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Price Flexible Transportation Procurement Contracts for Food Aid Delivery in Developing Countries

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Abstract. It is common practice among the international aid organizations to resort to local transport companies for delivering food aid in regions plagued by hunger and malnutrition. The reliability of the transportation services provided by these third parties is essential for ensuring food security that is much needed in these regions. Transporters in developing countries often inflate their rates in order to protect themselves from the expected price increases in the future. They also tend to allocate their trucks to other jobs when the long-term contract rates are significantly lower than that of the spot market. Using data gathered from the Kenya-based operations of the United Nation's World Food Programme, we demonstrate that the variation in transport spot market prices can be attributed to the volatility in fuel prices. In this paper, we devise a new barrier-type options contract that can be adopted to reduce the transporters' downside risk and mitigate their incentive to bid defensively. Our findings through numerical experiments on the real-life data set demonstrate that significant risk reductions can be achieved on transport corridors that are not very desirable for the transporters, without a sizeable additional cost to the aid organization. This is encouraging from the perspective of improving the sustainability of food aid delivery to the most impoverished regions in a developing country.

Keywords. Food aid, transportation contract, real options, humanitarian logistics.

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1 INTRODUCTION

Food security means that people have sustained access to sufficient food for active and healthy lives. As of 2017, extreme hunger and malnutrition are still among the major barriers to development, hampering productivity and making people more prone to diseases. According to the United Nations (2016) nearly 800 million people worldwide lack food security, the majority of whom live in developing countries. East Africa constitutes the region, where hunger is the most prevalent as approximately one out of every four people suffers from it. In-kind food aid distribution remains a major component of all humanitarian operations, and it entails rather complex supply chains (Rancourt, et al., 2015). Indeed, multiple stakeholders are involved in food aid supply chains: donors, humanitarian organizations, logistics providers, governments, non-governmental organizations (NGOs), and beneficiaries. The World Food Programme (WFP) plays a key role in the global food aid system and delivers 7.5 million tons of in-kind food aid (three million of which distributed in East Africa) per year worldwide.

This research is undertaken in collaboration with the WFP Kenya Office, and it is inspired by the logistics challenges experienced in delivering in-kind food aid in East Africa. Currently, the 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. For its transportation operations within the region, the WFP signs long-term contracts with local carriers 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 (The World Bank, 2016). To lower its costs, the WFP currently contracts with carriers that offer the lowest rates through a request for quotation (RFQ) process. Consequently, the transporters often fail to honour the 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 supposed to last for a six-month-period, WFP often extends them because the RFQ process is resource consuming. As a result, transporters may suffer losses by offering their services at the WFP 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 channeling aid to people in need (Pedraza Martinez, et al., 2011). This is a problem that all humanitarian agencies that distribute in-kind aid items by operating long-term contracts with local seller. The aim of this study is to provide a framework for drawing up more flexible contracts to overcome the operational challenges that both the transporters and humanitarian shippers face. In this paper, we show that the WFP could cover some of the transporters' risks caused by the volatility of the market without incurring excessive increases in its own costs. This would arguably incentivize the transporters to provide better service to WFP. The methodological framework that we propose comprises econometric and real options models. The literature that pertains to the dynamics of the transport markets in East Africa is scarce. Thus, we first devise an econometric model from a real-life contract dataset to explain the determining factors of the transportation rates. We are particularly interested in the factors that tend to change during the contract. Then, we incorporate the results of this econometric model in a real options scheme, which enables WFP to make adjustments to the long-term contracts so as to share the transporter's risk associated with the market volatility. Our data set includes over 200 contracts from over 60 carriers and the latest transport rates incurred by the WFP Kenya office. This data set is rather unique given the scarcity of information in African transportation markets. 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 and the work on service procurement contracts is fledgling. Note that for service procurement 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 long-term service under a fixed rate policy, where the total amount of the cargo to be shipped is unknown at the outset. In addition, the WFP is unable to impose penalties when the transporters breach the contract by not being available to offer service at the time of WFP's shipment request. The novelty of our study is to introduce the ability to modify the contract rate through the course of the contract in order to remain as an appealing business opportunity for the transporters.

The remainder of this paper is organized as follows. Section 2 presents the description of the context of this study and the data collection process. Section 3 provides an overview of the literature related to transportation outsourcing. The econometric analyses and their insights are discussed in Section 4. Section 5 explains the overall framework of the new contract scheme. Section 6 provides numerical results for the highest volume lanes in our case and compares these results with current WFP contracts. Section 7 presents the conclusions.

2 THE CASE OF WFP KENYA

In this section, we first describe the context of this study. Then, we describe the data collection process and present its main outputs, that is, the information used to develop econometric models and to identify the determinants of transportation rates in Kenya.

2.1 THE WFP SUPPLY CHAIN IN KENYA

Food aid distribution typically starts with the shipment of internationally procured or donated commodities to the receiver country. From the point of entry (POE) up to the beneficiaries, the most common mode of transportation is trucks. In this section, we focus on the logistics activities that WFP performs in Kenya on a supply chain linked to the many other countries. After its entrance to the country, the food aid travels along the major hubs (MH) which can be within Kenya or neighboring countries including Uganda, South Sudan, Ethiopia, Somalia, and Congo, then to extended delivery points (EDP) and final delivery points (FDP) where food aid is handed out to beneficiaries.

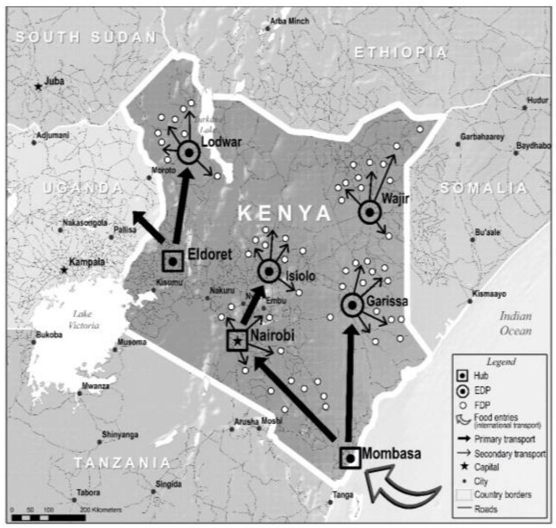

Figure 1 Part of the Supply Chain Network of WFP Kenya

As depicted in Figure 1, Mombasa Port is the POE of the WFP Kenya's supply chain. There are three major hubs: Mombasa, Nairobi, and Eldoret. These major hubs enable planners to stock the food in proximity to the beneficiaries before the demand is known. Once the stock levels in the EDPs decrease, commodities are shipped from the major hubs to the EDPs. EDPs are used for longer-term storage since it is cheaper to operate them. Currently, there are 19 EDPs in Kenya. Food distribution to beneficiaries is performed monthly at the FDPs. The food rations are transported from EDPs on the day of the distribution since the FDPs are not suitable for storage. This is evident from Figure 2 that illustrates an example FDP visited by the first author.

The shipments from MHs to EDPs and from EDPs to FDPs are done by contracted transport companies in Kenya. The contracts are not effective for a single shipment but for multiple shipments during a time window. During the period of the contract, WFP may reach any of the contracted transporters for a particular shipment and request trucks by formally issuing a Landside Transportation Instruction (LTI).

LTI is a document that represents the origin, destination, total tonnage, and expected time frame for the delivery.

Figure 2 A final distribution point (taken from the author's camera).

2.2 CURRENT CHALLENGES WITH CONTRACTING

Considering the fact that WFP needs to transport millions of metric tons each year, constructing the best terms in the contracts regarding rates and service level is crucial. The transportation market in Africa is not nearly mature as in Europe or North America, where the rates are highly and 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, rainy seasons, and security levels. Also, estimating the actual value of the service poses a significant challenge for the inexperienced business owners.

To obtain a reasonable price for the services, at the beginning of each bidding season, WFP sends an RFQ to the shortlist of transporters for each origin-destination (O-D) pair including an estimation for the total tonnage to be delivered within the contract. Transporters choose the O-D pairs that they want to provide service and submit their bids (quotes) to the WFP. Based on these bids, WFP chooses the transporters that are going to be awarded. In order to decrease their high logistics costs, WFP uses the lowest bid received as a counter-bid to the five lowest bidders. Although this contracting scheme has lowered the transportation costs, WFP managers pointed out that the quality of the service has declined. Indeed, new entrants to the transport sector view WFP's contracts as an opportunity to promote themselves in the market, and hence they bid aggressively to make it to the five lowest bidders. Upon receiving the WFP LTIs, however, they cannot fulfill the requirements promptly. Also, other transporters, who accept the counter-offers, often send their trucks to the spot market for other customers who pay better rates and, whenever they receive a WFP LTI, they look for ways to delay the expiration time. There is no consequence of doing so for them since the contracts do not contain penalty or premium measures. WFP, an organization that relies on donations, would seek ways to minimize its logistics costs. For the same reason, it is not possible for WFP to pay premiums for receiving high-quality service. However, investigating better designs for contracting would benefit both WFP and the transporters.

Another problem with the WFP contracts is the fixed rates during the contracting term, that is, there are no updates 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, since almost all spare parts of the trucks and the diesel is imported, and this is reflected in the quality of the service. A new approach to longer term and dynamic contracts can be the best if not the only remedy for these problems. The need for a tool that calculates reasonable counter bids based on the market dynamics and the alterations in the contracts are inevitable. In this paper, we address these two issues relying on real data and novel approaches.

2.3 DATA COLLECTION

The first author made a two-month field trip to Kenya in April and May of 2015 to gather qualitative data through observations and semi-structured interviews. This allowed us to develop an accurate understanding of transportation market dynamics and transporter behavior and thinking. She 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: the Port of Mombasa, the international border with Uganda in Malaba, the Kakuma refugee camp, EDP in Lodwar, and the major logistics hubs in Nairobi, Eldoret, and Mombasa. She also interviewed transportation company owners and directors at the two largest hubs (five at Mombasa and five at Nairobi). The data obtained from the fieldwork was essential to the research in three ways. It ensured that all the important tangible variables were considered in our econometric models, the interpretation of our results is reliable, and our contracting recommendations are feasible from an implementation perspective. We collected data concerning WFP's contracted rates and also approached all the transporters in WFP's short list (90 transporters) and inquired their pricing practices with other shippers to develop a solid understanding of the transportation spot market in Kenya. We asked for the following information about their most important national lanes and international corridors with their other clients: contracted rate, start, and end of the contract, type of commodity transported, the total load carried during the contract, number of trucks used, anticipated road conditions, and average traveling time. Out of 90 transporters, 61 of them responded 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. This is a rich dataset considering little empirical research has been conducted in East Africa (Teravaninthorn & Raballand, 2010).

Table 1 Description of the WFP's transportation network

	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 (USD/mt): 176.73 Average distance (km): 1,246.94 Average rate per km (USD/mt-km): 0.14 STD of rate per km (USD/mt-km): 0.05	Average rate (USD/mt): 53.90 Average distance (km): 556.35 Average rate per km (USD/mt-km): 0.11 STD of rate per km (USD/mt-km): 0.09

Moreover, secondary data was obtained from open sources. The origin and destination population numbers were taken from the United Nations Statistics Division database (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.

3 LITERATURE REVIEW

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 & Raballand (2010) have used a carrier 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 transportation market and the international corridors originating from the port of Mombasa by using data from contracts that involve multiple shippers and time periods. 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 and R&D projects (Huchzermeier & Loch, 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 to ours is by Tsai, et al. (2011) that focused on a long-term option contract for transportation procurement where the cargo-owner may either 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 even in North American setting is quite challenging. 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 applications of contract rate adjustments mostly applied for the lease contracts. Al-sharif & Qin (2015) propose a flexible contract for vessel leases where both the lessor and the lessee have one 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 & Ward (2000) propose a barrier-type option, classified as an ***Exotic*** option, for adjusting store leases in shopping malls, where the lease is updated if the sales volume hits a certain barrier. Since there are similarities between a lease contract and a service procurement contract, we will also adopt barrier-type approach.

In our paper, unlike the literature reviewed above, we design a contract to solve WFP's problem but model it from transporters' perspective. In our case, the issue for WFP is the low service levels provided by the transporters. Nonetheless, we cannot address this matter accurately without taking the transporter's point of view. Secondly, we developed an econometric model to understand the fluctuations of the transport spot market prices. In this way, we can precisely address and model the components of the underlying mechanism of the price changes, instead of treating the overall cost as a random process. 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. 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 in our problem is not the choice between spot market and the contract, but instead adjusting the contracts to reflect the fluctuations in the spot market to ensure higher service rates.

4 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 spot market prices and the main determinants of their volatility. This section aims at filling the gap in the literature concerning the transportation spot market prices in East Africa. Thus, we develop a multiple linear regression model with high explanatory power predicting the transportation spot market rates *t* as a function of a set of line-haul factors *L* and a set of contract specific factors *C*. We aim to determine which factors have a significant impact on transportation rates and to use the results to design better contracting approaches. We stipulate that, $T = f(L, C) + \epsilon$, where ϵ stands for the random errors caused by unobservable factors.

4.1 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 line-haul factors pertaining to the O-D lane and the contract-specific factors. Below we provide a detailed discussion of each of these factors.

4.1.1 Line-haul Factors

Distance (continuous)***:*** The distance is the length of the haul between the origin and destination points measured in kilometers. The length of the haul is an important determinant of variable transportation costs since it has a direct impact on the resources required to move shipments.

Fuel price (continuous)***:*** We used the monthly pump price of diesel (USD/lt) published by the Kenyan Energy Regulatory Commission (2016). Fuel cost has a significant impact on overall transportation costs, as was confirmed by many of the transporters interviewed for the present study. All the transporters and cargo owners closely monitor oil prices, which vary 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 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 have asked transporters to score the road conditions using a five-point Likert scale, where one corresponds to the best possible conditions five 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 trucking 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 they 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 crossing and Refugee camp (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 (Perouse de Montclos & Kagwanja, 2000). Today Kenya hosts the largest (Dadaab) and the third largest (Kakuma) refugee camps in the world. Other refugee camps are located in the neighboring countries (Sudan, Uganda, Ethiopia, etc.) and served from the Port of Mombasa. We add a dummy variable for refugee camp destinations as well.

4.1.2 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 dry 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 transportation services because transit times to destinations 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.

4.1.3 Descriptive Statistics

Table 2 contains descriptive statistics for the main variables of interest. It shows, for the line-haul and contract 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 is destined to refugee camps, 35 of them is for heavy cargo transport, 118 of them covered rainy season and 148 of them has a length less than six months.

Table 2 Descriptive Statistics

Variable	Average	St. Deviation	Median	Min.	Max.
Dependent variable					
rate (T) (USD/mt)	109.25	88.28	83.00	0.33	400.00
Line-haul factors					
distance (km)	867.60	477.94	785.00	36.70	2,148.00
fuel price (USD)	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 (mt)	856.43	3,144.31	144.00	15.00	31,000.00

4.2 ECONOMETRIC MODELS

We now explain how the variables were selected in developing our final regression model. Table 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 & Watson (2003).We first regressed the rates (Model 1) 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 1, 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 2 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 2 or that the link function 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 specification (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 3 Regression models

Variables	**Model 1**	**Model 2**	**Model 3**
Line-haul factors			
fuel price (USD/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 (USD-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 (mt)		-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 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.

4.3.1 Insights from the Results Obtained for the Line-haul Factors

The most critical factor with a significant impact on the transportation rates is the interaction term between the fuel price and the distance. Fuel consumption, usually measured in liters/100km, varies depending on multiple factors, including the age and efficiency of the truck, the weight of loads, the speed of delivery, the road inclinations, and conditions. 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. Note that, among all the ones considered, this is the only variable 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 more incidents and by the higher maintenance costs as the trucks drive further from the origin in a sparse and poor road network like the one in East Africa. As expected, the coefficients of the variables average perceived road conditions (12.1 USD/mt), and border crossing (50.1 USD/mt) are significant and positive. It implies that rates per trip are higher when road conditions worsen and that there is a 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 USD/mt), 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 than in other rural areas with similar characteristics. The variable that indicates a large population concentration at the origin is a significant positive value, whereas the variable that indicates a large population concentration at the destination, is a significant negative value. Consequently, 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.

4.3.2 Insights from the Results Obtained for the Contract Factors

Economies of scale do not appear to be important in the truckload 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 during the interviews. 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. 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

USD/mt. 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 simple contracts are preferable.

5 A BARRIER-TYPE OPTION FOR TRANSPORT RISK SHARING

We use a real options approach in order to incorporate flexibility into the long-term fixed-rate contracts so as to allow a shipper to share the transporters' risk due to 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 the only significant dynamic factor influencing 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 very 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 will adopt this approach to update contracts based on the fluctuations of the fuel price, but the update will be possible only after the fuel price hits a certain threshold.

5.1 METHODOLOGICAL FRAMEWORK

The methodology framework presented in this section aims to incorporate flexibility in transport contracts so that they are responsive to the changes in the market. 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 3, 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 computing 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 option using backward induction on the spot market prices tree for a given contract setting. By solving this problem for multiple rates and thresholds, we obtain an efficient frontier of the contract settings, which can be helpful for the negotiations between the shippers and the transporters.

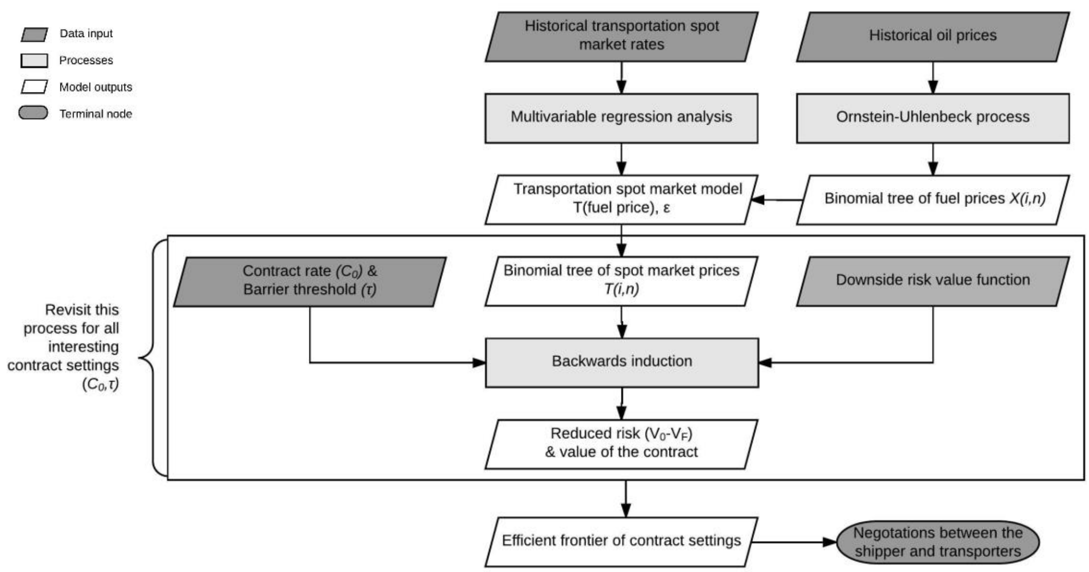

Figure 3 Methodological framework

Now we turn to a detailed account of the proposed framework (except the part that has already been discussed in Section 4). The common approach to solve the real options using a binomial tree was first suggested by Cox et al. (1979). In this study, we adapted the approach presented in the recent book by Guthrie (2009). Concerning the first task mentioned above, there are two commonly used processes to model the price fluctuations of fuel prices: (i) random walk with a drift and (ii) mean reverting process, specifically, one-period autoregressive process. 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 I, to choose the best fit out of these two models. Since, random walk is indeed a special case of one-period autoregressive process, AR(1), we can confirm which model is a better fit to our data through regression. For this, we used 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) for representing the fuel price fluctuations. In a stationary AR(1) process, price shocks are not permanent, and the prices tend to return their long-term averages, which is called a "mean-reverting" behavior.

5.1.1 Construction of the Binomial Tree for Fuel Price

In order to calculate the levels of up and down movements in the binomial tree, 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. We estimate the $X_{(i,n)}$ values through an Ornstein-Uhlenbeck (O-U) process that generalizes AR(1).

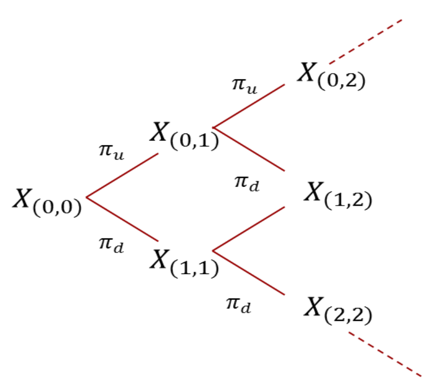

Figure 4 Binomial tree representation of fuel price fluctuations

The log-price difference between two periods in AR(1) is given by:

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

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

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

Here γ, ρ and σ are constants, and they represent the mean, the mean-reversion rate and the volatility respectively. According to (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:

$$\alpha_0 = \left(1 - e^{-\rho\Delta t}\right)\gamma, \quad \alpha_1 = -(1 - e^{-\rho\Delta t}), \quad \phi^2 = \frac{\sigma^2}{2\rho}(1 - e^{-2\rho\Delta t}). \tag{3}$$

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

$$\hat{\rho} = \frac{-log(1 + \widehat{\alpha_1})}{\Delta t}, \qquad \hat{\gamma} = -\frac{\widehat{\alpha_0}}{\widehat{\alpha_1}}, \quad \widehat{\sigma^2} = \widehat{\phi^2}\frac{2log(1+\widehat{\alpha_1})}{\widehat{\alpha_1}(2+\widehat{\alpha_1})\Delta t} \tag{4}$$

As suggested by Nelson & 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:

$$log\, X_{(i,n)} = logX_{(0,0)} + (n - 2i)\hat{\sigma}\sqrt{\Delta t}. \tag{5}$$

Then, each value in the tree can be estimated:

$$X_{(i,n)} = X_{(0,0)}{}^{(n-2i)\hat{\sigma}\sqrt{\Delta t}}. \tag{6}$$

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 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 spot market oil prices to adjust our probabilities. The details of risk-free probability calculations are given in Appendix II, where we also show that there is almost a perfect linear relationship between the futures and the spot prices. Using that relationship, we can use the futures values of oil prices to estimate the spot market oil prices after taking the exponentials of both sides of it as follows:

$$F_{(i,n)} = e^{a_0 + a_1 log X_{(i,n)}}. \tag{7}$$

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

$$\pi_{u(i,n)} = \frac{F_{(i,n)} - X_{(i+1,n+1)}}{X_{(i,n+1)} - X_{(i+1,n+1)}}. \tag{8}$$

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.

5.1.2 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

In general, the transportation spot market changes have no influence on 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. During these periods, transporters are reluctant to send their trucks to the contracted shipper, in the hope of finding a better paying job in the market. Consequently, they delay their response to the shipping requests by coming up with excuses. Once they are confident that they cannot find a better job, they aversely fulfill the transportation request of the shipper 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. 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 $X_{(i,n)}$ from the binomial tree for fuel prices to the rate estimation model and calculate $T_{(i,n)}$. Note that, our regression function uses diesel pump prices, where the calculations in Section 4 use crude oil prices. The details of converting the crude prices to the pump prices can be found in Appendix III.

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

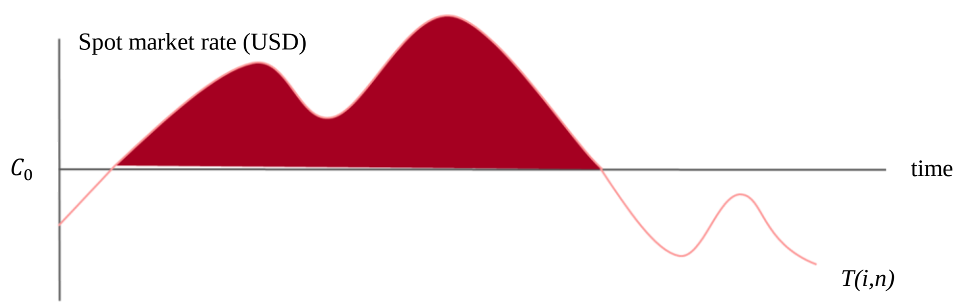

Figure 5 Downside risk under the original contract

In Figure 5, 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 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:

$$V_{C(i,n)} = \left[\left(T_{(i,n)} - C_0\right)\mathbf{1}_{\{T_{(i,n)}>C_0\}}\right] load_n + \frac{\pi_{u(i,n)}V_{C(i,n+1)}+\pi_{d(i,n)}V_{C(i+1,n+1)}}{1+r_f}. \tag{9}$$

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 USD/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 USD/lt then, we will update the contract as long as the price remains above this level. But obviously, we will not increase the contract rate by 15%, instead, we will use the elasticity (ε) dictated by the rate estimation model in Section 4. For each O-D, we can calculate the point 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 $C_0^\tau = C_0(1 + \tau\varepsilon)$.

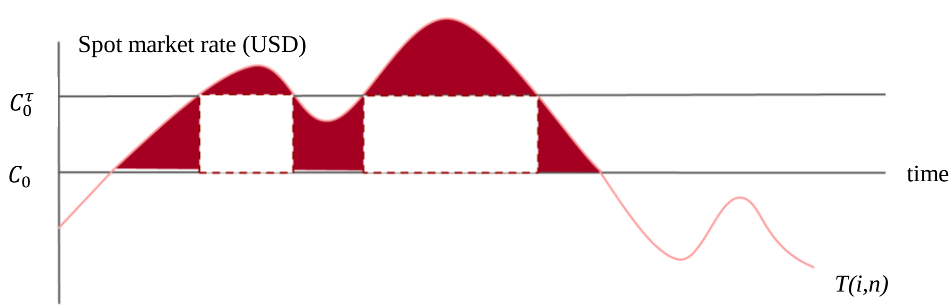

Figure 6 Downside risk under the flexible contract

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. Nonetheless, the downside risk for the transporter is reduced and, it is represented as:

$$V_{F(i,n)}(C_0,\tau) = \left[\left(T_{(i,n)} - C_0\right)\mathbf{1}_{\{C_0^\tau > T_{(i,n)} > C_0\}} + \left(T_{(i,n)} - C_0^\tau\right)\mathbf{1}_{\{T_{(i,n)} > C_0^\tau\}}\right] load_n + \frac{\pi_{u(i,n)}V_{F(i,n+1)} + \pi_{d(i,n)}V_{F(i+1,n+1)}}{1+r_f}. \quad (10)$$

Value of introducing flexibility

We can calculate the 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 (N) is zero:

$$V_{C(i,N)} = V_{F(i,N)} = 0, \forall i. \quad (11)$$

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 discounted 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 value of introducing price-flexibility to our model using the barrier option. This difference amounts to the expected downside risk aversion by the transporter.

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 transporters, the rate as per the current contract, namely 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. 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 $C_L^{\tau} = C_L(1 + \tau\varepsilon)$.

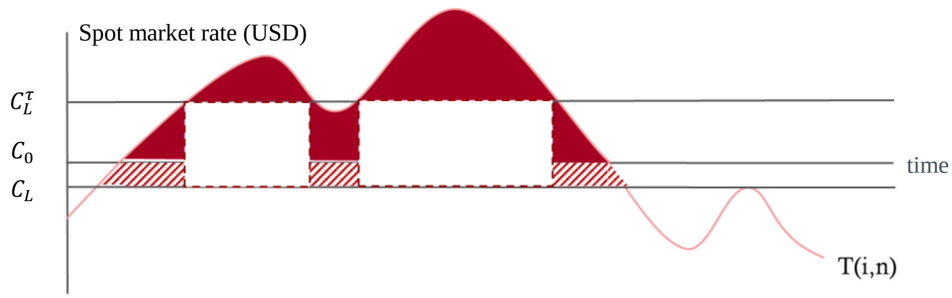

Figure 7 New (lower) base rates

It is evident from Figure 7 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 do not deviate much from what is effectively being paid under the current contracts.

6 NUMERICAL RESULTS

In this section, we test the performance of the suggested contracting scheme using 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, Kenya 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, we report the details pertaining to these O-D pairs using 2014 data. The same contract rates were in effect by the time we collect this data around mid-2015.

Table 4 Description of the top five origin-destination pairs

Origin	Destination	Distance (km)	Rate, C_0 (USD/mt)	Load (mt)	Contract Value (USD)
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 8 depicts these locations on the map.

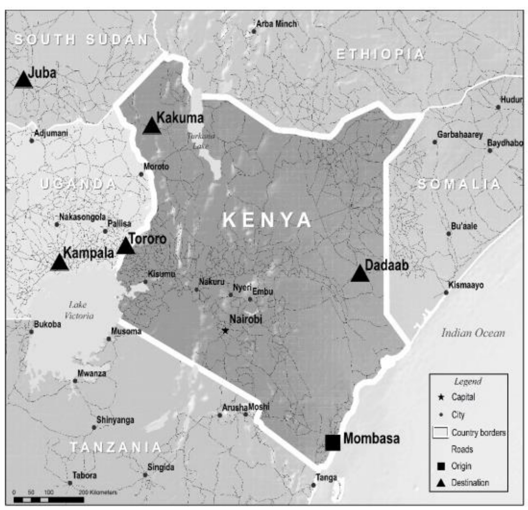

Figure 8 Port of Mombasa (origin) and top 5 Destinations

For each O-D pair, we calculated and compared the downside risks 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.

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. Naturally, the binary tree for the fuel prices is the same for all O-Ds. By varying the oil price, we also empirically estimate the elasticity (ε) of the fuel price.

For each O-D, we have explored a wide range of alternative contract values, $C_L \in [0.75C_0, C_0]$, and 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:

$$Risk\ Reduction(C_L, \tau) = V_{F(0,0)}(C_L, \tau) - V_{C(0,0)} \tag{12}$$

Not all contract values and thresholds in our solution space yield a positive risk reduction. As C_L keeps decreasing, the 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 level of the updated contract is $C_L^\tau = C_L + C_L\tau\varepsilon$. However, if we keep increasing the threshold, there would be less chance for fuel price to hit the barrier and as a result the contract rate remains not updated for longer periods. Figure 9 depicts that reduced risk is monotonically decreasing in C_L and concave in τ. Note that, this graph does not include points that yield non-positive risk reduction values.

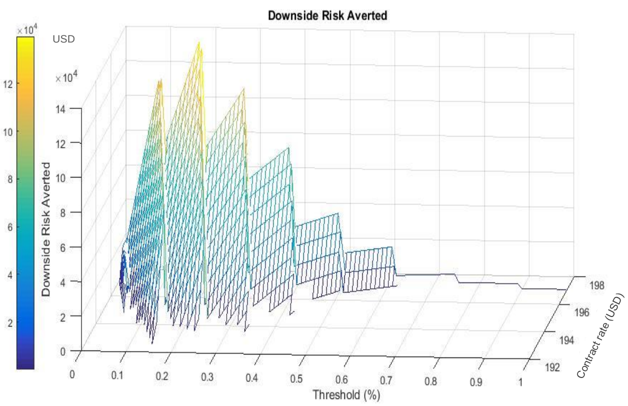

Figure 9 Downside Risk Averted as a function of different contract settings (rates and thresholds)

There can be multiple threshold values providing a positive downside risk aversion 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 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 elevated payment when the fuel price increases 18% or more. On the other extreme i.e., in the first setting, the transporter expects to receive 156,175 USD less, where her expected risk reduction accounts only for 13,207 USD. However, if we take a closer look to instance 6, we see that there is still significant risk reduction (33%), and also the total expected payment remains almost equal to the current contract. In fact, by only manipulating the contract setting, with no additional costs to none of the stakeholders, a significant risk reduction is achievable. Although, a risk reduction of 92,488 USD may not seem substantial for a contract valued almost 15.7 M USD, it actually corresponds to a 6% increase in the net profits, again at no cost, given that the transporters report a 10% profit margin in the overall contract value.

Table 5 Numerical results for Mombasa - Juba

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

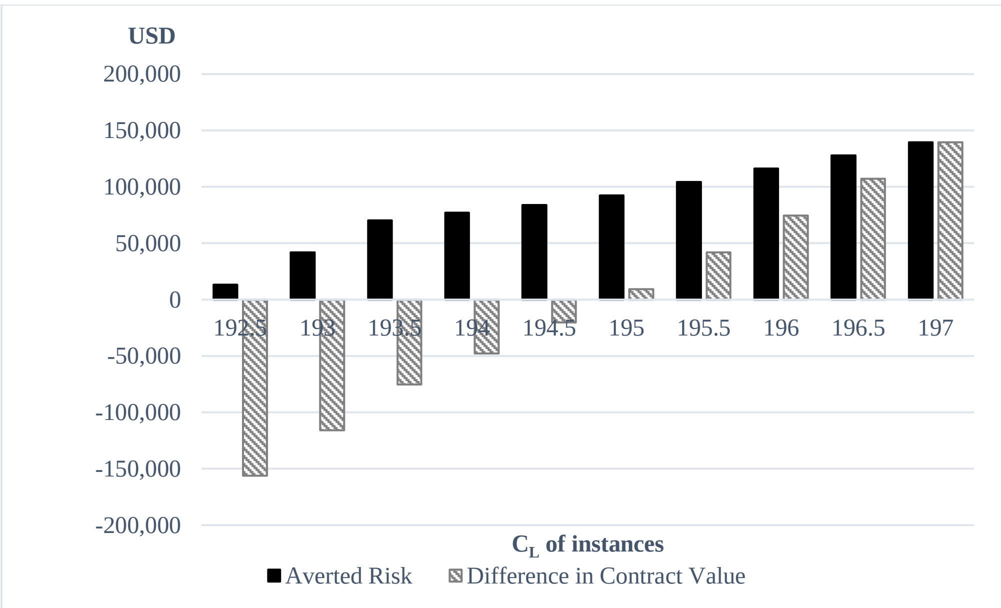

Figure 10 Efficient frontier of risk reduction and total payment for Mombasa – Juba lane

Figure 10 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 USD) 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 150,000 USD. 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 USD/mt seems reasonable for a risk neutral transporter, whereas rates of 194.5 USD/mt or even 194 USD/mt 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 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 6 An overall performance of flexible contracts on selected OD pairs

Origin	**Destination**	**Actual Contract, C_0 (USD)**	**Spot price at $T(0,0)$ (USD)**	**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. The high level of supply on these two routes may justify why transporters are willing accept contract 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. 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.

7 CONCLUDING REMARKS

Sustainable food aid transportation is an essential component of providing food security at 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 at the pump 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) the aid organization with higher service levels than the current practice. The novelty of the proposed data-driven methodology is the adoption of a 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.

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APPENDIX I

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:

$$p_{j+1} - p_j = \alpha_0 + \epsilon_{j+1}, \qquad \epsilon_{j+1} \sim N(0, \phi^2). \tag{13}$$

where $\epsilon_{j+1}$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:

$$p_{j+1} - p_j = \alpha_0 + \alpha_1 p_j + \epsilon_{j+1}, \qquad \epsilon_{j+1} \sim N(0, \phi^2). \tag{14}$$

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 exists 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 7 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.

APPENDIX II

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:

$$V = \frac{\pi_u Y_u + \pi_d Y_d}{1+r_f}. \tag{15}$$

Where the risk-free probabilities are defined as

$$\pi_u = \frac{Z(1+r_f) - X_d}{X_u - X_d}. \tag{16}$$

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:

$$\pi_u = \frac{F - X_d}{X_u - X_d}. \tag{17}$$

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 8 The regression analysis of log crude oil prices on 1-period ahead futures prices

Variables	Model
log fuel price (USD/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.

$$F_{(i,n)} = e^{0.1268+0.9736*logX_{(i,n)}}. \tag{18}$$

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 increases 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:

$$\pi_{u(i,n)} = \frac{F_{(i,n)} - X_{(i+1,n+1)}}{X_{(i,n+1)} - X_{(i+1,n+1)}}. \tag{19}$$

APPENDIX III

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.

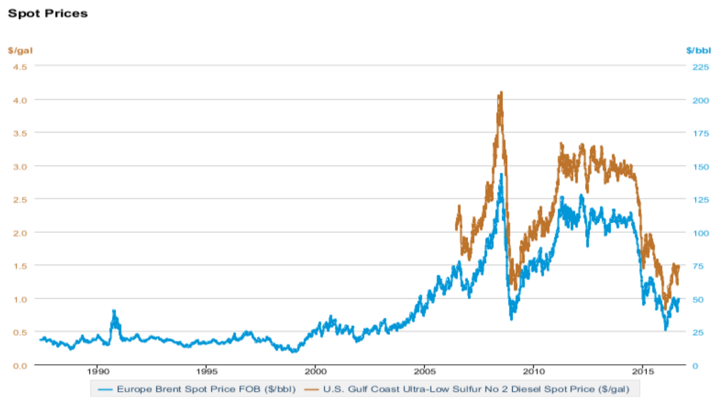

Figure 11 The close relationship between the crude oil prices and the diesel prices

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.

Table 9 The regression analysis of crude oil prices on diesel prices

Variables	Model
Crude oil price (USD/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: $P_{USDiesel} = 13.33163 + 1.045072 P_{Crude}$. (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 (The World Bank, 2014) data which not very populated, but at least reliable.

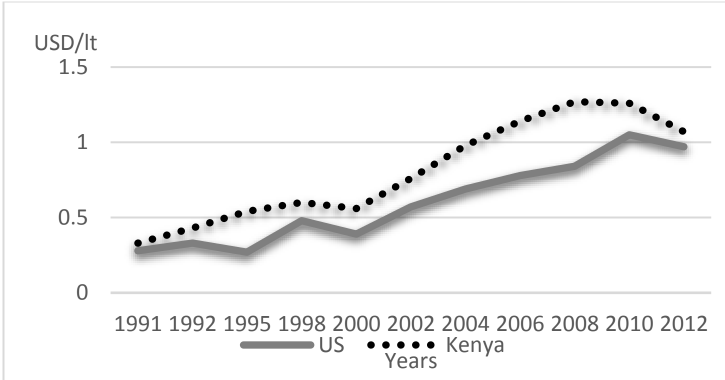

Figure 12 Diesel pump price trends in US and Kenya

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 written as follows:

Table 10 The regression analysis of US diesel pump prices on Kenyan diesel pump prices

Variables	**Model**
US diesel pump price (USD/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: $P_{KDiesel} = 1.163 * (13.33163 + 1.045072 * P_{Crude})$.