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Demand forecasting and order planning for humanitarian logistics: An empirical assessment

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ABSTRACT

Humanitarian aid organizations are most known for their short-term emergency relief. While getting aid items to those in need can be challenging, long-term projects provide an opportunity for demand planning supported by forecasting methods. Based on standardized consumption data of the Operational Center Amsterdam of Médecins Sans Frontières (MSF-OCA) regarding nineteen longer-term aid projects and over 2000 medical items consumed in 2013, we describe and analyze the forecasting and order planning process. We find that several internal and external factors influence forecast and order planning performance, be it indirectly through demand volatility and safety markup. Moreover, we identify opportunities for further improvement for MSF-OCA, and for humanitarian logistics organizations in general.

1. Introduction

Humanitarian aid organizations are most known for their short-term emergency relief, even though long-term projects are an important part of their operations (Minear, 1996). The logistics of getting (medical) aid items to those in need is in some respects similar to commercial logistics (Van Wassenhove, 2006), although the circumstances can be challenging: demand uncertainty is typically high, road and IT infrastructures are often poor or non-existing, skilled personnel are in poor supply and the local government and population are not always supportive. Long-term projects, though, provide an opportunity for demand planning supported by formal forecasting methods. Better forecasting and planning reduces stock-outs, over-stocking and expiration of goods, which in turn saves time, reduces costs, improves patient outcomes and care and may even save lives. Moreover, it facilitates accountability to donors and the public in general.

While literature is equivocal regarding the difficulties of humanitarian aid operations, to our knowledge no (quantitative) empirical evidence has been offered to determine the impact of these challenges on demand planning performance. This paper provides such evidence through a case study at one of the operational centers of Médecins Sans Frontières (MSF) located in Amsterdam (MSF's Operational Center Amsterdam, or MSF-OCA). MSF-OCA coordinates projects in about 25 countries worldwide offering medical assistance to victims of conflict, natural disasters, epidemics and health care exclusion (www.msf.org). MSF has been one of the first humanitarian organizations to realize that logistics is at the core of its operations, but also that logistics planning can be difficult and time consuming due to lack of (standardized) data, lack of proper logistics support systems and lack of metrics for performance measurement and improvement (Van der Laan et al., 2009b). According to MSF's logistics vision: “Our supply chain in the field is time consuming and error prone. Whilst many improvements have been made, …, it is not delivering as it should. We cannot forecast, do not focus enough on timely delivery of goods, no real quality control for medical local purchases, and lack clarity between med and logs (time consuming, tools are not modern, not as accountable as we want it to be.” (MSF-OCA 2015, internal document, p.11). Moreover, the organization's logistics strategy states as their key objective to “have an improved ability to consistently deliver the right goods when needed (forecasting, sourcing, data analysis, reception, controlled dispensing” (MSF-OCA 2015, internal document, p.15). Since the end of 2012, MSF-OCA has collected field consumption data along with project information about nineteen of her projects. In this present study, the combined consumption and forecast data are used to gain insight

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into the influence of project characteristics on order planning performance.

The main contributions of this paper are threefold. First, we provide insight into the demand planning and distribution operations of one of the front runners in humanitarian logistics, through a detailed case study at MSF-OCA. Secondly, we empirically explore the impact of internal and external factors on forecasting and order planning performance, through an extensive statistical analysis of monthly consumption and forecasting data for over 2000 medical items, 2013. Thirdly, we identify opportunities for further improvements in the operations of MSF-OCA, and of humanitarian logistics organizations in general.

The paper is organized as follows. Section 2 positions our research within the humanitarian context and relevant forecasting literature and provides a classification of internal and external factors that may impact humanitarian logistics operations. Section 3 presents an in-depth case study of MSF-OCA's forecasting and order planning operations. Section 4 outlines the research design and methodology. Findings are presented in Section 5, whereas implications for theory and practice are discussed in Section 6.

2. Theoretical background

2.1. Humanitarian logistics

Humanitarian logistics has been defined as 'the process of planning, implementing and controlling the flow and storage of goods and materials as well as related information, from point of origin to point of emergency, for the purpose of meeting the end beneficiary's requirements' (Van der Laan et al., 2009a, p. 365). Mitigating the ' … urgent needs of a population with a sustainable reduction of their vulnerability in the shortest amount of time and with the least amount of resources' (Van Wassenhove, 2006, p. 480) is typically the main performance target. The humanitarian sector spends billions of dollars annually (Thomas and Kopczak, 2005) to counter the increasing need for humanitarian response. According to Thomas and Kopczak (2005) humanitarian logistics is a critical element of the disaster response process for three reasons: it is the main driver for speed and effectiveness; it is at the nexus of several information flows with a potential for process evaluation and improvement; and it is the most expensive part of the response process (Van Wassenhove, 2006), including the activities of procurement and transportation. In terms of recognition and infrastructure, however, humanitarian logistics used to lag some 15 years behind private sector logistics (Van Wassenhove, 2006), and things have been changing only slowly. This is evidenced by recent developments at MSF where much work is done to improve international supply for the MSF movement, other NGOs and UN. Implementation or attempts of ERP systems have been slow and painful but are happening and should reap rewards in terms of supply chain visibility at the minimum. “What many NGOs and UN have struggled to monitor is the last leg of the supply chain to the patient/beneficiary. MSF in that sense has a unique vantage point as a direct service provider in many and varying contexts” (Begench Dzhumageldyev, Logistics Advisor for Afghanistan, Bangladesh, Kenya, Pakistan, South Sudan, MSF-OCA).

Humanitarian logistics differs from commercial logistics in terms of, for instance, objectives pursued, decision making structure and supporting systems (Holguín-Veras et al., 2012), and it faces specific resource and process constraints that challenge operations. It also differs from military supply chains, which have a clear command and control structure (Van Wassenhove and Pedraza Martinez, 2012) and adopt possibly different attitudes towards the principles of neutrality, impartiality and humanity (Tomasini and Van Wassenhove, 2009).

2.2. Factors that affect humanitarian logistics performance

The humanitarian context comes with several conditions that make humanitarian operations particularly challenging. A distinction can be made between: endogenous factors, which relate to the way operations are managed; non-situational exogenous factors, which are generic conditions that influence project outcomes, outside immediate project control; and situational exogenous factors, which are project specific determinants of performance. These factors are elaborated below.

Endogenous performance determinants originate from within the supply chain, and can be directly influenced by the supply chain actors themselves. Examples are factors related with personnel, information systems and coordination of activities. Humanitarian organizations often struggle with attracting, training and withholding skilled staff (Van Wassenhove, 2006; Thomas and Kopczak, 2005). High staff turnover rates lead to difficulties in knowledge transfer (Kovács and Spens, 2009; Van der Laan et al., 2009a,b). Limited access to and use of technology (Beamon, 2004; Van der Laan et al., 2009a,b), such as information systems and software tools, make it hard or impossible to retrieve, store, distribute (Lee and Lee, 2007; Van Wassenhove and Pedraza Martinez, 2012; Van der Laan et al., 2009b) and analyze field data. Lack of standards and performance indicators (Thomas and Kopczak, 2005; Van der Laan et al., 2009b) impede proper improvement of supply chain processes. Lack of coordination with supply chain actors (Thomas and Kopczak, 2005; Kovács and Spens, 2007; Samii, 2010) and external stakeholders (Van der Laan et al., 2009a) may lead to oversupply in some regions and under-supply in others, while competing for the same resources drives up prices. The negative performance impact of these endogenous factors may be expected to be mitigated over time, as the role of logistics is more and more acknowledged within the supply chain (Thomas and Kopczak, 2005; Van der Laan et al., 2009b).

By contrast, situational exogenous factors originate from outside the supply chain and hence are beyond the immediate control of supply chain actors. Kunz and Reiner (2012) propose a classification of these factors consisting of infrastructural factors, like local transportation capacity and road/mainport accessibility, environmental factors (influencing the demand for certain medicines), socio-economic factors (influencing the supply of goods and skilled labor), and governmental factors (the political climate is often volatile, trucks might be stopped or blocked by rebel forces in times of war, looting of the supply might occur, or vehicles are even completely deviated from the intended location).

Furthermore, non-situational exogenous factors are characteristics of the humanitarian relief environment, not connected to the disaster-affected area. Examples are the uncertainty about the size, timing and location of demand for aid (Beamon, 2004). Other examples are: the presence of a large number of stakeholders, which complicates the relief effort; the complexity of circumstances, which can obscure the precise nature of the aid request; and the time pressure, which calls for quick action (Van Wassenhove, 2006).

Additionally, the type of relief, emergency or longterm (Minear, 1996), the time elapsed since the start of the relief, the scale of the operation and the criticality of product demand may influence the amount of data and knowledge available. These factors have not been mentioned in the literature, but they are routinely recorded by MSF-OCA and considered relevant: “The institutional memory of our project locations affects the quality of our forecasts. The assumptions the forecasts were based on are also often lost in our history. Where the quality of consumption and morbidity data is poor and the data history is short, our ability to forecast is impaired” (Anna Eschweiler, Medical Supply Pharmacy Advisor MSF-OCA).

2.3. Forecasting for demand planning

As for commercial supply chains, the importance of adequate forecasting is paramount for supporting operations management (Oliva and Watson, 2009). In view of the high stakes and the limited budgets that humanitarian organizations face, demand forecasting might even be considered more essential in the humanitarian context. However, many endogenous factors can complicate the collection of relevant field data and the use of forecasting techniques, while exogenous factors may negatively influence forecast accuracy. According to Van Wassenhove and Pedraza Martinez (2012), demand forecasting is possible, while best practices indicate that demand forecasting can generate more than 7% savings on annual operating costs. The forecasting process needs to be flexible, though, to react to a changing context. Oloruntoba and Gray (2006) plead for an 'agile' humanitarian supply chain that responds to real demand as it is fed by field data to diminish forecasting errors. Time-series data from the field would enable the use of formal forecasting techniques. But even in commercial supply chains with sophisticated information systems in place and access to readily available statistical forecasting methods (see e.g. Ord and Fildes, 2012), forecasting relies on human judgment (Lawrence et al., 2006).

To our knowledge there is no literature on forecasting methods specifically designed or applied to order planning in the humanitarian context. Studies that deal with forecasting focus on emergency prediction (see e.g. Maile, 2005; Chantarat et al., 2008), rather than long-term response after the start of an emergency, which is the focus of this present paper. Virtually no empirical data about forecasting or demand planning performance exist. A previous study at MSF-OCA (Van der Laan et al., 2009b) has revealed that forecasting or assessing needs was deemed challenging due to the ever changing project context and medical needs and the large number of beneficiaries. Meanwhile, MSF-OCA has developed an information systems to collect field consumption data suitable for analysis and decision support.

3. Operations of MSF-OCA

3.1. Structure and process

Forecasting at MSF is part of the order and procurement process, and involves actors throughout its organization. The organizational structure consists of a hierarchy of internationally active operations centers (MSF-OCs), nationally operating missions, and local project sites (Van der Laan et al., 2009a,b). The order process is typically initiated by the operation centers' centralized procurement and supply units, which prompt projects to order medical supplies at fixed times during the year, usually every four or six months under service level agreements (SLAs). Projects are hierarchically linked to a mission, which usually operates within a single country. These projects commonly follow the same order cycle, which allows the mission coordination team to efficiently prepare all orders and the operation centers to cost-effectively combine shipments. Each project works with a standardized list of medical items that can be ordered from the Amsterdam Procurement Unit (APU). This list is constantly updated based on program needs, newly available products and availability of sources.

The responsibility of ordering medical supplies is shared between the medical and logistics teams of the mission. The medical team makes forecasts of the required medical supplies, while the logistics team converts these forecasts into orders and collaborates with the OC's procurement division to organize the shipments. Administrative responsibilities are clearly distinct. The logistics team is not in a position to convert program objectives and morbidity data into required quantities, to indicate which medical products can be considered substitutes, or to gain access to, e.g., clinic attendance data. Likewise, the medical team does not know about, e.g., current stock levels in the base medical store, the quantity of stocks on order or the lead-time for order arrival. At MSF, spreadsheet tools have been developed to record actual field-level consumption of medical items and forecasts, the so-called consumption tool and total stock review, respectively. The collection of consumption data is a delicate process subject to the challenges of maintaining a proper administration in humanitarian aid regions: "Collection of consumption data in a standardized way meant that MSF-OCA had to ensure consistent product information and master data to feed into our consumption tool as well as agreed lists for each medical activity in a project area and the training and monitoring of staff to ensure good data quality. We do this in many contexts where staff often have poor literacy and numeracy skills. It has been a big effort by all to get this far" (Anna Eschweiler, Medical Supply Pharmacy Advisor MSF-OCA).

3.2. Making forecasts and preparing the order

MSF-OCA defines consumption as the quantity of a medical item used for patient care. This differs from the quantity that leaves the pharmacy or that has been lost due to waste or other causes. First, consumption data are collected and aggregated at the project level, which is the responsibility of the medical teams. Second, the collected consumption information is compared with weekly recorded health issues and service delivery data, which enables early recognition of changes in consumption patterns. Third, forecasts are made based on the collected consumption data and information about expected health issues. In the case of existing projects, forecasts are based on average consumption over the past year adjusted for planned changes in the program and expected changes in demand for services. Forecasts for new projects are based on expected patient numbers and service delivery. Subsequently, forecasts of the required laboratory reagents and supplies are determined based on expected medical activities and associated lab procedures.

The forecast generated by the medical team has three components: monthly consumption forecast, an emergency preparation (e-prep) level, and a safety classification. The e-prep level is a type of safety stock that needs to be in stock to cope with emergencies; it is consumption invariant. The safety classification defines the criticality of medical items as either critical, normal or low. Along with the classification, criticality parameters for individual projects define the number of months that supplies have to be held as safety stock. The safety markup that combines the safety classification and the criticality parameters, differs per item and project. Once the medical supply forecasts have been approved, they are handed over to the logistics team which converts the medical supply forecast into an order, rounding up to reflect packaging size. Currently available stock and stock on order are subtracted, while safety stock and stock expiring before the end of the target order period are added. The supply logistics officer checks the calculations before generating an order based on the forecast.

Forecast performance has immediate consequences for the stock levels maintained in the mission warehouse and the project's central pharmacy, and thus for the medical services provided. Systematic over-forecasting leads to excessive stocks and corresponding cost inefficiencies, while under-forecasting may cause stock levels to be too tight and thus adversely affect the quality of medical services. For a humanitarian organization like MSF, the impact of ruptures, that is no or limited access to health care, caused by under-forecasting is considered worse than piling up over-stock or having losses due to expiration: "The impact of

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ruptures, apart from the quality of care, disrupts the supply chain at all levels. A critical rupture means the supply staff in the project, mission and HQ effectively have to stop everything to identify a source and a quick supply of the product. The time frame to manage and reduce overstocks is in general less disruptive to MSF programs and the supply chain" (Nontas Papadimitriou, Logistics Coordinator, India, MSF-OCA).

4. Data and measures

4.1. Data

Our empirical study uses consumption and forecast data about drugs, medical materials and equipment of nineteen projects operated by missions in eight countries: Bangladesh, Congo, Ethiopia, Haiti, Nigeria, Pakistan, South-Sudan and Yemen. All projects are supplied by MSF's operation center in Amsterdam (MSF-OCA). Data are at the SKU level, and refer to the year 2013. Additionally, contextual data have been collected about the age and the nature of projects, the type and size of the target population. The data about the sample projects include two order cycles as part of the standard reporting processes of MSF-OCA for December 2012 and April 2013.

At the time of research, 2223 medical items were identified and used as a basis for compiling the monthly consumption data about the nineteen projects, January-December 2013. The identified items were used to collect the order data consisting of monthly consumption forecast (in units per SKU), safety stock classification (expressed as normal, critical or low for each SKU) and associated criticality parameters (in number of months for the normal and critical SKUs), e-prep levels (in units per SKU), and the lead time and order period. The combined consumption and forecast data, discarding records with missing information about monthly consumption, forecast and emergency preparation, contain 11,486 usable records for analysis.

4.2. Forecast performance measures

A variety of forecast performance measures exists, which can be categorized into: scale-dependent measures, percentage-error measures, symmetric measures and scaled-error measures (Hyndman and Koehler, 2006). First, scale-dependent metrics, like mean forecast error (*Me*) and root mean square error (*Rmse*), are directly based on the forecast error, and consequently have the same measurement level as the underlying series. This is fine when the same series is evaluated under different conditions, but can be misleading when evaluating widely different SKUs (Armstrong and Collopy, 1992), as is the case for MSF. Second, percentage-error metrics, like the mean percentage error (*Mpe*) and the popular mean absolute percentage error (*Mape*), are based on forecast errors divided by actuals. As these measures are scale-independent, they are frequently used to compare the results of forecasting methods across multiple series. An obvious disadvantage of these measures is that they are not defined when actual consumption is zero. This is a serious issue for the MSF data, for which around 40% of the SKUs have zero consumption. Moreover, under- and over-forecasting are weighted differently by the often-used mean absolute percentage error. Its maximum is equal to 100%, when under-forecasting, while it can be arbitrarily large when over-forecasting. This is undesirable for humanitarian organizations, as under-forecasting potentially leads to stock-outs that can have a severe impact on the quality of the health care provided. Third, symmetric measures, like the symmetric mean absolute percentage error (*sMape*), address the imbalance of *Mape* by using the sum of actual and forecasted consumption as a divisor instead of only actual consumption (Hyndman and Koehler, 2006; Makridakis and Hibon, 2000). This adjustment reduces the problem of dividing by zero. Though the measures are not truly symmetric when the denominator of the metric becomes negative (Goodwin and Lawton, 1999), this has no practical relevance for the MSF data as actual and forecasted consumption are non-negative throughout. Fourth, scaled-error metrics, like Theil's U, are relative measures comparing the forecast error with the error generated by some baseline model, like a naive forecast (Hyndman and Koehler, 2006). Even though these measures have attractive properties, they are impractical for the present study as past performance data do not yet exist.

Following the properties of the various metrics, we choose two symmetric measures to indicate forecast performance, *sMape* and *sMpe*. We denote the actual consumption of project p of medical item s during order cycle t as A_{tps}, and the corresponding forecast as F_{tps}. The symmetric mean absolute percentage error (*sMape*) is defined as:

$$sMape_{tps} = \frac{|A_{tps} - F_{tps}|}{A_{tps} + F_{tps}} \tag{1}$$

Considering that actual and forecasted consumption at MSF are non-negative, *sMape* is always between zero, when forecast errors are zero, and one when actual consumption is either extremely over-forecasted or under-forecasted. However, *sMape* does not reflect the direction of the forecast error. Therefore, the symmetric mean percentage error (*sMpe*) is introduced as:

$$sMpe_{tps} = \frac{A_{tps} - F_{tps}}{A_{tps} + F_{tps}} \tag{2}$$

Its interpretation is largely conform that of *sMape*, except that negative values indicate over-forecasting and positive values are evidence of under-forecasting. The measure is also known as forecast bias. The calculation of the performance measures results in missing values when aggregate monthly consumption and aggregate monthly forecasts add to zero, or when either is missing.

4.3. Order planning performance measures

Though existing stock levels are unobserved, placed orders partly reflect the significance of adequate inventory. Orders consist of forecasted monthly consumption, a consumption-invariant emergency preparation (e-prep) level, and a safety stock that varies with forecasted monthly consumption. The potential of orders to satisfy consumption provides an alternative measure of order performance.

Explicitly writing the ordered amount for each SKU, project and order cycle, as the sum of forecasted consumption F_{tps}, emergency-preparedness level E_{tps} and safety stock S_{tps}, the consumption and order performance measures are determined similar to (1) and (2) as:

$$sMapeOrder_{tps} = \frac{|A_{tps} - (F_{tps} + E_{tps} + S_{tps})|}{A_{tps} + F_{tps} + E_{tps} + S_{tps}} \tag{3}$$

and

$$sMpeOrder_{tps} = \frac{A_{tps} - (F_{tps} + E_{tps} + S_{tps})}{A_{tps} + F_{tps} + E_{tps} + S_{tps}} \tag{4}$$

Here, A_{tps} is actual consumption, and S_{tps} denotes safety stock, which is exogenously determined as the consumption forecast times the safety markup c_{ps}, $S_{tps} = c_{ps}F_{tps}$. Consistent with the consumption forecast bias, the order forecast bias *sMpeOrder* is negative in the case of over-stocking, and positive in the case of under-stocking.

Though informative, the order performance measures do not provide a direct handle on operational improvement. For this purpose, we developed a categorical performance metric with outcomes: 'risk of expiry', 'good ($A < F$)', 'good ($A > F$)', 'rupture' and 'extreme rupture'; its definition is illustrated in Fig. 1. The line labeled 'forecasted consumption' represents the aggregate monthly consumption forecast. If the actual consumption is greater than the consumption forecast ($A > F$), but the difference can be absorbed by the safety stock level (and the Eprep level, if applicable), then this is still considered a good forecast. If the difference cannot be absorbed by existing stocks, the projects of MSF-OCA have the possibility to place an emergency order outside the international order cycle, or to buy on a local market. Both options are undesirable as they either come with higher costs or with product quality issues: a 'rupture' is said to have occurred. If the difference between the consumption and the forecast is larger than the expected demand during the order lead time, then there is a high chance that even an emergency order or local buy will not solve the problem and an 'extreme rupture' is said to have occurred. Note that stockouts may cause actual demand to be underestimated, as consumption rather than actual demand is recorded. Hence, the subsequent forecasts may underestimate the risk of rupture. If the consumption turns out to be lower than forecasted ($A < F$), overstocks are produced, which is undesirable as aid items, in particular medicines, can expire. A 'risk of expiry' occurs when the produced overstock is too large to be fully consumed before expiry. As detailed shelf-life information about SKU levels was not available at the time of research, it was decided to set the shelf life equal to twelve months of historic consumption.

4.4. Determinants of forecast performance variation

Table 1 lists the situational (S) and non-situational (N) exogenous factors (Section 2.2), which possibly influence consumption and order forecast performance. The majority of these factors are project characterizations, with the exception of demand volatility and safety markup. Demand volatility is measured by the coefficient of variation of the actual monthly consumption of SKUs during the order cycle, and is taken to reflect demand uncertainty. Project-specific non-situational exogenous factors consist of *Main activity*, which indicates the main focus of the project, like basic health care or acute epidemic response; *Causal agent*, which defines the motivation for the project, such as social violence and armed conflicts; and *Age*, which indicates the years elapsed since project start. Moreover, project-specific situational factors comprise *Target Population*, which specifies the size of the targeted population; *Population Setting*, which indicates whether the targeted population is set in an urban, rural or mixed setting; *Context* referring to the stability of the situation in which the project operates; and *Population Type*, which reflects whether the general population or refugees are targeted.

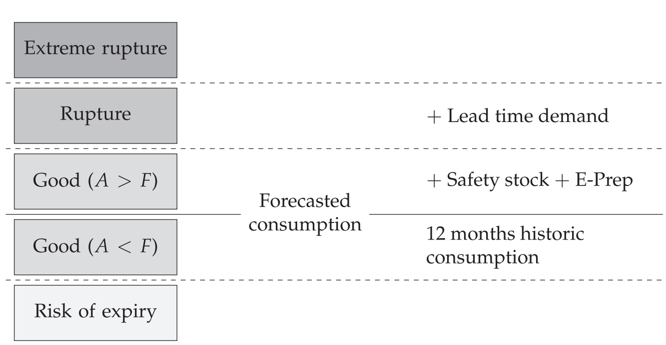

Fig. 1. Definition of the order forecast performance metric at MSF.

Table 1
Observed situational (S) and non-situational (N) exogenous factors.

Classification	Factor	Values
Demand uncertainty (N)	Demand variation	Numeric
Type of relief effort (N)	Main activity	Hospital with surgery
		Hospital without surgery
		Basic health care
		Reproductive health
		Specific disease treatment
		Nutritional response
		Acute epidemic response
	Causal Agent	Social violence/health care
		Endemic/epidemic
		Armed conflict
Duration of relief effort (N)	Age	Numeric
Scale of relief effort (N)	Target population	1.000–9.999
		10.000–249.999
		250.000–499.999
		500.000–999.999
Environmental (S)	Population Setting	Rural
		Mixed urban/rural
		Urban
Socio-economic (S)	Context	Instable situation
		Stable situation
		Armed conflict
		Post-conflict
	Population type	General
		Displaced
		Mixed

In addition, the safety markup, or item criticality, is set by MSF to cope with unwanted outages of supply. It is defined as the number of monthly forecasts to take on safety stock, which is obtained by weighing the SKU-specific safety classification (low, normal, critical) with the project-specific criticality parameter (the number of monthly forecasts required as safety stock dependent on safety classification). The latter safety markup, though numeric, will be treated as categorical in the empirical analysis, in view of its reliance on classification.

5. Results

5.1. Consumption and order forecast performance

The performance of the monthly consumption forecasts is evaluated using the forecast error measures *sMape* and *sMpe* defined previously. Table 2 presents descriptive statistics. The majority of medical items, 69.7%, is over-forecasted; the mean *sMpe* is −0.205 (sd = 0.412). Close to 5% of all cases has a *sMpe* larger than 0.5, meaning that aggregate consumption during the order cycle is more than three times the aggregate monthly forecasts. These results are noteworthy, because monthly forecasts are not supposed

Table 2
Descriptives and Pearson correlations of selected variables ($N = 8984$).

	Mean	*Std*	*sMape*	*sMpe*	*sMapeOrder*	*sMpeOrder*
sMape	0.361	0.284				
sMpe	−0.205	0.412	−0.560			
sMapeOrder	0.412	0.285	0.939	−0.699		
sMpeOrder	−0.310	0.393	−0.499	0.988	−0.661	
Demand volatility	0.996	1.119	0.466	−0.350	0.445	−0.325

All correlations are significantly different from zero at the 0.1% level, that is $p < 0.001$.

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to consider safety stocks. Similar results are obtained for the order performances, where the mean order forecast bias *sMpeOrder* is equal to −0.310 (sd = 0.393), and the majority of order forecasts (aggregate monthly forecasts plus safety stocks) suffices to cover aggregate consumption during the order cycle (80.9%).

Moreover, Table 2 shows that the measures of forecast accuracy (*sMape* and *sMapeOrder*) are negatively correlated with forecast bias (*sMpe* and *sMpeOrder*): the more demand is over-forecasted, the larger the forecast inaccuracies. Though technically intuitive, it illustrates the consequences of MSF's efforts to prevent stockouts through excessive forecasts, as opposed to maintaining high safety stock levels. Additionally, consumption and order forecast inaccuracy appear to be positively correlated with demand volatility ($r = 0.466$ and $r = 0.445$, respectively), while the corresponding forecast biases are negatively related with demand volatility ($r = -0.350$ and $r = -0.325$, respectively), all significant at the 0.1% level. So, the more demand uncertainty, the larger the extent of over-forecasting and the less accurate forecast performance.

Table 3 gives percentages of the specified order performance qualifications described in Fig. 1. About 22% of all medical items suffer from rupture, i.e. situations where aggregate consumption exceeds aggregate forecasts and safety stocks. More than two-thirds (67.8%) of these items are subject to extreme ruptures, when the difference between aggregate consumption and forecast exceeds safety stocks and lead time demand. These incidents are potentially serious as they may impact humanitarian conditions, and require additional logistics efforts to replenish stocks. At the other extreme, around 38% of the medical items runs a risk of expiry. According to MSF-OCA, the substantial risk of expiry is a consequence of a deliberate choice to be able to provide humanitarian aid, while the rupture percentage is considered reasonable given the circumstances in which humanitarian operations take place. The high level of extreme ruptures is explained through the incidence of sudden, unexpected surges in demand, which is typical in the humanitarian context. These SKUs do guarantee a certain humanitarian service level, but their excessive order forecasts may lead to inefficiencies. Furthermore, considering the 3965 emergency preparation cases, we find that slightly over 5% of all items (5.65%) has aggregate consumption above the ordered emergency levels.

5.2. The effect of project characteristics

Variation in consumption forecast and order forecast performance have various causes, some of which are of a more systematic nature. This subsection describes performance differences related to project characteristics, such as main activity, causal agent, population setting, population type, size of the target population and project age. One-way anova is routinely applied, more elaborate analysis is in the next section.

Though these project characteristics have significant effects on all performance measures, the presentation focuses on those project characteristics that have a relatively large effect size on forecast biases: target population (0.013/0.018), project context (0.008/0.012), and main activity (0.007/0.0012); values between parentheses refer to the adjusted R^2 values for *sMpe* and *sMpeOrder*, respectively. The influence of population setting and causal agent is less strong, while the impact of project age on forecast biases is not significant.

Table 3
Order performance metric, emergency preparation (ePrep) cases excluded.

Situation	Percentage	Cumulative percentage
Risk of expiry	37.83	37.83
Good $A < F$	30.32	68.15
Good $A > F$	9.53	77.69
Rupture	7.19	84.88
Extreme rupture	15.12	100.00

5.2.1. Target population

The size of the target population significantly influences forecast accuracy (*sMape*: $F = 38.111$, $p < .0001$; *sMpe*: $F = 41.156$, $p < .0001$). Generally, the larger the target population, the more accurate the forecasts: the extent of over-forecasting becomes less. Likewise, the order forecast accuracy significantly depends on population size (*sMpeOrder*: $F = 55.209$, $p < .0001$). Here, accuracy marginally differs between population sizes below 500,000 people, while considerably lower than the order forecast accuracy of larger populations. Additionally, demand volatility differs significantly between populations with different sizes ($F = 21.676$, $p < 0.001$). Roughly, volatility decreases with population size: it is the highest for targeted populations between 1000 and 10,000 people (1.189) and the lowest for targeted population sizes over half a million (0.656).

5.2.2. Project context

Mean forecast performance differs significantly between these contexts (*sMape*: $F = 18.642$, $p < .0001$; *sMpe*: $F = 24.260$, $p < .0001$). Forecast accuracy is the highest for projects in internally unstable contexts (*sMape*: 0.326; *sMpe*: −0.166), and the lowest for projects in post-conflict areas (*sMape*: 0.401; *sMpe*: −0.277). A similar pattern is observed for the order forecast performance (*sMpeOrder*: $F = 37.603$, $p < .0001$), which takes into account safety stocks and emergency preparation levels. Mean order forecast accuracy is the highest in cases of armed conflict (*sMpeOrder*: −0.273), and the lowest for projects in post-conflict situations (−0.396) and stable environments (−0.336). Demand volatility is only mildly related with project context ($F = 2.125$, $p = 10.095$) being relatively low in unstable contexts (0.945) and high in post-conflict situations (1.042). At first glance these results may seem counter-intuitive, but post-conflict settings are often contexts in which there is a change in the activities undertaken by the project. The historic consumption data may not be of help to forecast new activities. Similarly, in these contexts there are often fluid changes in demographics and population numbers in a project area. In this regard, increased volatility would be expected. Similarly the context will determine the viable program modalities. Nutrition and primary health care activities are seen in more unstable and high security contexts. In these activities, the number of SKUs to manage is lower and the consumption less intermittent. Another factor is that more experienced staff are involved in making forecasts for emergency interventions.

5.2.3. Main activity

Forecast performance differs significantly between projects with different main activities, both for the consumption forecasts (*sMape*: $F = 11.441$, $p < .0001$; *sMpe*: $F = 10.330$, $p < .0001$) and the order forecasts (*sMapeOrder*: $F = 15.294$, $p < .0001$; *sMpeOrder*: $F = 18.844$, $p < .0001$). Mean forecast inaccuracy is comparatively high in the case of acute epidemic response as a consequence of systematic over-forecasting (*sMape*: 0.537; *sMpe*: −0.420), and is relatively low for hospitals without surgery (*sMape*: 0.427; *sMpe*: −0.359). Likewise, demand volatility is significantly affected by main activity ($F = 12.756$, $p < .0001$). It is relatively high for projects with a specific disease treatment (1.211), and low for nutritional response (0.885), acute epidemic response (0.887) and reproductive health (0.891).

Summarizing, we find that all project characteristics show a significant and relevant impact on consumption and order forecast

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performance. The biasing effect on forecasts is found to be larger for some factors, like target population, project context and main activity, than other, like causal agent or project age. The observed influences of project characteristics render support to assertions in extant literature that these impacts exist and it indicates that operational performance could be improved if these factors are systematically taken into account. However, these project characteristics are also significantly related with demand uncertainty, which is significantly associated with forecast performance. The question therefore arises whether project conditions have a direct influence on forecast performance in addition to demand volatility, or rather have an indirect influence mediated by SKU-specific factors, like demand volatility and the implemented safety markups. This will be further explored in the following section.

5.3. The effect of SKU-related factors

Variations in forecast performance may have various antecedents varying from demand or order specific features to humanitarian project characteristics. Specifically, we expect that forecast performance will be influenced by the demand uncertainty and the criticality of medical items as reflected by their safety markups. The more volatile the demand, the more difficult it will be to forecast the demand and the lower will be the expected forecast accuracy, *sMape* and *sMapeOrder*, while the forecast bias, *sMpe* and *sMpeOrder* may remain unaffected. Moreover, higher safety markups for more critical items may be expected to have no influence on the consumption forecast performance, *sMape* and *sMpe*, but to promote over-forecasting of orders yielding a higher *sMapeOrder* and a more negative *sMpeOrder*.

As safety markups are part of the definition of the order forecast performances, (3) and (4), and serve to explain performance variation, one may suggest these equations potentially suffer from endogeneity bias. However, there is no reason to think this is the case. First, the safety markup is a strictly exogenous quantity, set by MSF based on considerations that are not part of the model. Specifically, it is not determined based on forecast performance (in fact, MSF did not have information about this forecast performance before the current project). So, causality unambiguously runs from the explanatory variables to the dependent. Secondly, and related with the previous, order performance is measured conditional on the safety markups. Consequently, the order performance models explain variations of actual consumption away from the order forecast, conditional on the safety markups. Similar approaches are seen, for instance, in models of per capita production dependent on population size (e.g., Milanovic, 2015; Feyrer and Sacerdote, 2013), and models of labor productivity dependent on firm size (e.g., Griffith et al., 2006; Mithas et al., 2012) to capture scale effects.

In addition, forecast performance may be influenced by the systematic differences between projects, as indicated in the previous section. In view of the hierarchical structure of our data consisting of information about many SKUs from a limited number of projects (19) and two order cycles, we use mixed effect regression models to assess the influence of the various conditions on forecast accuracy, defining projects as random effects. In the case of ruptures, mixed logistic regression models have been applied. Information about the order cycle has been included to control for the influence of unspecified sources of variation related with time. The estimation results are presented in Table 4.

Several observations can be made from these results. Demand volatility, measured by the coefficient of variation of the actual consumption during the order cycle, has a significant influence on forecast inaccuracy, both for consumption and order forecasts. The combined effects for *sMape* (0.211) and *sMpe* (−0.215) as well as for *sMapeOrder* (0.201) and *sMpeOrder* (−0.188) suggest that a high demand volatility comes with systematic over-forecasting. This is somewhat unexpected, as it suggests that demand uncertainty is incorporated through the consumption forecast instead of, or in addition to, the safety stocks embedded in the order forecast. In the case of ruptures, demand volatility seems to lower the odds of excess-consumption (−0.293, $p < 0.001$), which is consistent with its impact on the consumption forecast. Extreme ruptures, however, are not significantly related with volatility (0.076, n.s.).

Furthermore, the safety markups, measured by the number of monthly forecast to take on safety stock, significantly affect forecast performance in all models, except for *sMape*, as indicated by the likelihood ratio tests (LRT Safety markup). In general, higher safety markups for more critical items tend to increase inaccuracy through over-forecasting. The fact that this is more apparent for order forecasts (*sMapeOrder*, *sMpeOrder*) than for consumption forecasts (*sMape*, *sMpe*) again suggests that the former are over-adjusted as the consumption forecasts already considers demand uncertainty. The results for ruptures complement these outcomes revealing that incidences of ruptures are comparatively more likely to occur for products with low safety markups, and less likely for SKUs with high criticality. This can be interpreted as relatively favorable, if SKUs with low safety markups.can indeed be considered less critical for humanitarian support. But it urges reconsidering the criticality classification, if this is not the case.

Projects do add to the explanation of variation in forecast performance. The share of the project variation in the estimated total variance varies from 6.2% in the case of *sMape* and *sMpeOrder* to 7.1% in the case of *sMapeOrder*, and is significant in all cases. It is not possible, however, to attribute this variation to particular project conditions. Using anova, we related the estimated random project effects with the project characteristics, but no systematic differences were observed. These project effects therefore seem to be specific for individual projects, and do not reflect common project conditions, at least not in the sample at hand. Additionally, we have explored the complementary contribution of the project conditions to the systematic parts of the estimated models, but none of these conditions appeared to be significant. Given their significant relation with both forecast performance and demand volatility observed previously, we conclude that project conditions, however important they are, influence forecast performance indirectly through demand volatility and safety markup.

6. Discussion and conclusion

This study has provided an in-depth description and empirical analysis of the demand planning and distribution operations at MSF-OCA. It is the first to present such detailed process information and the first to present a large empirical performance analysis. Over the past five years, MSF-OCA has considerably invested in its data collection and order procedures, which currently appears to pay off. In particular, she has been able to systematically record actual consumption of medical items together with associated forecasting information, which is a major achievement in humanitarian operations. According to Begench Dzhumageldyev, logistics advisor at MSF-OCA: "The dataset in this paper is a product of MSF's proximity to its patients and its ability to collect consumption data of good quality. The analysis of this data set in this and future papers will aid humanitarian organization better understand medical supply in varying humanitarian contexts and hopefully identify viable approaches to improve forecasting performance and the supply chain in general".

Variation in forecast performance has been related with item-specific features, like demand variability and criticality, and with project-specific conditions, like context, main activity and target population, to explore potential antecedents of forecast

Table 4
Mixed model results forecast performance without outliers ($N = 8941$).

	sMape	*sMpe*	*sMapeOrder*	*sMpeOrder*	Ruptures	
					Both types	Extreme only
Intercept	0.172***	−0.001	0.209***	−0.104***	−1.043***	−2.193***
	(0.015)	(0.025)	(0.016)	(0.023)	(0.123)	(0.138)
Demand volatility	0.211***	−0.215***	0.201***	−0.188***	−0.293***	0.076
	(0.003)	(0.005)	(0.003)	(0.005)	(0.043)	(0.049)
Order cycle	0.014**	−0.032***	0.020***	−0.031***	−0.134*	−0.139
	(0.005)	(0.008)	(0.005)	(0.008)	(0.058)	(0.075)
Safety markup 0	−0.030	0.100**	−0.028	0.091**	0.448*	0.561*
	(0.022)	(0.035)	(0.022)	(0.033)	(0.213)	(0.237)
Safety markup 1	−0.018	0.117*	−0.061*	0.176***	0.899**	0.939*
	(0.028)	(0.046)	(0.029)	(0.044)	(0.319)	(0.394)
Safety markup 3	0.011	−0.043*	0.029*	−0.070***	−0.492***	−0.348
	(0.013)	(0.020)	(0.013)	(0.020)	(0.147)	(0.183)
Safety markup 4	−0.019	−0.020	0.032**	−0.084***	−0.619***	−0.469**
	(0.011)	(0.017)	(0.011)	(0.016)	(0.114)	(0.144)
Safety markup 6	−0.050	0.118	0.024	−0.006	−0.280	−0.386
	(0.040)	(0.064)	(0.041)	(0.061)	(0.411)	(0.451)
Safety markup 7	0.017	−0.147**	0.143***	−0.273***	−1.603**	−1.232*
	(0.032)	(0.052)	(0.033)	(0.050)	(0.488)	(0.617)
AIC	−989.764	7419.572	−753.624	6671.118	8335.288	5658.944
Log Likelihood	505.882	−3698.786	387.812	−3324.559	−4157.644	−2819.472
LRT Safety markup	8.053	37.117***	42.940***	106.930***	78.354***	37.798***
Variance Project	0.003	0.009	0.004	0.008	0.180	0.195
Variance Residual	0.052	0.132	0.053	0.122	n.a.	n.a.

$p^{***} < 0.001$, $p^{**} < 0.01$, $p^{*} < 0.05$. Estimation results for mixed effects regression (*sMape*, *sMpe*, *sMapeOrder* and *sMpeOrder*) and logistic regression (*Ruptures*) models with random *Project* effects. The latter do not report estimates of the residual variance. The number of observations is 8941, the number of projects is 19. Estimated standard errors are reported between parenthesis. *Demand volatility* is the coefficient of variation of the monthly consumption ($\times 10^{-2}$). 43 observations with extreme volatility, a coefficient of variation larger than 300, were removed; this slightly affects effect size, but not the direction or the significance of the estimated effect. *Order cycle* indicates observations of the 12 M order cycle, with 04 M the reference category. *Safety markup* is the additional number of months of monthly forecasts on top of safety stocks; *SafetyMarkup2* (two months) has been taken as the reference category. *LRT Safety markup* is the likelihood ratio test for the joint contribution of the safety markup. *Variance Project* is the estimated variance due to the random project component, *Variance Residual* is the remaining variance.

inaccuracies and biases. Among other, these analyses have shown that project conditions are related with consumption and order forecast performance, but that their influence is mediated by item demand volatility and criticality. Specific findings about the overall bias towards over-forecasting, the causes of variation in forecast performance, and the incidence of extreme under- or over-forecasting, are briefly highlighted.

A main finding is that considerable bias appears to exist towards over-forecasting of consumption. Ideally, these consumption forecasts are unbiased, while the order planning takes up any presumptions about demand uncertainty through the safety stocks. If otherwise, bullwhip-like effects may occur, resulting in unnecessarily high stock levels that are prone to obsolescence. This is particularly relevant when different departments or actors in an organization are involved in the preparation of consumption forecasts and order forecasts, as is the case for MSF-OCA. The medical team has an incentive to overestimate demand, in particular for slow moving, intermittent demand items, to ensure that they have inventory at hand in the case of an emergency. This is fundamentally different from the traditional notion of a forecast as an unbiased estimate of expected demand. Our results indicate that significant biases exist at both the demand forecast level and the order planning level, which are driven by demand characteristics. Apparently, expectations about demand variability and product criticality cause planners at both levels to over-forecast. Currently, MSF-OCA is in the process of identifying forecasting techniques that will improve forecast performance. The intention is to support in the short term the subjective forecast of field staff with forecast advice. Steps are under way to better capture qualitative data on forecasts and make available data streams that potentially aid in optimizing field forecasts, such as morbidity and project contextual data. Further, MSF-OCA is developing a health information system that will potentially provide a rich data source (morbidity data and prescribing practices, for example) for further analysis forecast performance.

Furthermore, we found ample empirical evidence that various exogenous factors impact the consumption forecast and order planning performance, though indirectly via item demand volatility. Considering these factors in the order planning process, provides opportunities to further improve the estimation of demand uncertainty and reduce forecasting errors, which may lead to improved performance. Additionally, based on the classification of factors in Section 2.2, more factors could be recorded and exploited in a similar way. Examples of factors that are feasible to record and directly affect demand uncertainty and forecasting errors, are type of medical item, the presence of local suppliers, the quality of the road infrastructure, the type of economy, and the level of corruption. In 2014, MSF-OCA introduced a new version of the consumption tool, which allows a much richer and deeper analysis of demand and forecast performance. Data at the activity level is recorded as well as matching patient figures, which can be used, for instance, to identify possibly different dynamic consumption patterns reflecting differences in the way medications are used to treat patients. Further investigation will be needed in determining useful exogenous factors to include in future analysis and how to categorize this data. More recently, in 2016, MSF-OCA has initiated a supply improvement plan with commitment of the MSF-OCA management team, which will look at supply chain modalities, supply processes and information system improvements.

Besides our analytic findings, the qualitative case study also indicates certain improvements. The current information system records consumption rather than actual demand. This implies that actual demand may be under-stated in the case of stockouts, and as a consequence the risk of rupture be underestimated. An obvious remedy would be to separately record unsatisfied demand due to stock-outs. Also, MSF-OCA counts the ruptures that occur, but does not record the cause of these ruptures: demand uncertainty or

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supply uncertainty. It will be helpful to accurately measure these sources to acquire a better understanding of the factors that impact performance and to decide what actions should be taken to improve it.

All humanitarian logistics organizations could benefit from MSF's forecasting and planning processes, which can be consider 'best practice'. It is encouraging to see that after moving from an exclusive focus on aid delivery to the design and implementation of logistics processes, the humanitarian sector has now developed into the third phase of logistics development: that of standardized data collection and planning to extrapolate past needs into the future. Once proper data collection and analysis infrastructures and frameworks are in place, one could even think of predicting demand, based on situational and non-situational exogenous factors as put forward in Section 2.2.

In terms of theoretical contributions, our classification of endogenous and exogenous factors, situational and non-situational, will be helpful for further studies in humanitarian operations performance. Likewise, our identification of forecast performance measures to empirically and systematically assess humanitarian operations and validate the impact of environmental factors, supports the exploration of logistics operations performance. Much has been learned and can be learned from forecasting insights pertaining to commercial organizations. In the words of Van Wassenhove (2006), although humanitarian operations are different from normal retail operations in many ways, there are also similarities. Evidently, MSF-OCA has made important moves in this respect. However, in order to learn how to deal with the very specific challenges that humanitarian organizations are faced with, many more empirical studies are needed.

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