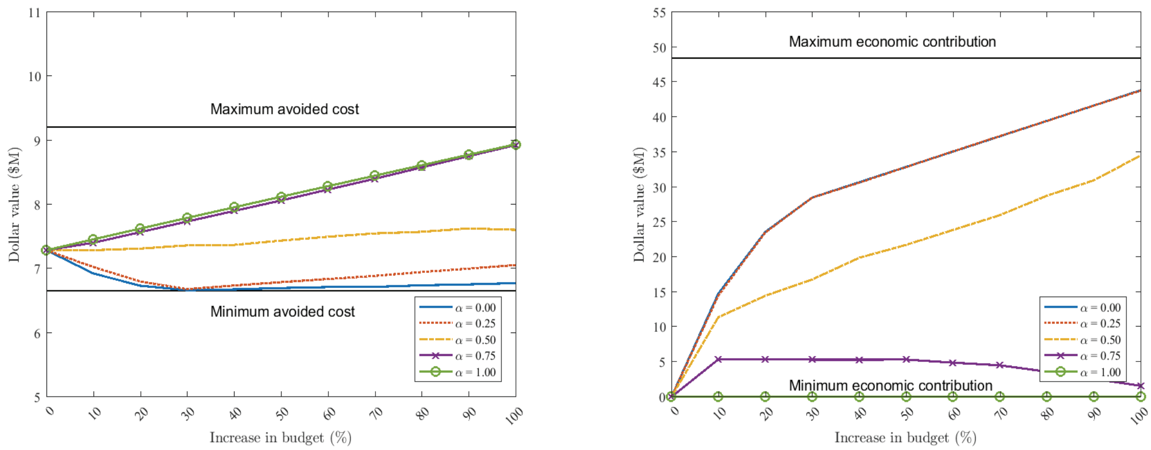


Figure 6-16 Objective values as budget and α increases

In Figure 6-16b, the effect of α (=1-β) on economic contribution to the local economy is in the opposite direction, as expected. For lower values of α (α=0.00, 0.25), meaning higher values of β, the economic contribution first grows quickly as WFP distributes less in-kind and more cash. After the completion of the switch to the cash modality (at 30% budget increase), economic contribution continues to grow linearly – parallel to the budget increase. Assigning equal weights does not inhibit this growth either. But if WFP chooses to put more weight on nutrition, then we observe very limited (α=0.75) or no (α=1.00) economical contribution. It is clear from these graphs that the objective values are highly responsive to the weight changes. However, from a policy evaluation perspective; just by solely investigating the modality distributions or the objective function values, it is not clear whether WFP should increase the program budget or not, and if so, how much. Each of these three objective functions are in monetary terms, so that an overall combination of these costs and benefits can be calculated.

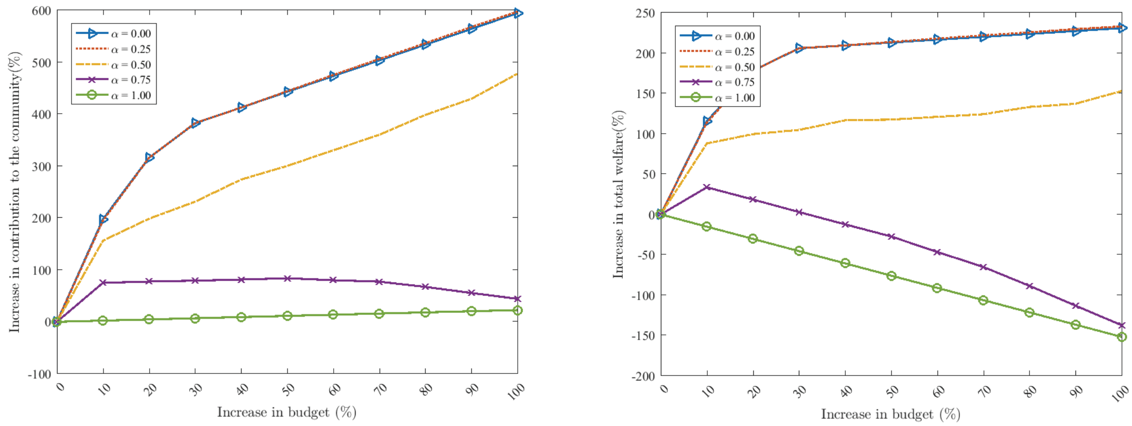


Figure 6-17 Contribution to the community and total welfare changes as budget increase

Figure 6-17a shows that how much the two objectives (objective 1 and objective 2) combined is changed relative to the base case. Recall that at the beginning of the Section 6.3 we call this combination of two objectives as the **contribution of the aid program to the community**, since it reflects the well-being of the beneficiaries and the non-beneficiaries simultaneously. In this figure, contribution to the community grows with extra budget regardless of the chosen α value. The overall growth is much faster when the emphasis is on the economic contribution rather than the nutrition due to the difference in the upper-bounds of each objective: economic contribution can increase up to \$45 million, while avoided malnutrition cannot go beyond \$9.1 million.

On the other hand, WFP pays for the program costs to achieve these contributions to the community. If we reflect the program costs on the contribution to the community, we attain the change in the **total welfare generated by the program,** i.e., the combination of all three objectives to reflect all stakeholder's perspective including WFP's. Figure 6-17b represents the change in the total welfare for all α values. It is evident that choosing an α too high, i.e., 1, do not contribute on total welfare since it weighs nutrition too much – an objective which has a very limited monetary contribution in comparison to the other two objectives. On the other hand, a 10% budget increase improves the total welfare significantly, for $\alpha \leq 0.75$. Furthermore, a 20% budget increase can be considered if WFP choses an $\alpha \leq 0.50$. However, a budget increase beyond 30% is not worthwhile, regardless of the decision maker's α value. In short, a budget increase can bring significant improvements (up to 200%) on total welfare, as long as WFP puts some weight on economic contribution. However, increasing budget indefinitely is not reasonable, since the total welfare function flattens, if not decreases beyond a budget increase of 30%.

6.4.2 Educating Beneficiaries on Nutrition

In the model, there are three types of households: polygamous male-headed, monogamous male-headed, female-headed. These types are differentiated in terms of the household populations and their taste functions as explained in 6.2.1. The taste functions are based on their conjectured consumption behaviors under a certain increase in their cash-flows. In a Kenya based survey, female headed households claim they would spend on their money in nutritious food (prudent behavior), while male-headed households put the alcohol in the second place after food in their spending priorities (hedonistic behavior). The lower-level model is designed to mimic this behavior. In this section, I investigate the possibility of educating households and its effect on the program outcomes. Accordingly, WFP can plan and execute an education program on nutrition effectiveness. The main assumption here is that, an education program can convert *hedonistic* households to *prudent* households. In other words, such a program can change the taste function of the family head, in a way that he starts to value tasty food more than the temptation food.

Such programs are already executed in Kenyan refugee camps (WFP, 2016) and it has been observed that beneficiaries change their food expenditures and improve their nutrition after these programs. However, expecting similar results in rural households is not realistic. First of all, in refugee camps, the markets are few and they are under surveillance for the commodities that they are providing. Secondly, tracking transactions of beneficiaries is possible to some extent. Finally, handling education programs in a condensed area of population is less challenging compared to the extremely sparse beneficiary distribution in arid lands. But before WFP starts to design an effective education program in rural areas, we want to test whether it is worthwhile or not.

To test the results of such a program, we assumed the program converts the taste functions of male-headed households similar to the female-headed households, so that males would not spend the extra budget on temptation items anymore. Then, we re-solve the instances and compare the results with the instances in Section 6.4.1. Table 6-13 summarizes these results of this experiment; the numerical comparison of the results is provided in Appendix C.2.

Table 6-13 Summary table of results when all beneficiaries are prudent

Component	Effect (For $\alpha \leq 0.5$)
Modality Distribution	In kind distribution decreases 10-15%. Voucher distribution down to 40%. Cash increases up to 50%.
Avoided malnutrition cost (O2)	Decreases slightly (difference from base case <100K).
Economic contribution (O3)	Econ contribution increases $1.5-2 million

For $\alpha > 0.5$, we do not observe a deviation from base case since WFP mostly provides in-kind in these scenarios, and even if cash is provided, it is only sufficient to cover the calorie constraint. Household type matters if WFP provides more cash than calorie requirements. In that case beneficiaries' taste functions determine how to spend the extra cash beyond the basic calorie requirement. In previous experiments, we observe extra cash distribution only if $\alpha \leq 0.5$. If all beneficiaries become prudent, the results show that WFP distributes more cash instead of in-kind, knowing that it will not be misused. The economical contribution increases up to $2 million. From a policy evaluation perspective, these results suggest that pursuing an educational program targeted to male-headed households can be considered if WFP can execute it for a budget less than $2 million.

6.4.3 Centralized Fortification of Staple Food

Our experiments in 6.4.1 showed that in-kind food aid is not only the lowest cost modality but also the most cost-efficient one. The model choses an in-kind-only solution if WFP fully prioritize nutrition objective over economic impact since this least costly option is also fortified with micronutrients. If WFP wants to shut down its in-kind aid operations, one important step would be lobbying with government for a mass-fortification policy of the local basic food. In this section, I investigate effects of such a policy on WFP's aid program.

Food fortification is administered during the processing stage of grains (i.e., milling, packaging, etc.) by adding vitamins and minerals that are not originally contained in the food. All vitamins and minerals under consideration in this problem are eligible for food fortification. According to World Health Organization (WHO) and Food and Agricultural Organization of the United Nations (FAO), fortification provides health benefits with minimum risk to the population. These two organizations place fortification among the four strategies to reduce the nutrient deficiencies at the global level (World Health Organization and Food and Agricutural Organization, 2006). Although market-driven fortification is more common in developed world, e.g. brands with vitamin D fortified milk, mass fortification is the way to go for an inclusive population coverage. Mass fortification requires the governmental bodies to mandate and regulate the efforts.

In 2011, Kenyan Government mandated fortification of all packaged wheat and maize flour with vitamins A, iron and zinc. However, the progress of the coverage was not instantaneous. Fiedler *et al.* (2014) estimated a coverage of 28% after three years of the legislation, and a more recent report by Kenyan Ministry of Health indicates 40% of the total maize flour production is fortified (Atinda, 2016). In this section, we tested the case, where the mass fortification policy be successful and achieve a full coverage rate. For this, we have increased the local maize nutrition values to the fortified level and compared the results with the original scenario. Note that, we assumed the fortification costs are subsidized by the government, at least until the program reaches full coverage.

The computational results under a successful fortification policy are not deviating from the original case when α=1.00 since it consisted of only in-kind aid distribution.

Similarly, for α=0.00 no significant deviation is observed since the nutrition component has no weight in the combined objective function. For other α values at least one objective improves greatly and the other deteriorates slightly, thus, I explain the results for α=0.50, where both objectives improve significantly.

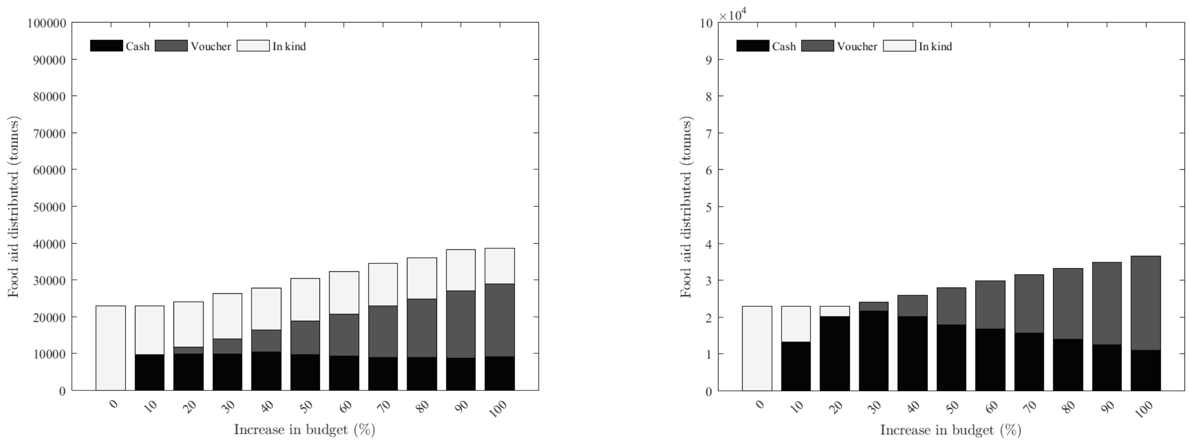


Figure 6-18 Amount and modality of food aid under the original scenario and with mass fortification policy

Figure 6-18 depicts the basic food aid distribution amounts under both scenarios for α=0.50. Under the mass fortification policy, in kind distribution decreases significantly. Instead, cash distribution almost doubles, while basic voucher distribution also increases, so together they replace the in-kind food aid.

Figure 6-19 compares the objectives under the original and the fortification scenario. The nutrition objective increases by $600 thousand in mass fortification scenario if WFP increases its budget at least by 30%. Improvements in the economic contribution is not that modest; a whopping $10 million increase is achievable with local fortification. With this increase, the contribution to the community, i.e., combination of the two objective values, goes beyond the program costs and carries the program to a positive total welfare state.

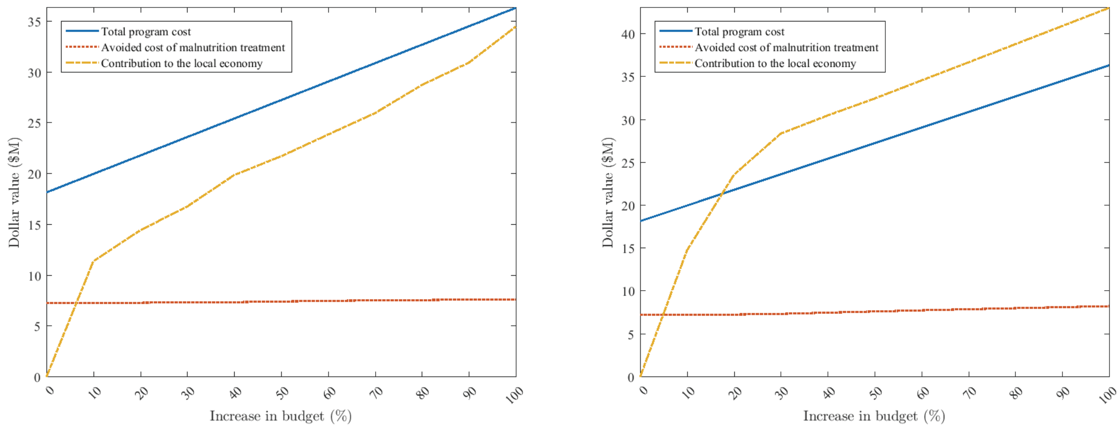


Figure 6-19 Nutrition and economic contribution changes under the original scenario and with mass fortification policy

In the original setting of the problem, the two objectives were behaving antagonistically: the nutrition objective was favoring cheaper and more nutritious in-kind option, whereas the economic contribution objective was pushing a cash or voucher-based program. However, the fortification policy turns this situation upside down and enable the cash and voucher modalities to contribute both of the objectives simultaneously. Given this significant increase in their local economy with a bonus of improved nutrition of the nation, Kenyan Government should not hesitate to undertake the mass fortification policy's implementation costs.

6.5 Conclusions

In Chapter 5, I developed a model for the food aid program design process which enables the decision makers to choose aid modalities to be distributed to different households. This model takes into account the welfare of all the stakeholders linked to the food aid system and accommodates them in the objective function. While doing so, I build a bi-level optimization model, in order to represent the hierarchal dynamics of the aid distribution activities between the beneficiaries and the aid agency. In Chapter 6, I demonstrated how this model can be used in both designing an aid program and evaluation of nutrition improvement policies that are commonly administered in the presence of an aid program.

Our experiments based on Garissa data showed that, in-kind aid is the best option for WFP under the current cost structures of the modalities and food commodity prices in the local markets. On the other hand, even a 10% decrease in the local prices makes cash distribution more cost-efficient for the households that are close to the main markets. I also established that for other aid organizations which have higher in-kind aid distribution costs, providing cash would be more cost-efficient. Then, I evaluated three policies commonly adopted to improve nutrition and measured the contribution of the aid program on the community represented as the combination of the avoided malnutrition treatment costs and the contribution the local economy. These three policies are increasing the program budget, educating the beneficiaries on nutrition and centralized fortification of the basic food. I observed that the aid program can achieve substantial improvements on the nutrition and economic contribution objective if WFP increases its budget 10%-20%, however the improvements diminish quickly after this point. Additionally, an education program in Garissa region targeted to male-headed households can be considered if these efforts will cost less than $2 million, otherwise the costs will outweigh the benefits. Finally, the mass fortification of the basic food improves both objectives significantly. It is possible to increase the local economic contribution by $10 million just by food purchases of the beneficiaries in Garissa. Therefore, a collaboration between WFP and the Kenyan government to accelerate the ongoing efforts on mass fortification is suggested since it would pay off significantly decreasing the Kenya's dependency on international food aid commodities.

One major contribution of the suggested model is that it enables a program design where multiple aid modalities can be administered simultaneously. As explained by Gentilini (2007), favoring a certain modality over the others and executing a single modal-program is not necessarily optimal. An assumed dichotomy of favoring in-kind aid during emergencies and cash or vouchers during recovery efforts is outdated. A combination of these modalities may provide superior outcomes in terms of program's objectives, as shown under different scenarios in this chapter.

Another contribution of our model is to incorporate the beneficiaries' consumption behavior by modeling them as economic agents maximizing their utility. So far, in the literature, it is widely stated that cash transfers provide a greater choice over consumed commodities to the beneficiaries. In fact, for this very reason, some programs and donors avoid cash distributions completely with the fear of cash misuse. With the beneficiary component, FAIMS model can evaluate the outcomes of a cash distribution model by taking into account the cash misuse behavior and provide an aid program accordingly, instead of simply ruling out the cash for all beneficiary population in the region.

Despite the fact that FAIMS model is inspired by WFP's problem and shaped by a food aid distribution setting, it can be used for non-food aid program designs by simple modifications. One major difference would be the adaptation of the nutrition outcomes. By definition, DALY is a very comprehensive measure to account the burden of any health condition, so other health-related outcomes of the program can also be assessed in τ calculations similarly in non-food aid modality decision contexts. A very relevant example could be the averted treatment costs of malaria cases by insecticide-treated bed net distribution programs. Modality selection problem is being faced in all sections of the humanitarian efforts including HIV protection, clothing and footwear distribution, malaria prevention and clean water solutions. Therefore, the modelling structure and the outcomes that are discussed in the previous chapter will hopefully reach to wider audiences.

Attempting to develop a decision-making tool for such a complex problem that has many inter-connected factors and ever-changing dynamics is prone to shortcomings in entirely capturing and reflecting the reality, and this study is no exception. Many reports and guidelines in the literature enunciates the fact that the success of the cash and voucher programs are closely tied to continuous monitoring of the prices. Our experiments also accentuate the importance of up-to-date local price monitoring by showing how the results are sensitive to the prices. As we have access to the point estimates of the local commodity prices, the analyses emanated from these inputs are as robust as these estimates. Since we design our model for a tactical decision of investing in certain modalities, we have not considered the food price fluctuations or availabilities throughout the year. However, an operational level model would require incorporation of such information. Another limitation of our model is the assumption that beneficiaries directly consume all the aid that they receive. In reality, beneficiaries can sell the distributed in-kind aid or vouchers to obtain cash. Our assumption is reasonable, especially given that we mostly focus on general food distribution in rural areas, which are relatively isolated communities. Nevertheless, we would like to note that, a model for refugee settlements should definitely take into account the selling behavior since it is commonly observed in those settings (WFP and UNHCR, 2012).

Chapter 7

Concluding Remarks

In this thesis, I have studied the logistical challenges that aid organizations face during food aid delivery to the malnourished beneficiaries in developing countries. Food aid organizations operating in developing countries have to deal with obstacles including means of access to beneficiaries, underfunding, conflicts and immature markets, as explained in Chapter 1. Long-term development issues such as hunger and poverty are often overlooked by both the academic community and by the media and donor networks. Therefore, the aid agencies operating in hunger response are restrained not only by the physical challenges of delivering food aid to geographically dispersed areas, but also by tight budgets and lack of scientific approaches as the literature review provided in Chapter 2 revealed.

7.1 Summary of Research Findings

Throughout this thesis, I collaborated with WFP's Kenya Office that serves the East and Central African region incurring the highest operational costs per beneficiary within the organization. Despite the fact that the other regions lower their logistics costs significantly, as of 2016, ECA region still spend 35% of their budget on logistics costs. To understand the underlying mechanisms that drive the logistics costs and examine the supply chain operations closely, I have performed a field trip to Kenya in the spring of 2015 as explained in Chapter 3. Our initial meetings with the logistics department yielded to following research agenda for further exploration.

1. Determining the transportation rates accurately and designing a new contract structure that decreases WFP's in-kind aid transportation costs and increases the service levels.
2. Exploring the applicability of cash and voucher programs as these modalities incur lower logistics costs than in-kind aid and estimating the effects of the new modalities on program costs, beneficiary nutrition and local economy.

As one of the very few field studies conducted in the development logistics domain, I follow an exploratory research structure to capture the realities as accurate as possible. To this end, I conducted semi-structured interviews composed of open-ended questions with WFP logistics officers and the transporters that provide transportation service to WFP. In addition, I performed visits to critical points of WFP's in-kind aid distribution supply chain. Finally, I collected the transportation rates for common origin-destination pairs of other aid agencies to compare them with WFP rates. Before the field study, WFP was suspecting that the transporters demand higher rates as a defense mechanism against the WFP's new contracting system that awards fixed-term contracts to the lowest bidders at the lowest bid. WFP was also complaining about the low service levels of the transporters, who were responding WFP's shipment requests late or not responding at all. The field research revealed that WFP's rates are not as high as suspected. WFP managed to sign contracts at rates that are lower than most of the other aid agencies operating in Kenya. In fact, these rates are the very reason why the transporters respond WFP's requests reluctantly. Since WFP contracts have no penalty or bonus terms, transporters choose to reserve their trucks for better paying requests and WFP's shipments are delayed.

The rates obtained from other aid agencies do not provide conclusive results, although they indicate WFP's rates may not be reflecting the true market rates. In Chapter 4, I build an econometric model based on over 200 contracts provided by the Kenyan transporters to estimate the statistically significant variables that determine these rates. Two sets of candidate variables are considered based on the findings in the field trip: lane specific factors (fuel price, distance and the interaction among these two, road condition, border-crossing, refugee camp delivery, and populations of origin and destination cities) and contract specific factors (total load, rainy season, contract length, cargo type). Among those the following factors are determined to be significantly correlated with transportation rates: interaction among fuel price and distance, distance squared, road condition, border-crossing, refugee camp delivery, origin and destination population, and cargo type. Even if WFP's contract rates are re-determined based on these factors, fuel price can fluctuate throughout the contract period. Thus, the transporter may still need to assume a down-side risk of underpayment if it allocates their trucks during a fuel price surge or else it again fails to respond WFP's requests. Since WFP employs neither bonus nor penalty terms in their contracts, I suggest a new flexible barrier-type contract, which updates the rate as the fuel price increases beyond a pre-determined threshold. I model the fuel price fluctuations as an Ornstein-Uhlenbeck process and with this price trajectory, I determine the expected reduction in the transporters' risks under the proposed contract scheme. Although there are different options contracts that can be used to adjust the contracts, I chose barrier contracts since they yield intuitional and easy-to-comprehend contract terms.

I tested the performance of the proposed contracts over the top five origin-destination pairs in terms of the total food transported. The results indicated that the proposed contract design yield significant risk reductions for the lanes where the transporters are reluctant to send their trucks due to poor road conditions and remote distance. The exception to these results are the lanes with significant competition from both the supply and the demand sides. Since securing WFP contracts on such lanes mean job-security under the fierce competition, the transporters are willing to accept lower-rate contracts. This means the main source of the risk of underpayment assumed by the transporter is the contract rates themselves, not the fluctuations in the fuel prices. All in all, the proposed framework with the market rate estimation and barrier contract components generates alternative contract settings, i.e., contract rate – barrier pairs, among which WFP can negotiate with transporters to achieve either better service levels for higher rates or lower service levels in exchange of transportation cost reductions.

One reason that East and Central Africa region lags behind the overall trend of decreased logistics costs compared to the other regions is that the transition towards cash and voucher distribution in the ECA region remained quite modest except a few pilot programs in refugee camps. In Chapter 5, I introduce a new problem to the literature called Food Aid Modality Selection Problem (FAIMS) that decides the aid modality to be administered by the agency in the upper-level. Also, it reflects the cash-spending behavior of different geographic and demographic groups of beneficiaries in the lower-level model. The feasible solutions of this bi-level optimization model are evaluated through a multi-criteria objective function based on their costs, nutritional benefits to the beneficiaries and their effect on the economy.

In Chapter 6, the FAIMS model is solved for the Garissa county instance. This instance is constructed through a meticulous parameter estimation procedure. The optimal solution for the base case indicated that under the given commodity prices in the local markets, in-kind aid distribution is the least costly modality for the whole county. However, even a 10% decrease in the commodity prices makes the households located near main markets eligible for cash distribution. On the other hand, improving the other two program outcomes, namely the nutritional status of the beneficiaries and the contribution to the local economy is not viable with the current program budget of WFP. By combining all three objectives, as a **total welfare function**, I conclude that budget increases up to 30% yield notable improvements in these objectives, yet further increases do not contribute to the total welfare. I have also evaluated the effects of two commonly administered nutritional improvement policies on the total welfare functions: educating beneficiaries and centralized fortification of the food commodities. The results suggest that education of beneficiaries for more responsible cash spending can be considered if the education program costs for Garissa county do not exceed US$ 2 million. On the other hand, a central food fortification policy in collaboration with the local government leads to contributions as high as US$ 10 million to the local economy while also boosting the beneficiary nutrition without increasing the program budget significantly.

Overall, the projects in this thesis, which aim to improve the strategic and tactical decision-making processes of food aid programs have the following underlying common themes.

- **Authenticity:** The research projects and outcoming frameworks are designed to answer the real-life problems that humanitarian organization face in the field. The methodologies are developed in light of the findings from the conducted field trip to WFP Kenya office. As a result, rather new problems are introduced to the literature, i.e., designing flexible contracts for transportation procurement and food aid modality selection problem.
- **Applicability:** Although the literature does not fall short in terms of noteworthy applications of OR/MS models to the humanitarian logistics domain, most of these studies can benefit from more realistic assumptions to close the gap between the theory and the practice. Thus, in this thesis I put a strong emphasis on the ease of implementation of the frameworks by adopting more intuitive definitions and methodologies for the practitioners. I validate my assumptions and findings with WFP's logistics officers to establish realistic approaches without compromising the theoretical rigor.
- **Objectivity:** The existing pilot studies and guidelines that the humanitarian organizations follow in their decision-making processes, e.g., decision trees, have plenty of room for subjective judgement. On the other hand, mathematical formulations that quantify the effects of all these factors and incorporate them into to the decision-making process would yield superior solutions. Accordingly, I collect extensive amounts of qualitative and

quantitative data during my field trip as well as the secondary sources such as WFP reports, World Bank Database and Global Burden of Disease Database. Then, I develop two data-driven decision-making frameworks: one for transportation contracting operations (tactical decision) and one for aid modality selection process (strategic decision).

7.2 Future Research

The following extensions to the frameworks presented in this thesis are worthwhile to investigate:

1. Future research directions of the transportation contracting framework

Although I particularly focused on the design of the transportation contracts, it is also essential to examine the existing auctioning processes of WFP. Financial rules and regulations of UN mandate that "when a formal invitation to bid has been issued, the procurement contract shall be awarded to the qualified bidder whose bid is evaluated to be the one with the lowest cost to the United Nations." However, it is well established in the literature that Vickery auctions, which awards again the lowest bidder, but at the second-lowest bid, incentivize the auctioneers to bid the true value of the service (Ausubel & Milgrom, 2005). In other words, implementing a Vickery auction or its generalized version, a Vickery-Clarke-Groves mechanism would eliminate the aggressively low bidding behaviour resulting low service levels. However, an adaptation of these mechanisms is required for the WFP setting rather than a straight-forward application. More than one bidder are often awarded for each lane, and most of the transporters are awarded for more than one lane, yet the auctions are not combinatorial. Suggesting a change that conflicts with the UN Financial Rules and Regulations would pose bureaucratical challenges, however an alternative auction mechanism would worth investigating especially if it creates a strong case of yielding better service levels at reasonable costs.

Once reasonable contract rates that are acceptable for both parties are established with the help of the developed market rate estimation model, double-sided barrier contracts can also be implemented, i.e., the option of decreasing the rates if the fuel prices decrease significantly. In addition, multiple barriers can be considered so that the rates can be updated for multiple thresholds once both parties are accustomed to the new contracting scheme.

2. Future research directions of the aid modality selection framework

In Chapter 6, I demonstrated how the FAIMS model can be used for evaluation of nutrition improvement policies such as beneficiary education and local maize fortification. Another interesting policy to investigate would be providing food subsidies to the beneficiaries. The sensitivity analyses on commodity prices had shown that even slight decreases in local market prices can make cash distribution eligible. FAIMS model can estimate the effects of government subsidization of food commodities in the form of price discounts for extremely poor households. If the potential economic contributions of the aid program are greater than the cost of subsidies, the government would implement such a policy.

In FAIMS model, the local commodity prices are assumed constant throughout the year, as I have access only to point estimates of these prices. Since FAIMS model is designed for a strategical decision of investing in certain modalities, I have not considered the food price fluctuations or food availabilities throughout the year. More importantly, I have not modeled the price changes resulting from the increased demand due to cash and voucher injections to the local economy. For this specific case, where the least costly solution was in-kind distribution, ignoring the cash and voucher-based price changes possibly would not change the findings. Additionally, one can argue that introduced market capacities for the vouchers also prevent the price surges at least for the voucher distribution. Incorporating a dynamic equilibrium model that tracks the supply and demand changes and their effects on commodity prices would enable the FAIMS model to provide more realistic insights on the food market dynamics. A food aid program emanating from such an equilibrium model would protect both the beneficiaries and the non-beneficiaries from supply failures and price surges.

Finally, a robust optimization approach can be used to model the food supply shocks such as famine scenarios. Such shocks also increase the number of people in need of food aid drastically. These scenarios can be constructed based on the rainfall and crop vegetation indexes. In addition, more diverse types of households can be represented in the model again in a robust optimization structure. Instead of assuming all households belonging to a specific household type behave in a certain way, different needs or preferences can be modeled in more detail. For example, a male-headed household may value nutrition more than temptation goods if there are pregnant women or toddlers in the family.

All in all, this study is a first step towards data-driven aid modality selection approaches based on analytical frameworks rather than guidelines and expert opinions. Eventually, I aim to design a higher-resolution model that can easily be modified, and integrated in social protection programs, safety net designs and food shortage preparedness plans developed by governments and INGOs.

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Appendix A

Transporter Interviews and Results

A.1 Interview Questions Directed to the Transporters

Company Profile

1. What is the fleet size of the company (i.e., number of vehicles and their capacities)?
2. What is the average fleet age of the company?[7]
3. For how many years does the company carried cargo for WFP?
4. What is the percentage of WFP operations among the total workload?

Market Perception

5. Which origin-destination couples are the most profitable?
6. What origin-destination couples are the least profitable?
7. Which factors do you think have the highest impact on market prices other than distance and fuel price?[8]
8. What are the main challenges that affect timely deliveries of WFP orders?

Bidding and Contracting

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[7] Most of the companies did not provide a clear answer to this question. Kenya has certain regulations about the truck age, trucks older than 12 are not allowed to operate, so we did not demand definite answers for the sake of obtaining answers to other questions.

[8] Questions 7 and 8 are asked in an open-ended format. No factors are provided to the transporters. The table represents common answers.

9. How does the company calculate the bids submitted to WFP?[9]
10. Have you lost contracts after the last bidding season?[10] Why do you think you lost contracts?
11. Do you have the opportunity to obtain return cargo? Do you consider this while bidding? If so on which lanes, during which seasons?
12. Do you find WFP's counter-bids reasonable compared to other shippers? If not, which companies provide higher rates and for which OD couples?
13. Are you willing to share those contracts with our research team?
14. Currently, WFP issues contracts for a six-months period. Do you prefer shorter or longer contracts? Why?
15. Does your bid preparation for WFP differ from the way you bid for other organizations? What is marked differently?

Communication Behavior

16. How often do your company share market information (e.g., prices, safety condition of the roads, better routing options, market demand, etc.) with WFP?
17. How often do your company share market information (e.g., prices, safety condition of the roads, better routing options, market demand, etc.) with other transporters in the market?
18. How often do your company share market information (e.g., prices, safety condition of the roads, better routing options, market demand, etc.) with other shippers that your company has a contract with?
19. Any other comments that you like to add?

[9] No transporter provided a clear answer to this question.
[10] Answers to the first part of the question are tabulated below. Answers to the second part listed under comments.

A.2 Transporter Interviews

		Q1	Q3	Q4	Q5	Q6	Q7					
Base	Company						Road Conditions	Security	Weather	Maintanence /Spare part costs	Border Crossing	Load
Mombasa	Coastal Terminals	15	5	40%	Juba, Wajir	Kakuma	+	+	+			
	Dalmar	75	9	>50%	Any destination with tarmac	Kakuma, Lodwar	+	+		+		
	Tasam	80	15	>50%	-	Kakuma, Dadaab						
	Hafsa	25	16	~100%	-	-	+			+		
	Spedag	-	14	-	-	-		+			+	
Nairobi	Pelican	30	15	70%	Goma, Juba, Kigali	-	+	+		+	+	
	Roy Haulers	180	5	10%	Kampala	Kakuma	+	+		+		
	Credible	80	5	60%	Kampala, Juba	Kakuma	+			+		
	Multiple Transports	400	10	10%	Juba, Kampala, Bujumbura	Inland Kenya	+	+		+		+
	Siginon	195	25	25%	Dadaab	Kakuma				+		

		Q8						Q10	Q11	Q12	Q13	Q14	Q15
Base	Company	Late LTIs	Queues at EDPs	Weather	Borders	Security	Road Conditions					(L)onger or (S)horter	
Mombasa	Coastal Terminals	+						N	N	Y	Y	L	N
	Dalmar		+					N	N	N	Y	L	Y Less profit margin
	Tasam							N	N	N	N		N
	Hafsa			+	+	+		Y	N	N	Y	L	N
	Spedag				+			Y	N	N	N	L	N
Nairobi	Pelican	+	+		+			Y	Y*[11]	Y	Y	L	Y Security
	Roy Haulers	+		+	+		+	N	Y*	N	Y	L	N
	Credible		+	+	+			Y	Y*	N	Y	L	Y Road Condition
	Multiple Transports		+		+			N	Y*	Y	Y	L	N
	Siginon		+		+			N	Y*	Y	Y	L	N

[11] *The companies that admit return cargo opportunities also state that these opportunities are available at the end of the rainy (harvest) season and mostly concentrated around large cities such as Juba, Kampala, Eldoret.

		Q16	Q17	Q18	Q19
Base	Company				Any other complaints, suggestions for WFP logistics officers?
Mombasa	Coastal Terminals	N	Y	N	WFP does not consider the dynamics of the market. Fixed rate contracts are not working well. They prefer further notice for LTIs.
	Dalmar	N	N	N	They decrease their profit margins significantly to be in the lowest five bidders. They also prefer further notice for LTIs.
	Tasam	N	N	N	WFP is their lowest-paying client. WFP should determine the market price rather than the lowest bid while deciding rates.
	Hafsa	N	N	N	After 16 years of collaboration, they lost contract last year. WFP contracts are not profitable anymore. Thin margins do not compensate for extra costs incurred in WFP specific rural destinations.
	Spedag	N	N	N	WFP does not aim for a long-term, loyal business partnership. Quality of the service is not considered while providing contracts. They lost contracts after 14 years of collaboration to a new company without expertise.
Nairobi	Pelican	N	Y	Y	They lost WFP contracts after 15 years of collaboration. WFP was constituting 70% of their workload. Prices should be updated throughout the contracting season.
	Roy Haulers	N	Y	Y	WFP bids are not reasonable, and the workload is not regular.
	Credible	N	N	Y	They prefer longer contracts that enables to get bank loans. Hard to move large LTIs at once. WFP wants to make sure the trucks are available before issuing an LTI. It is not always possible due to capacity constraints.
	Multiple Transports	N	N	Y	They find WFP's rates are low for the cargo that they assign. Such low prices can be compensated only with higher volumes.
	Siginon	N	Y	N	They request a second round (post-bidding negotiation). The current system lacks communication channels, transporters submit bids, then either get the contract or lose. No room for negotiation.

Appendix B

Binomial Tree Parameter Estimations

B.1 Ornstein-Uhlenbeck Process Parameter Estimations

Let p_j denotes the logarithm of the j^{th} observation in the historical fuel price data. Log-price is said to follow a random walk if the difference between two periods can be represented as,

$$p_{j+1} - p_j = \alpha_0 + \epsilon_{j+1}, \qquad \epsilon_{j+1} \sim N(0, \phi^2). \tag{B.1}$$

and ϵ_{j+1} is the error term with a constant variance ϕ, and α_0 is the mean change in log prices. As one can notice, variance of the log price increases as we try to estimate future prices. Consequently, the log price is not forced to stick around the drift, where the expected value of the change is μ. This means, under this model, the shocks are permanent, in addition, long-term trend is unpredictable. However, there are certain criticism for the utilization of the random walk for modelling the commodity prices. First of all, some economists believe the long-term trends of commodity can be determined to some extent, meaning it is not completely random. Secondly, when a price shock occurs, the market will adjust itself and eventually the prices will move back to the pre-shock levels. For example, a peak in the gold prices will quickly be followed by an increase in the supply of the gold in the markets and this will cause a decrease in the price, until the supply and demand balanced, and vice versa. In other words, the shocks may not be permanent, and the prices tends to return their long-term averages.

A first order auto-regressive process (AR (1)), which is our second modelling option, model these "mean-reverting" behaviors. Suppose that, log-price difference between two periods follows:

$$p_{j+1} - p_j = \alpha_0 + \alpha_1 p_j + \epsilon_{j+1}, \qquad \epsilon_{j+1} \sim N(0, \phi^2). \tag{B.2}$$

where α_0, α_1, ϕ are constant and α_1 is negative. This process reflects mean reversion in the following way: if there is a significant increase in prices (i.e., p_j gets too high), then $\alpha_0 + \alpha_1 p_j$ becomes also negative since $\alpha_1 < 0$. Which means, the expected value of the log price difference will be negative meaning p_{j+1} likely to be lower then p_j. Same principle also holds for price decreases, thus the prices under AR (1), follows a path where the ever-lasting shocks are not present and so, we can observe mean reversion. Although there exist strong arguments in favor of mean-reversion process, instead of arbitrarily deciding it, we let the data itself decides the model to be used. Since, (1) is special case of (3) where $\alpha_1 = 0$, we can confirm which model is a better fit to our data. For this, we used the monthly spot Brent Crude Oil prices, which is widely used as a benchmark of the oil industry, belonging to 2009 -2015, to determine the oil price fluctuations. Basically, we regressed the log prices (p_j) on the difference in log prices ($p_{j+1} - p_j$) to see whether α_1 turns out as a significant variable (hinting a mean reverting process) or not (hinting a random walk). Here are results of this regression analysis:

Table B-1 The regression analysis of log crude oil prices on 1-period log price changes

Variables	Model
log fuel price (USD/lt)	-0.079*
	(0.042)
Constant	0.367*
	(0.194)
number of observations	60
R-squared	0.041
Root MSE	0.0725

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

As one can see, the coefficient α_1 is significant in 10% level, and almost at 5% level. In particular, the estimated coefficients in Equation 3, namely $\widehat{\alpha_0}$, $\widehat{\alpha_1}$ and $\hat{\phi}$, take the values 0.367, -0.079 and 0.0725, respectively, which are used in O-U parameter estimation.

B.2 Risk Free probability Calculations For the Binomial Tree of the Oil Prices

While calculating the risk-free probabilities, the main assumption that is commonly relied on in the literature is the infamous: "no-arbitrage" principle. In other words, the prices of two portfolios which generate the same cash-flow should be the same. Following (Guthrie, 2009), if we would like to estimate the market value of a one-period cash-flow, which have a return of Y_u with risk-free probability of going up π_u and Y_d with risk-free probability of going down π_d; we create a portfolio that replicates this cash-flow composed of two different assets. The first one is a risky asset with a price Z and a return of X_u and X_d when the price goes up and down, respectively. And the second is a one-period risk-free asset with a price 1 and a pay-off $1 + r_f$, where r_f is one-period risk free interest rate. If our replicating portfolio has enough units for both types so that the expected value of it equals to the market value of the cash flow under consideration, then the costs of these should also be equal due to the no-arbitrage principle. Thus, the discounted yield of the replicating portfolio should also be equal to the market value of this cash flow:

$$V = \frac{\pi_u Y_u + \pi_d Y_d}{1 + r_f}. \tag{B.3}$$

Where the risk-free probabilities are defined as:

$$\pi_u = \frac{Z(1 + r_f) - X_d}{X_u - X_d} \tag{B.4}$$

One way of estimating the risk premium Z associated with the commodity is using the existing futures or forward contracts, since these contracts carry the information of market's anticipation of the risk associated with that commodity. A forward contract is basically an agreement between two parties to exchange an item from a pre-determined price F, on a pre-determined date. The difference between the spot market price and the futures contract price of a commodity helps us to identify the market's risk perception related with it. If we use 1-period ahead futures contracts of the fuel, then the pay-off, like Z, is determined by the levels of X_u and X_d. Therefore, we can replace Z with 1-month-discounted futures option pay-off $(F/(1+r_f))$. The resulting the 1-period-risk-free probability formula will be:

$$\pi_u = \frac{F - X_d}{X_u - X_d} \tag{B.5}$$

It is easy to calculate this, given today's spot and futures price of the crude oil. Yet, in our binomial tree we have several periods and different estimated spot market prices for the fuel and 1-period-ahead future prices for these spot market estimates are not available today. As a result, we need to understand the relationship between the spot and futures prices using the historical data. One way of doing this, matching the historical spot and futures prices to obtain an approximation in the form of $F = f(X)$. So, we estimated this relationship by regressing the logarithm of the Brent Crude Oil spot market prices on the historical futures prices:

Table B-2 The regression analysis of log crude oil prices on 1-period ahead futures prices

Variables	Model
log fuel price (US $/lt)	0.974***
	(0.011)
Constant	0.127**
	(0.049)
number of observations	120
R-squared	0.984

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

The results show that there is almost a perfect linear relationship between futures and spot prices that we can safely use to estimate futures values for our binomial tree after taking the exponentials of both sides of it.

$$F_{(i,n)} = e^{0.1268+0.9736*logX_{(i,n)}} \tag{B.6}$$

The fact that the slope coefficient is less than 1 (i.e, 0.97) means that the shocks to the spot market price is not fully passed on to the futures price. For instance, if spot market prices increase 1%, then the futures prices increase approximately 0.97%.

Since, we have already filled the $X_{(i,n)}$ values on the tree and find the relationship between the spot and futures prices, now we can finally calculate the risk-free probabilities for each node:

$$\pi_{u(i,n)} = \frac{F_{(i,n)} - X_{(i+1,n+1)}}{X_{(i,n+1)} - X_{(i+1,n+1)}} \tag{B.7}$$

B.3 Estimating the Diesel Pump Price in Kenya

In our risk-free probability calculations, we needed to use Brent Crude Oil Spot market prices, because crude oil itself is a traded commodity in the markets and therefore, the futures options are available for it, unlike the diesel. However, for our further calculations we need the diesel pump price in Kenya. As a result, we use a two-step price conversion to pursue realistic calculations of the transportation rates. Although, there are certain formulas represented in different sources for these conversions, we followed a data-driven approach. First, we have estimated the relationship between the Brent Crude prices to the New York Harbor Ultra Low Sulfur No 2 diesel spot price Oil (U.S Energy Information Administration, 2016). These two data sets extracted from the same source, in order to make reasonable comparison.

In this figure, which represents crude oil and diesel pump prices, one can see that diesel spot price closely follows the crude oil. The first one is price per gallons, and the second is price per barrels, so we converted both to the liters and then run a simple regression analysis, which clearly indicates there is almost a perfect linear relationship between crude oil and diesel prices.

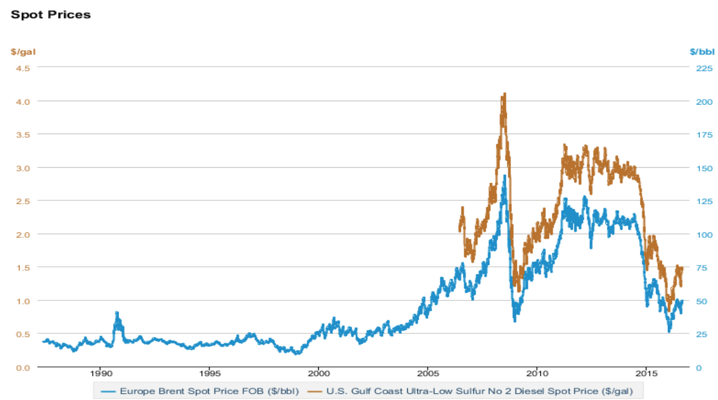

Figure B-7-1 The close relationship between the crude oil prices and the diesel prices

Table B-3 The regression analysis of crude oil prices on diesel prices

Variables	Model
Crude oil price (US $/lt)	1.045***
	(0.016)
Constant	13.332*
	(1.521)
number of observations	60
R-squared	0.986

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

So, we can use the relationship: $P_{USDiesel} = 13.33163 + 1.045072P_{Crude}$. (i)

Now, we need to convert the US Diesel prices to Kenyan diesel prices. Unfortunately, there are only very few sources that reports both of the data, thus use the same seasonality and inflation adjustment parameters. So, we used World Bank data (The World Bank, 2014) which is not very populated, but at least reliable.

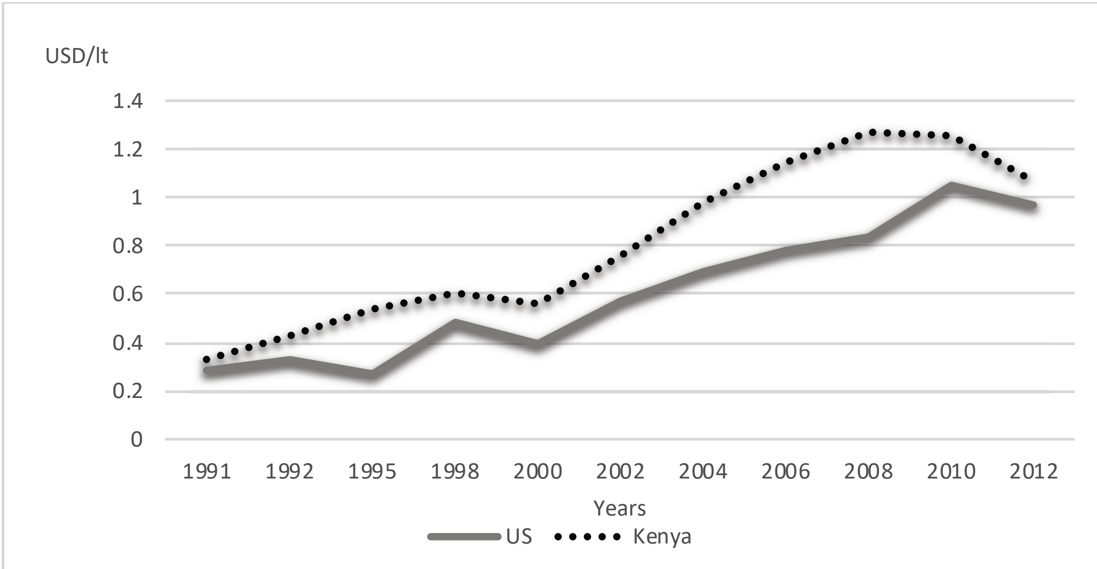

Figure B-7-2 Diesel pump price trends in US and Kenya

As expected, the relationship is not as strong as the previous, due to taxes, currency differences, etc. Still, we observe similar trends. And this relationship can be formulated as follows:

Table B-4 The regression analysis of US diesel pump prices on Kenyan diesel pump prices

Variables	Model
US diesel pump price (US $/lt)	1.163***
	(0.131)
Constant	0.110
	(0.086)
number of observations	11
R-squared	0.887

Since the constant of the model is insignificant, we have the following equation: $P_{KDiesel} = 1.163 * P_{USDiesel}$ (ii). If we put (i) and (ii) together: $P_{KDiesel} = 1.163 * (13.33163 + 1.045072 * P_{Crude})$.

Appendix C

Computational Results

C.1 Alternative Optimal Solutions

The following three solutions provide same objective, i.e., economical contribution to the local economy with the budget increase 80%:

Statistics	Original Solution	Solution #2	Solution #3
Cash (US $)	32,077,426	19,200,067	20,563,063
Basic Voucher (tonne)	0	2900	10,823
Tasty Voucher (tonne)	0	676	0
Temptation Voucher (tonne)	0	4029	242
In-kind (tonne)	0	0	0
Nutritional Benefit (US $)	6,741,000	6,673,500	6,660,100

C.2 Comparison of the Original Scenario vs. Educated Beneficiaries

			Program Budget Increased (%)										
			0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
α =0	Original Scenario	Economic Impact ($1000)	-	14,769	23,584	28,495	30,687	32,879	35,071	37,263	39,455	41,647	43,839
		Nutritional Impact ($1000)	7,289	6,925	6,734	6,665	6,678	6,698	6,713	6,716	6,741	6,755	6,775
		Total Cost ($1000)	18,177	19,994	21,812	23,630	25,448	27,265	29,083	30,901	32,718	34,536	36,354
		Cash ($1000)	-	12,007	19,174	23,167	24,949	26,731	28,513	30,295	32,077	33,859	35,641
		Basic Voucher (t)	-	-	-	-	-	-	-	-	-	-	-
		Tasty Voucher (t)	-	-	-	-	-	-	-	-	-	-	-
		In-kind (t)	22,960	9,817	2,896	-	-	-	-	-	-	-	-
		Basic Food Consumed (t)	22,960	22,960	22,960	22,877	22,727	22,584	22,442	22,408	22,176	22,050	21,888
		Tasty Food Consumed (t)	-	-	-	277	774	1,246	1,718	2,112	2,600	3,018	3,555
	Beneficiaries are educated	Economic Impact ($1000)	-	14,769	23,584	28,495	30,687	32,879	35,071	37,263	39,455	41,647	43,839
		Nutritional Impact ($1000)	7,289	6,925	6,734	6,665	6,678	6,698	6,713	6,716	6,741	6,755	6,775
		Total Cost ($1000)	18,177	19,994	21,812	23,630	25,448	27,265	29,083	30,901	32,718	34,536	36,354
		Cash ($1000)	-	12,007	19,174	23,167	24,949	26,731	28,513	30,295	32,077	33,859	35,641
		Basic Voucher (t)	-	-	-	-	-	-	-	-	-	-	-
		Tasty Voucher (t)	-	-	-	-	-	-	-	-	-	-	-
		In-kind (t)	22,960	9,817	2,896	-	-	-	-	-	-	-	-
		Basic Food Consumed (t)	22,960	22,960	22,960	22,877	22,727	22,584	22,442	22,408	22,176	22,050	21,888
		Tasty Food Consumed (t)	-	-	-	244	769	1,273	583	80	-	3,162	236

			Program Budget Increased (%)										
			0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
α =0.25	Original Scenario	Economic Impact ($1000)	-	14,478	23,512	28,495	30,625	32,861	35,094	37,288	39,449	41,657	43,782
		Nutritional Impact ($1000)	7,289	7,027	6,801	6,681	6,738	6,790	6,840	6,888	6,949	7,000	7,057
		Total Cost ($1000)	18,177	19,995	21,813	23,630	25,448	27,266	29,084	30,901	32,719	34,537	36,354
		Cash ($1000)	-	11,771	19,115	23,167	21,185	21,114	21,211	22,984	19,769	20,879	18,723
		Basic Voucher (t)	-	-	-	-	4,040	6,129	7,603	7,586	13,011	13,712	18,018
		Tasty Voucher (t)	-	-	-	-	64	90	135	140	229	244	310
		In-kind (t)	22,960	10,122	2,954	-	-	2	2	-	-	-	9
		Basic Food Consumed (t)	22,960	22,960	22,960	22,884	25,822	27,846	28,975	28,816	33,192	33,771	36,944
		Tasty Food Consumed (t)	-	-	-	253	68	90	244	719	229	560	319
	Beneficiaries are educated	Economic Impact ($1000)	-	14,478	23,511	28,495	30,687	32,863	35,096	37,288	39,448	41,655	43,848
		Nutritional Impact ($1000)	7,289	7,027	6,801	6,684	6,735	6,792	6,839	6,891	6,948	7,000	7,050
		Total Cost ($1000)	18,177	19,995	21,813	23,630	25,448	27,266	29,084	30,901	32,719	34,537	36,354
		Cash ($1000)	-	11,771	19,115	23,167	24,948	21,121	21,199	22,981	19,796	20,907	22,681
		Basic Voucher (t)	-	-	-	-	-	6,053	7,570	7,609	12,958	13,680	13,687
		Tasty Voucher (t)	-	-	-	-	-	104	144	136	232	243	244
		In-kind (t)	22,960	10,122	2,954	-	-	-	-	-	-	-	-
		Basic Food Consumed (t)	22,960	22,960	22,960	22,877	22,727	27,776	28,944	28,824	33,136	33,743	33,600
		Tasty Food Consumed (t)	-	-	-	277	774	104	248	744	241	566	1,055

			Program Budget Increased (%)										
			0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
α =0.5	Original Scenario	Economic Impact ($1000)	-	11,396	14,451	16,787	19,887	21,735	23,872	25,987	28,759	30,956	34,508
		Nutritional Impact ($1000)	7,289	7,289	7,314	7,364	7,371	7,438	7,498	7,550	7,576	7,628	7,607
		Total Cost ($1000)	18,177	19,995	21,813	23,630	25,448	27,266	29,084	30,901	32,719	34,537	36,354
		Cash ($1000)	-	9,265	10,036	10,080	10,514	9,810	9,639	9,200	9,250	8,998	9,397
		Basic Voucher (t)	-	-	1,868	4,136	6,101	9,168	11,285	13,967	15,898	18,378	19,831
		Tasty Voucher (t)	-	-	29	11	107	13	38	9	139	80	351
		In-kind (t)	22,960	13,330	12,300	12,199	11,302	11,564	11,666	11,645	11,099	11,128	9,764
		Basic Food Consumed (t)	22,960	22,960	24,073	26,241	27,780	30,396	32,313	34,537	35,935	38,169	38,702
		Tasty Food Consumed (t)	-	-	129	121	224	108	152	109	247	188	465
	Beneficiaries are educated	Economic Impact ($1000)	-	11,396	15,235	18,608	20,498	22,965	25,025	27,341	30,044	33,145	34,423
		Nutritional Impact ($1000)	7,289	7,289	7,289	7,284	7,351	7,393	7,447	7,498	7,523	7,520	7,628
		Total Cost ($1000)	18,177	19,995	21,813	23,630	25,448	27,266	29,084	30,901	32,719	34,537	36,354
		Cash ($1000)	-	9,265	12,311	15,129	13,590	13,944	12,864	12,822	12,993	13,018	12,267
		Basic Voucher (t)	-	-	-	-	3,533	5,539	8,694	11,049	12,815	15,201	18,094
		Tasty Voucher (t)	-	-	19	-	16	3	19	-	80	231	32
		In-kind (t)	22,960	13,330	11,604	10,358	10,596	10,348	10,401	10,320	9,828	8,805	9,780
		Basic Food Consumed (t)	22,960	22,960	22,845	22,726	25,507	27,407	29,811	32,073	33,341	34,927	37,911
		Tasty Food Consumed (t)	-	-	380	775	634	668	599	574	698	789	611