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Fleet management policies for humanitarian organizations: Beyond the utilization–residual value trade-off

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ABSTRACT

Four-wheel drive vehicles play a pivotal role in securing the last-mile distribution of goods and services in humanitarian development programs. To optimize the use of their fleets, humanitarian organizations recommend policies aimed at enhancing the utilization of vehicles while preserving residual value. Although these decisions have a significant impact on cost, there is limited empirical evidence to show that the recommended policies are actually implemented and that they produce the expected benefits. This paper theoretically and empirically examines the complex and inter-related effects of vehicle-to-mission allocation decisions and of alternative vehicle usage patterns on vehicle utilization and residual value in humanitarian development programs. The results suggest that humanitarian organizations could break the utilization–residual value trade-off by adopting different policies than the ones currently in place. They also reveal that organizations need to realize that what seems logical from the headquarters' perspective may be illogical or inconvenient for the field, and as a result, the field may do the opposite of what is recommended or even instructed. Therefore, they either need better data and analysis combined with audits or they need to improve mechanisms that incentivize field delegations to follow standards recommended by the headquarters.

1. Introduction

In humanitarian development programs, the delivery of humanitarian services to beneficiaries, known as last-mile distribution (LMD), is one of the most critical operations (Balcik et al., 2008). The centerpiece of LMD is the vehicle, which is used to transport food, materials, and humanitarian workers. LMD typically requires large and expensive fleets (Apte, 2009) whose management presents several operational challenges: Purchasing the right quantity of vehicles with features appropriate to the typically substandard road networks, allocating them to different types of missions, and reselling used vehicles before they become too old are all important decisions that affect both LMD performance and cost.

These challenges are further amplified by the difficult environmental conditions in which humanitarian organizations (HOs) operate and by their distinct decision-making processes. In most HOs, fleet management policies are set centrally by the headquarters (HQ) but are implemented locally by sub-delegations (i.e., operating units located close to beneficiaries that are directly confronted by local problems such as civil conflicts, rugged terrain, or a lack of infrastructure). Because HQs often have limited visibility related to local operations, policies and vehicle allocation rules are often set with little understanding of field issues, and may not be followed in practice. Therefore, information asymmetries and incentive misalignment problems induce sub-delegations to deviate from the HQ's recommendations and policies.

HOs have an obvious interest in utilizing their vehicles as much as possible to maximize demand coverage and the number of missions they perform. However, as HOs resell vehicles at the end of their operational life, overutilizing these vehicles may reduce their recovery value and consequently reduce the budget available for future operations, thereby indirectly affecting future service levels. Therefore, the trade-off between utilization and residual value is clear. The following three decisions at the core of any fleet management policy affect the utilization–residual value trade-off: (1) how to assign vehicles to different types of missions, (2) how to modify a vehicle's utilization over its operational life (i.e., how to identify a vehicle's optimal usage trend), and (3) when to replace a used vehicle with a new one.

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HQs typically recommend policies based on their a priori estimate of the presumed effect of the different operational decisions on vehicle utilization and residual value, often under the assumption that these objectives cannot be attained together. However, to implement policies that enable HOs to achieve both goals, they need to understand the causes of the loss of vehicles' resale value and the parameters that affect the utilization of vehicles during their life cycle. To the best of our knowledge, there is a surprising lack of empirical research that examines the mechanisms through which operational decisions affect the utilization and the residual value of vehicles and validates these policies. Moreover, there is insufficient evidence to show that the policies are actually implemented. The present paper, which is one of the first attempts to conduct a rigorous empirical analysis of fleet management processes at the field level, aims to fill this research void.

In this paper, we quantify the specific impact of operational decisions on utilization and residual value to identify why and where trade-offs originate. We address these questions empirically by analyzing the fleet management operations from 2000 to 2014 of one of the largest international HOs in four countries representative of its operational environment. We first examine the allocation rules used to assign vehicles to missions and analyze the impact of different types of missions on residual value. In addition, we consider the impact of different usage trends on vehicle utilization, accident rate, and residual value. Furthermore, we analyze whether the standard vehicle replacement policy recommended by most HOs is effective and comprehensive. Finally, our analysis clarifies the nature of utilization–residual value trade-off and examines its root causes.

This study makes several contributions to the humanitarian operations literature. First, it challenges the validity of the policies currently in place in many organizations. The results provide evidence of counterintuitive allocation rules and demonstrate that the vehicle usage policy recommended by HQs is not properly followed by sub-delegations. Moreover, they reveal that organizations need to realize that what seems logical from the HQ's perspective may be illogical or inconvenient for the field, and as a result, the field may do the opposite of what is recommended or even instructed. Therefore, they either need better data and analysis combined with audits or they need to improve mechanisms that incentivize field delegations to follow standards recommended by the HQ. Finally, the paper brings the trade-off perspective into the humanitarian context. While trade-offs between competitive priorities have been extensively analyzed for manufacturing and service operations, their role in the humanitarian framework is still not fully understood. This paper reveals that humanitarian vehicles are also subject to the utilization–residual value trade-off, but only when they are kept in the fleet for a long time, regardless of their cumulative mileage. This implies that well-designed fleet management policies that intensively utilize new vehicles can help HOs to avoid trade-offs, whereas the common practice of adopting a decreasing usage trend as the vehicle ages does not have a positive impact on utilization, nor does it preserve residual value.

The rest of the paper is organized as follows: In §2, we review the relevant literature on humanitarian fleet management. In §3, we develop testable hypotheses, while in §4, we describe the methodology, including the data collection process and the econometric model employed. Furthermore, §5 presents the results and some managerial insights, and finally, §6 explains the limitations of this study and suggests avenues for further research.

2. Literature review

In recent years, humanitarian logistics has generated considerable interest in the MS/OR research community. Many humanitarian scholars have focused on LMD in particular due to its complexity and potential impact on beneficiaries (Whiting and Ayala-Ostrom, 2009). Attention has been dedicated to questions at the strategic level, for example, by studying facility location and resource allocation problems (Barbarosoglu et al., 2002; Balcik and Beamon, 2008); at the tactical level, for example, by addressing delivery and distribution questions (Tzeng et al., 2007; Balcik et al., 2008; Kula et al., 2012; McCoy and Lee, 2014); and at the operational level, for example, by focusing on emergency response and operations scheduling (Simpson, 2006; Ingolfsson et al., 2008). The literature, however, has predominantly emphasized on relief operations (Malini et al., 2009).

Specifically considering the nascent, but steadily growing, literature on development programs, fleet management problems have received comparatively less attention. In this domain, decisions involve two general areas, as follows: "procurement" (e.g., determining fleet size) and "fleet management at the field level" (e.g., optimizing the use of vehicles after they have been purchased). Procurement problems have attracted a few recent studies. For example, Besiou et al. (2014) examine the relationship between the HOs' mandate and different fleet management structures (i.e., centralized, hybrid, and decentralized) to identify the structure that maximizes procurement effectiveness. Fleet sizing decisions for development programs have been considered both at the macro- and micro-level. At a macro-level and focusing on a centralized procurement model, Eftekhar et al. (2014) propose an optimal fleet vehicle procurement policy. Combining empirical analysis and analytical modeling, they study how to efficiently build fleet capacity over time for different demand requirements in the absence of detailed data. At a micro-level, Pedraza Martinez and Van Wassenhove (2013) determine an optimal vehicle replacement policy that minimizes HOs' fleet costs. In the first stage, they conduct an empirical study to identify the main drivers of vehicles' maintenance cost and residual value. Accordingly, they develop a dynamic programing model to determine the optimal policy. Pedraza Martinez et al. (2011) use a case-based approach to study field vehicle fleet management in four large HOs. They explain how HOs manage their vehicle fleets and depict the key elements that affect the objectives of HOs' field fleet management.

Although fleet management at the field level contributes to 50% of total fleet costs (Pedraza Martinez et al., 2011), the academic literature has so far offered limited guidance to HOs willing to optimize their fleet management at this level. By the same token, most research articles in humanitarian operations have taken a modeling approach, whereas empirical research is still scant (Altay and Green, 2006; Simpson and Hancock, 2009), primarily because of the difficulty in gathering reliable field data from sub-delegations; thus, it should be further developed, at least to validate the normative prescriptions from analytical models.

The contributions of this paper are twofold. First, it considers vehicle-to-mission assignment policy, vehicle usage patterns, and vehicle utilization–residual value trade-off, which have not been studied in the context of humanitarian logistics. Second, it provides a comprehensive empirical analysis of fleet performance, producing robust estimates of the variables influencing vehicle utilization and residual value. As most of the modeling papers in this area assume ad hoc values for critical variables, the results of this study can be successfully used to prime and validate these models. In addition, given the need for standardization in the humanitarian sector, the results of this study can shed further light on how vehicles should be effectively and efficiently utilized in the field.

It is worth noting that in transportation and economic literature, there are empirical studies that consider vehicle utilization and residual value. The drivers of vehicle utilization—often defined as "total miles driven"—are considered in Dargay (1997), Golob (1998), and Fang (2008). Estimation of the residual value of a vehicle at the end of its operational life is discussed in Alberini et al. (1995, 1998) and Engers et al. (2009). For instance, Engers et al. (2009) analyze whether the benefits from owning a vehicle—measured by total distance traveled—explains the price decline observed over the vehicle life. They show that the impact of vehicle age on annual distance traveled and market value depends on the user profile and the composition of the vehicle stock. Finally, Brosh et al. (1975), Engers et al. (2004), and Peck et al. (2015) discuss the relationship between maintenance costs and failure rate with vehicle age and mileage. Nevertheless, this study exhibits fundamental differences from the aforementioned literature. First, the context is clearly different, such that model specifications must include covariates specific to the humanitarian sector. The second difference underlies our econometric models. It is necessary to explicitly account for some endogeneity problems arising from the peculiar decision-making process in the humanitarian setting. Finally, taking the above elements explicitly into account, the paper contributes to the ongoing debate on the efficiency—service trade-off in the service operations management literature (Lapre and Scudder, 2004; Frei, 2006). We demonstrate that, in the context of our study, an efficiency—service trade-off is not unavoidable. We shed light on the factors that create this trade-off and suggest that, in some situations, organizations might be able to break the trade-off by adopting appropriate fleet management policies.

3. Theoretical framework and hypotheses

Due to the lack of papers related to our research questions, following Flynn et al. (1990) and Fisher (2007), we use either the literature of humanitarian or commercial fleet management combined with interviews with practitioners to develop our hypotheses. Hence, we first illustrate different components of a fleet management policy by referring to the operations of one of the largest international HOs, hereafter referred to as HumOrg for confidentiality reasons.

HumOrg's fleet management structure is centralized, in which the HQ procure vehicles for sub-delegations along with standards on how to effectively and efficiently utilize, maintain and replace vehicles. Vehicles are supposed to receive regular preventive maintenance in HumOrg's workshops in the field. However, sub-delegations may obey or ignore HQs' recommended policies. Similar to what we observed at most HOs, in HumOrg, used vehicles are subdivided into three groups, as follows: (1) vehicles not in working condition that are disposed of; (2) vehicles no longer appropriate for the organization's operations and that may not be interesting for the local market, which are donated to other organizations; and (3) vehicles in working condition that are no longer appropriate for the organization's operations. Often, these are sold in the local second-hand market. HumOrg sells these vehicles in the capital city of its country of operations through an open auction, where buyers know what the vehicle had been used for, that is, mission type, as well as its maintenance and accident history. Similar to most auctions, in HumOrg's auction, buyers are not allowed to take vehicles for a test drive before placing a bid. Therefore, the buyer makes a decision based on information that HumOrg shares.

Usually, a *durable good*, such as vehicle, provides productive services over multiple time periods. As it deteriorates with use and eventually wears out, the consumer prefers to exchange it well before the end of its operational life cycle (Rust, 1985). The residual value of humanitarian vehicles drops sharply with use and time, mainly because they are used intensively on poor roads or in off-road conditions and because the price of second-hand vehicles falls abruptly when a brand new vehicle becomes available on the market. Because some of the used vehicles are sold, limiting the rate at which they lose residual value is a goal for HOs. To that end, the standard replacement policies recommended by most HOs such as the International Committee of the Red Cross (ICRC), the International Federation of Red Cross and Red Crescent Societies (IFRC), or the United Nations High Commissioner for Refugees (UNHCR) require the replacement of vehicles after 5 years or 150,000 km, whichever comes first.

3.1. Vehicle-to-mission allocation

At the sub-delegation level, demand for transportation services originates from two types of missions, namely heavy-duty missions (i.e., long-distance field trips in limited access areas) and light-duty missions (i.e., shorter journeys usually carried out to perform administrative tasks within cities). Similarly, HOs use two types of vehicles in the field—“normal” vehicles and “specially equipped” vehicles. Normal vehicles are ordinary Land Cruisers equipped with electronic devices. Specially equipped vehicles are Land Cruisers with a stronger suspension, stronger bumpers and more electronic devices than normal vehicles. These vehicles are more resilient in rough terrain, safer in case of accident, and about US$ 4200 more expensive than normal vehicles.

In the humanitarian sector, vehicle reliability is a high priority of managers. Consequences of poor-quality infrastructure in which vehicles are used manifest in high failure rates that, for humanitarian workers, can range from minor inconvenience to life-threatening conditions in conflict zones. Given the potential impact of vehicle failures, most HOs recommend using specially equipped vehicles for heavy-duty missions within the first 2 years of their operational life (Stapleton et al., 2008) or before their odometer reaches 60,000 km (Herrmann, 2006) and assigning them to light-duty missions afterward. They also purchase normal vehicles to run light-duty missions. Likewise, HumOrg recommends that only new specially equipped vehicles be assigned to field trips, while it recommends using old and normal vehicles for administrative purposes in safer zones. Despite this recommendation, we realized sub-delegations assigning vehicles either to heavy-duty or to light-duty missions at the beginning of their operational life and never switching them thereafter. Therefore, it is reasonable to assume that if delegations do not change allocations over time, they should assign specially equipped vehicles to heavy-duty missions. Bearing this in mind, we formally propose the following:

Hypothesis 1. *In the context of humanitarian fleet management, there is alignment in the assignment of vehicles to missions: specially equipped vehicles are assigned to heavy-duty missions more often than to light-duty missions, while normal vehicles are assigned to light-duty missions more often than to heavy-duty missions.*

The different missions undertaken by HOs affect residual value to different degrees. There are two rationales for expecting such a relationship. First, heavy-duty missions are often long-distance field trips that increase vehicle usage in a short period. Several economic studies have demonstrated that assets used intensively lose value more rapidly (Bischoff and Kokkelenberg, 1987). In addition, in a recent study on personal vehicles used in the state of Pennsylvania, Peck et al. (2015) show that vehicle failure rates and depreciation in rural and urban areas are consistent, albeit it is slightly higher for vehicles used in rural regions. Second, humanitarian development programs are usually conducted in poor economies where the quality difference between rural roads and urban streets is enormous. As vehicles assigned to heavy-duty missions are used more intensively and in more difficult and craggier terrains than vehicles assigned to light-duty missions, it is reasonable to assume that heavy-duty missions will reduce the residual value of vehicles more significantly than light-duty missions. On the other hand, Hypothesis 1 implies that only more resilient vehicles are assigned to heavy-duty missions. Studies have shown that price decline is steeper for less reliable cars (Hendel and Lizzeri, 1999). If this is the case, the negative impact of heavy-duty missions on residual value may be attenuated. We maintain that after taking this endogeneity into account, the effect of the former mechanism prevails. Consequently, we suggest the following:

Hypothesis 2. *Controlling for vehicle model, accident history, age, and total mileage, heavy-duty humanitarian missions have a more negative impact on a vehicle's residual value than light-duty missions.*

3.2. Effect of the usage trend

The next set of hypotheses considers the effect of the second component of a vehicle usage policy, namely the vehicle usage trend. Whereas utilization refers to how intensively a vehicle is used throughout its operational life, on average, the term *usage trend* reflects how the utilization of the vehicle changes over time (Golob, 1998). A vehicle is said to display a *decreasing* usage trend if its monthly distance traveled decreases with its age and a *non-decreasing* usage trend otherwise. HumOrg HQ recommends a decreasing usage trend, that is, using a vehicle intensively at the beginning of its operational life cycle and less intensively when it gets older (see, for example, Eftekhar et al., 2014). Although this recommendation is mainly driven by safety concerns, its impact on vehicle residual value and utilization is unclear.

There are opposing, yet equally valid, arguments to estimate how the usage trend will affect residual value. On one hand, in the view of HOs, a vehicle with high total mileage has a higher probability of failing during a field mission, thereby putting humanitarian workers in danger. This is aligned with Pedraza Martinez et al. (2011) and Peck et al. (2015), who demonstrate that vehicle mileage may be the best predictor of failure rate.[1] Peck et al. (2015) also show that failure rate increases almost linearly during the first 4 years and 80,000 km. It then rises with a decreasing pace until it reaches a threshold, after which it remains constant. By the same token, high-mileage vehicles are expected to have a high risk of accident, which eventually increases price decline.[2] Similar to HOs' assumption, Peck et al. (2015) describe that even old vehicles that are less intensively used fail less often. In addition, if all vehicles receive similar preventive maintenance,[3] the residual value is expected to be higher for vehicles that display a decreasing usage trend.

In contrast, some researchers have suggested that the relationship between vehicle failure rate and age/mileage are best described by "bathtub curves" (Mudholkar et al., 1995; Nowlan and Heap, 1978, p. 46), starting with an infant mortality period—vehicle initial mileages—where the failure rate is high; then normal life, when the failure rate is constant and low; and finally, the end of life wear-out period,[4] when the risk of vehicle failures jumps suddenly. Accordingly, assuming that vehicles will be replaced in accordance with HumOrg's standard replacement policy, a decreasing usage trend does not affect the rate of accident and safety of humanitarian workers. Second, Engers et al. (2004, 2009) indicate that a decreasing usage trend might explain declines in price as a car ages.

The impact of usage trend on total mileage has been studied for household vehicles. For instance, Engers et al. (2009) explain that a decreasing usage trend might allow the vehicle to be a longer time, which eventually increases the vehicle's total miles traveled. However, we argue that the impact of such a policy depends on whether a vehicle is used for heavy-duty or light-duty missions. Recall that for a given average monthly distance traveled by a vehicle over its operational life, a decreasing usage trend implies covering above-average distances in the early phase of the vehicle's life and below-average distances in the later phase. Recall also that field missions are usually longer and have more variability than light-duty trips. For vehicles assigned to heavy-duty missions, the capacity lost by not using the vehicle intensively enough in the early phases of its operational life cannot be regained by using it more intensively at the end of its life. The above-mentioned safety considerations (i.e., HOs believe that the likelihood of failure increases over vehicle total mileage), unplanned maintenance interventions (which become more frequent as the vehicle ages), and the higher variability of demand for heavy-duty missions may prevent sub-delegations from using old vehicles for field trips even if they had originally planned to do so. In other words, a decreasing usage trend *fits* well with vehicle mileage capacity and the chance of failure. This is aligned with Rust (1985) who emphasizes that durables usually provide decreasing levels of service and/or impose increasing operating costs as the asset's condition deteriorates. Nevertheless, due to two reasons, this logic may not be applicable for vehicles that are used for light-duty missions: these missions are usually short distance trips and in safer zones that HOs have less safety concerns. Therefore, using vehicles assigned to heavy-duty missions according to a non-decreasing trend may result in lower utilization levels. Conversely, if a vehicle assigned to light-duty missions is used according to a decreasing trend, there might not be enough demand for city trips to generate above-average utilization levels in the early phase of its life. Thus, we expect vehicles assigned to light-duty missions to display higher utilization levels when their usage trend is non-decreasing. In summary, we propose the following:

Hypothesis 3a. *In a humanitarian setting, controlling for vehicle model, age, total mileage, mission type, accident history, and the impact of the local market, a decreasing usage trend positively affects vehicle residual value.*

Hypothesis 3b. *In a humanitarian setting, controlling for the level of conflict in each area, frequency of vehicle maintenance, accident history, and the quality of infrastructure, the impact of a decreasing usage trend on vehicle utilization is higher for vehicles used in heavy-duty missions than for vehicles used in light-duty missions.*

3.3. The trade-off between utilization and residual value

The operations strategy literature has long emphasized the existence of trade-offs among competitive priorities such as cost and service (Frei, 2006; Lapre and Scudder, 2004). Evidence of such a trade-off is also found in the humanitarian operations context (Pedraza Martinez and Van Wassenhove, 2013), where high service levels are usually associated with heavily utilized vehicles; greater utilization means that vehicles are driven more often and for longer distances, thereby performing more missions. However, higher vehicle utilization can only be achieved at the expense of greater losses in residual value. Because residual value is a decreasing function of a vehicle's total mileage (Pedraza Martinez and Van Wassenhove, 2013), the trade-off view implies that increasing

[1] Although Peck et al. (2015) illustrate that the failure rate depends on both vehicle age and mileage, they indicate that vehicle mileage might be a better predictor.

[2] Similarly, economists believe that durable goods are effectively different goods over time as they are usually subject to gradual deterioration with use (Rust, 1985).

[3] Usually every 3 months or 15,000 km (Stapleton et al., 2008).

[4] After 150,000 km for normal vehicles and above 200,000 km for specially equipped vehicles.

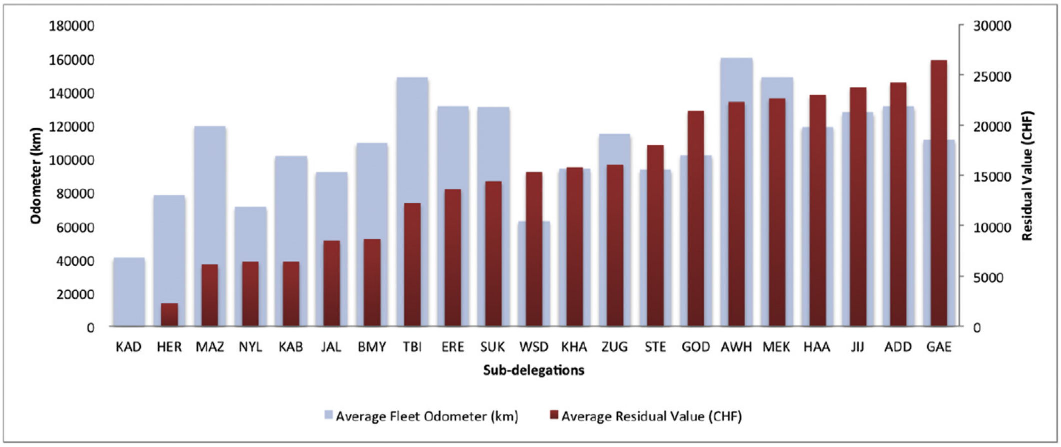

Fig. 1. Average fleet utilization vs. average residual values at HumOrg sub-delegations.

utilization will negatively affect residual value. Other considerations, however, cast doubt on the pervasiveness of the utilization–residual value trade-off in humanitarian operations, and suggest that the mechanisms driving it can be more nuanced than hypothesized. Fig. 1 displays the average vehicle utilization and the average vehicle residual value of a sub-sample of our dataset, namely 21 HumOrg sub-delegations whose fleets included at least four vehicles in all periods between 2000 and 2010. The figure suggests that some sub-delegations are not subject to trade-offs: On average, they achieve higher vehicle utilization and sell their used vehicles at a higher price than others. For example, the average residual value of vehicles at Mazar-i-Sharif (MAZ) is almost the same as in Kabul (KAB), but higher than in Herat (HER). At the same time, vehicle utilization at MAZ is higher than KAB and both are higher than at HER. As these three sub-delegations are located in the same country, Afghanistan, and their vehicles receive similar preventive maintenance services, the comparison raises the question of whether these differences occur randomly, are due to some contingency factors, or are caused by differences in the fleet management policies adopted at the local level. If the last possibility is the case, Fig. 1 suggests that in some cases an appropriate usage policy can both increase vehicle utilization and maximize residual value.

For vehicles subsequently sold and used for commercial purposes, the loss of residual value is primarily driven by the buyer's expectations about the vehicle's future ability to do work and the expected cost of preserving that ability over time (e.g., through maintenance). Both factors are directly linked to the vehicle's expected failure rate because more frequent failures imply not only costly repairs, but also, an opportunity cost for the time forfeited in not being able to use the vehicle. If failure rates are directly related to the vehicle mileage or age (Peck et al., 2015), and if potential buyers have full information about these parameters, then further utilizing a vehicle or keeping it in the fleet longer is expected to decrease its residual market value (i.e., one is likely to observe a trade-off between utilization and residual value). Conversely, if failure rates follow the bathtub curve (Mudholkar et al., 1995), one should not observe such a trade-off unless the vehicle reaches a critical odometer or age threshold where the failure rate starts to increase. Therefore, unless vehicles are replaced before they reach any of these thresholds, the probability of observing a trade-off should increase with an increase in vehicle age or total mileage, as formally stated in the following:

Hypothesis 4a. *There is a trade-off between vehicle utilization and residual value: Increasing the utilization of a vehicle decreases its residual value.*

Hypothesis 4b. *Controlling for variations in vehicle usage, mission type, and accident history, the probability of observing a utilization–residual value trade-off increases with an increase in vehicle age and mileage.*

4. Methodology

4.1. Research database

The main source of data in this study is archival data from HumOrg HQ, which provided us four different datasets, containing more than 101,000 observations overall. The data comprised relevant information on vehicle fleets in the four countries where HumOrg had its largest fleets from 2000 to 2014, namely Afghanistan, Ethiopia, Georgia, and Sudan. The information includes vehicle ID code, model, country of operation and sub-delegation (i.e., city) where the vehicle was used, mission type, time window (i.e., period in months), distance traveled in each period, date of purchase, cumulative odometer since purchase, sold/disposal date, sold price, age of vehicle in months, date and time of accident, and date and time of maintenance. After merging these datasets, we built a new unbalanced panel dataset containing information on 927 vehicles. We restricted our analysis to those vehicles that were not donated, stolen, or hijacked.[5] The final dataset, after removing outliers, includes 827 vehicles, of which 296 were in Afghanistan, 154 in Ethiopia, 154 in Georgia, and 223 in Sudan. To measure some proxies such as usage trend, we only focused on those vehicles whose number of observations covered at least 12 consecutive periods (or months). The observation period covered either the entire operational life cycle of a vehicle or a large proportion of it.

To estimate the characteristics of the operational conditions in which vehicles were used (our control variables), we complemented our dataset with some public data available on the World Bank and International Crisis Group (ICG) websites. The related variables and the method of estimating them are covered in the next subsections.

[5] The residual value of about 55 vehicles that were donated, stolen, or hijacked was reported as zero.

4.2. Operational measures

We define two dependent variables, namely vehicle utilization and vehicle resale value. Vehicle utilization has been defined either as total mileage driven or miles upon sale (Golob, 1998; Conlon et al., 2001; Fang, 2008; Peck et al., 2015) or kilometers driven in a certain period of time (Dargay, 1997; Engers et al., 2009). We built on these definitions and operationalized the utilization of vehicle i as its total mileage upon sale, denoting this as TM_i. Assuming that field manager assigns optimal load to vehicles, this is a convenient measure of fleet performance in the humanitarian sector as well. Also, fleet performance is a major component of the performance of LMD. Therefore, as there is no monetary flow from beneficiaries to HOs, and as the former cannot file formal complaints, if beneficiaries receive poor service (Oloruntoba and Gray, 2009), vehicle utilization becomes a viable alternative to assess LMD effectiveness because it is directly related to the number of missions completed. The second dependent variable, vehicle resale value, was operationalized as the percentage of vehicle price decline, denoted by PPD_i. We could simply use the resale value of used vehicles. However, as vehicle resale value depends on the initial price, it may not be an effective proxy to examine vehicles' depreciation when the dataset contains vehicles with different initial prices.

Explanatory variables include mission type and usage trend. To capture differences in mission type, we created the dummy variable $Mission_i$, which was set to 1 if vehicles were assigned to heavy-duty missions and to 0 otherwise. To measure usage trend, $Utrend_i$, for each vehicle, we regressed the monthly distance traveled against its age. If the estimated coefficient was negative and significant, we set $Utrend_i$ to 1, while we set $Utrend_i$ to 0 otherwise. Interestingly, all vehicles with decreasing usage trends had large negative slopes.

The first set of control variables pertains to vehicle characteristics. The dummy variable $Model_i$ accounted for the suitability of a vehicle for specific types of missions. It was set to 1 if vehicles were specially equipped and to 0 otherwise. Considering different models from a wide range of vehicle brands, Engers et al. (2009) argue that, unless they are very radical, it is unlikely that obsolescence effects can explain the magnitude of price decline. Besides, and given that all vehicles in our dataset are the basic Land Cruisers,[6] we only distinguish between normal and specially equipped Land Cruisers and disregard any new model that was introduced to the global market during the observation period. In addition, we controlled for vehicle age, Age_i. The frequency of maintenance, $FreqMnt_i$, and accident history, $Accid_i$, of each vehicle were also expected to affect both utilization and resale value. $FreqMnt_i$ was measured by the number of times that vehicle i was sent to workshop for preventive or major maintenance. This did not include repair services required due to accident. To control for accident history, we counted the number accidents in which a vehicle had been involved upon sale. Moreover, we controlled for the effect of individual vehicle usage variation in our model, indicated by $Uvar_i$. Usage variation was measured through the standard deviation of the monthly distance traveled during a vehicle's operational life. We used the standard deviation, a measure of *absolute* variability, over other measures of relative variability such as the coefficient of variation because the latter could create endogeneity problems with our utilization proxy. Individual vehicles' usage variation may also be affected by aggregated demand variation and some other environmental factors such as quality of infrastructure and level of conflicts. Therefore, we consider a second set of control variables.

Demand variation is assumed to exert a negative influence on fleet performance (Pedraza Martinez et al., 2011). For each vehicle i belonging to sub-delegation, j we calculated $Dvar_i$, the standard deviation of average demand at sub-delegation j over the periods in which vehicle i was active. To calculate $Dvar_i$, we computed the total transportation demand D_{ijt} as the sum of the actual distance traveled by each vehicle at each sub-delegation in each period in which vehicle i was active. D_{ijt} was then divided by the fleet size in period t to compute the average per-vehicle demand in that period, $\overline{D}_{ijt}$. Finally, we computed the standard deviation of $\overline{D}_{ijt}$, $t = \{1,\ldots,T_i\}$ during the observation periods of vehicle i and denoted this by $Dvar_i$.

Last, we had to control for several exogenous variables reflecting the vehicles' operational environment, as well as their technical characteristics. The quality of infrastructure, particularly roads, may affect frequency of maintenance and the probability of accident. It is likely that this influences resale value, because vehicles used in rougher terrain wear out more quickly. It also affects utilization because vehicles used in more difficult environments require more maintenance and are less frequently available to undertake missions. Finally, the quality of infrastructure also indirectly affects usage variation. Whereas in a country with good roads, fleet managers have flexibility in the choice of vehicles, in countries or regions without roads or with only badly maintained roads, managers are forced to use specially equipped vehicles. The quality of infrastructure in the country of operations was accounted for through the logistics performance indicator (LPI) of the country of operations, obtained from the World Bank database. We calculated the average LPI for each individual vehicle, denoted by $Qinf_i$, as the LPI of the country of operations during the period in which vehicle i was active in the fleet.[7]

The level of conflict in the country of operations affects aggregate demand because when violence reaches a critical level, HOs may decrease their activities and eventually pull out of the country. This negatively affects fleet performance and increases operating costs (Tomasini and Van Wassenhove, 2009; Pedraza Martinez et al., 2011). Following Pedraza Martinez and Van Wassenhove (2013), we examined reports by the ICG, which has monitored conflict levels in all countries from August 2003 onward.[8] The ICG reports the conflict situation in all countries and determines whether the conflict level has significantly worsened, improved, or remained unchanged. For each country, we assumed a reference conflict level as of August 2003. If the ICG's monthly report indicated a higher (lower) conflict level, we increased (decreased) the indicator by one unit. $Conf_i$ represents the average level of conflict in the country of operations during the periods in which vehicle i was used.[9] Fig. 2 displays the evaluation of the level of conflict in each country over the observation period. Finally, to control for the

[6] The basic HZJ model.

[7] We also used percentage of paved roads as the second proxy. However, as the results were consistent with LPI, we only report the results from the LPI.

[8] Unfortunately, data are only available from August 2003.

[9] It is always preferred to measure a control variable similar to the way it has been measured in related studies (Becker, 2005). While conducting this study, the only method that we could benefit from was Pedraza Martinez and Van Wassenhove (2013). Yet, to make sure that this is a reliable variable (and its measurement method is valid), we took further steps: For a sub-sample of about 300 vehicles, we estimated $Conf_i$ using three-unit, two-unit, and one-unit change. As results were consistent, we assume that this measure is fairly robust. Then, following Becker (2005) and Spector and Brannick (2011), we consider the correlations between $Conf_i$ and each of the dependent variables (i.e., TM_i and $Uvar_i$). Correlations were significant and fairly large (see Table 2), though the ones obtained from using a one-unit change in conflict level were slightly larger than the two others. Finally, we compared the results of a restricted model (i.e., without $Conf_i$), and unrestricted model (i.e., with $Conf_i$). Given that the result changed, we kept $Conf_i$ and trusted the way it was measured. It is certainly worth noting that a more solid measure to estimate variables such as the level of conflict would be very beneficial for related studies in humanitarian area.

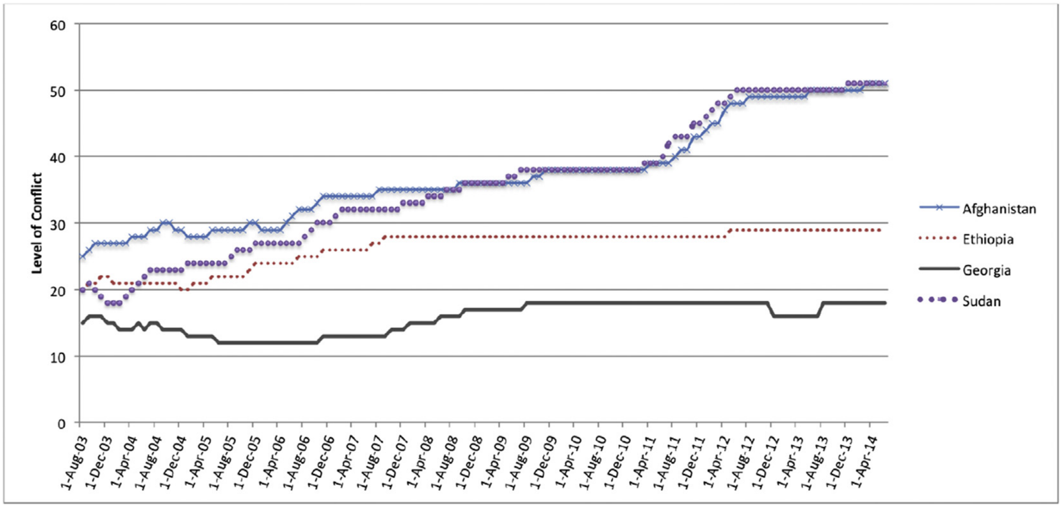

Fig. 2. Level of conflict in the countries of operations 2003–2014.

Table 1
Descriptive statistics.

Notation	Variable	Obs.	Mean	Std Dev	Min	Max
TM_i	Total odometer (km)	827	103436.60	63147.94	10045.00	304916.00
RV_i	Residual value (CHF*)	827	8564.21	7987.27	0.00	31842.00
$Uvar_i$	Usage variation	446	923.58	670.54	0.00	6488.51
$Dvar_{ij}$	Average demand variation	445	664.04	763.32	89.07	3952.49
Age_i	Sold age (months)	813	79.91	23.53	16.00	178.00
PPD_i	Percentage of price decline	827	72.78	25.24	0.18	100.00
$FreqMnt_i$	Frequency of maintenance	383	16.73	12.44	1.00	70.00
$Conf_i$	Average Conflict	449	31.19	11.51	12.13	51.00
$Accid_i$	No. of accidents	827	0.29	0.94	0.00	8.00
$Qinf_i$	Quality of infrastructure	827	1.88	0.31	1.65	2.51
$Utrend_i$	Usage trend	426	0.29	0.45	0.00	1.00
$Mission_i$	Mission type	521	0.70	0.45	0.00	1.00
$Model_i$	Vehicle model	819	0.90	0.29	0.00	1.00

*Swiss Franc.

impact of local market on vehicle residual value, we considered the country of operations where vehicle i was sold, Cnt_i.[10] Table 1 summarizes the notations and presents descriptive statistics while, Table 2 shows correlations between variables.

4.3. Econometric analysis

Given the nature of the dependent variables and the proxies used to evaluate vehicle usage policies, we had to convert our unbalanced panel data into a cross sectional format. Hypothesis 1—alignment of models and missions— was tested by estimating Eq. (1). As less reliable vehicles are less likely to be used for field missions require maintenance services more frequently, if assigned to heavy-duty missions, we control for vehicle repair history. $Mission_i$ is a binary variable; hence Eq. (1) was estimated through a probit model:

$$Mission_i = \eta_0 + \eta_1 FreqMnt_i + \eta_2 Model_i + u_{i1}. \qquad (1)$$

To test the hypotheses pertaining to the effect on residual value (2, 3a and 4a), we had to estimate Eq. (2). There are two econometric issues with this model. The first challenge is the presence of selection bias. If, as hypothesized, specially equipped vehicles are assigned to heavy-duty missions, the true impact of mission type on residual value may be underestimated. Theoretically, heavy-duty missions should cause a greater loss of residual value than light-duty ones. However, specially equipped vehicles are also more resilient and should be less affected by intensive use than normal vehicles. If specially equipped vehicles are mostly assigned to heavy-duty missions, the latter effect may reduce the influence of the former. As a consequence, an Ordinary Least Squares (OLS) estimation of the effect of mission type on residual value may produce biased estimates. To circumvent this challenge, we employed a two-stage approach. First, we used model (1) to estimate $Conf_i$ (i.e., the fitted value of $Mission_i$) using a probit regression on (1). Then, we estimated (2) after replacing $Mission_i$ with its fitted value TM_i from Eq. (1). Such a two-stage approach provides a quasi-natural experiment and mimics a random vehicle-to-mission assignment (Singh KC and Terwiesch, 2011). However, the results of this procedure and a more thorough examination of the HumOrg decision-making processes suggested that the endogeneity bias was not as severe as expected. The results show that neither the

[10] Due to two reasons, we do not incorporate a dummy variable for each delegation: First, we do not have detail information, such as the level of conflict and quality of infrastructure, at delegation level, though this information is available at country level. Second, we do not have solid reasons why delegations might have specific impact on vehicle price decline and utilization that is not captured by country-dummy variables. Therefore, we decided to take a more conservative approach and follow Spector and Brannick (2011) who advise against adding a new control variable "*just because it might affect the variable of interest*".

Table 2
Correlations.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TM_i	(1)	1.00											
$Uvar_i$	(2)	0.28***	1.00										
$Dvar_i$	(3)	−0.00	0.14**	1.00									
Age_i	(4)	0.52***	−0.01	0.20***	1.00								
PPD_i	(5)	−0.13***	−0.37***	0.02	0.12**	1.00							
$FreqMnt_i$	(6)	0.27***	0.05	−0.09*	0.39***	0.19***	1.00						
$Conf_i$	(7)	−0.67***	−0.38***	−0.12**	−0.39***	0.54***	−0.18**	1.00					
$Accid_i$	(8)	−0.14***	−0.10**	−0.15***	−0.11***	0.18***	0.47***	0.26***	1.00				
$Qinf_i$	(9)	0.52***	0.17***	−0.03	0.09**	−0.22***	0.14**	−0.72***	−0.09**	1.00			
$Utrend_i$	(10)	0.02	−0.12**	0.03	0.19***	0.16***	−0.02	0.14**	−0.03	−0.22***	1.00		
$Mission_i$	(11)	0.04	−0.02	−0.50***	−0.07*	0.01	0.22***	0.04	0.13***	−0.04	−0.08*	1.00	
$Model_i$	(12)	−0.07**	0.09**	0.11**	−0.11***	0.03	−0.05	−0.03	−0.08**	−0.06**	−0.01	−0.15***	1.00

Note: *10%, **5%, and ***1% statistical significance.

parameter estimates nor the model fit are affected much when using the two-stage approach, indicating that managers do not follow the hypothesized vehicle-to-mission allocation procedure that would create endogeneity problems. We further discussed this point with HumOrg. A potential endogeneity problem would occur when a rational and forward-looking manager would take the expected future loss of residual value into consideration when assigning vehicles to missions. However, this does not seem to be the case at HumOrg because the decision maker who assigns vehicles to missions is not the same person who sells used vehicles on the second-hand market, and she does not take residual value into account when making allocation decisions. Rather, these decisions are made by different individuals who do not coordinate and do not have aligned incentives[11]:

$$PPD_i = \alpha_0 + \alpha_1 TM_i + \alpha_2 Age_i + \alpha_3 Model_i + \alpha_4 Accid_i + \alpha_5 Utrend_i + \alpha_6 Mission_i + \alpha_7 Sudan + \alpha_8 Ethiopia + \alpha_9 Georgia + u_{i2}. \tag{2}$$

The second econometric issue with Eq. (2), which could also cause a bias in the estimates, involves the relations between some independent variables. For example, vehicle total mileage might depend on mission type and maintenance history. Similarly, the chance of accident may be lower for vehicles with a decreasing usage trend. Accordingly, each of these variables should be specified through a separate equation. Although a simple OLS regression on each of these variables will provide insight into the influence of each factor on regressands (i.e., utilization and price decline), it may not capture the indirect links between these factors. Therefore, it is likely that the error terms of these equations will be correlated. In this situation, we use the Seemingly Unrelated Regression (SUR) method, which assumes error terms are correlated across equations (Greene, 2012, p. 292–293).[12] In this method, an independent variable in one equation can be a dependent variable in another equation of the system. Our simultaneous equations model contains Eqs. (2)–(7):

$$TM_i = \beta_0 + \beta_1 FreqMnt_i + \beta_2 Age_i + \beta_3 Model_i + \beta_4 Utrend_i + \beta_5 Uvar_i + \beta_6 Qinf_i + \beta_7 Conf_i + \beta_8 Mission_i + \beta_9 (Mission_i \times Utrend_i) + \beta_{10} (Mission_i \times Qinf_i) + \beta_{11} (Mission_i \times Model_i) + u_{i3}. \tag{3}$$

To examine the impact on utilization, we estimated Eq. (3), in which we controlled for the effects of usage variation, frequency of maintenance, vehicle age, and model. To test Hypothesis 3b (moderating impact of mission type on utilization), we also added the interaction term of ($Mission_i \times Utrend_i$) to this equation. Frequency of maintenance is explained by Eq. (4), in which we control for total mileage and age of vehicle along with its model, usage trend, and the quality of infrastructure in which the vehicle had been used. While frequency of preventive maintenance might increase vehicle total mileage, it also is a function of vehicle total mileage and age (Engers et al., 2004, 2009). In addition, it might be affected by vehicle model (Peck et al., 2015) and mission type. Hence, we took all of these variables into account:

$$FreqMnt_i = \gamma_0 + \gamma_1 TM_i + \gamma_2 Age_i + \gamma_3 Model_i + \gamma_4 Utrend_i + \gamma_5 Qinf_i + \gamma_6 Mission_i + \gamma_7 (Mission_i \times Model_i) + u_{i4}. \tag{4}$$

As presumed by HumOrg, the accident rate decreases if a vehicle is used following a decreasing usage pattern. Reasonably, preventive maintenance and mission type are expected to affect the chance of accident. Hence, we added Eq. (5) to the system as well:

$$Accid_i = \delta_0 + \delta_1 FreqMnt_i + \delta_2 Age_i + \delta_3 Model_i + \delta_4 Qinf_i + \delta_5 Utrend_i + \delta_6 Mission_i + \delta_7 (Mission_i \times Model_i) + u_{i5}. \tag{5}$$

It is likely that vehicles are only kept longer in fleet due to financial limitations. However, there might be other reasons that affect vehicle selling age. For instance, usage trend (Engers et al., 2009), mission type, maintenance, and accident history are some key variables that affect vehicle sold age. Hence, we included Eq. (6) in the system:

$$Age_i = \xi_0 + \xi_1 Mnt_i + \xi_2 Accid_i + \xi_3 Utrend_i + \xi_4 Mission_i + \xi_5 Model_i + u_{i6}. \tag{6}$$

[11] We also note that, given the small correlation between mission type and vehicle model (−0.15), $Model_i$ is not an ideal instrument. In such a case, OLS provides unbiased results. Our approach is supported by a recent contribution by Larcker and Rusticus (2010) demonstrating that when the instrument is only weakly correlated with the regressor and the instrumental variable (IV) is even slightly endogenous, IV methods can produce highly biased estimates and more likely provide incorrect statistical inference than simple OLS estimates that make no correction for endogeneity.

[12] We also ran a Breusch-Pagan test of independent errors, a specification test that is often used for a SUR model. The test examines whether the errors across equations are contemporaneously correlated. The results confirmed that the errors of Eqs. (2)–(7) are not independent. In addition, to make sure that SUR was the most efficient method, the system of equations was estimated using OLS, SUR, and Two-Stage Least Square (2SLS). A Hausman test suggested that SUR was the most efficient method.

Finally, we noted that the usage variation of individual vehicles might be driven by aggregated demand variation (Pedraza Martinez et al., 2011) and the level of conflict. Moreover, the usage variation of vehicles might increase when they are out of service (e.g., for maintenance purposes). This may eventually affect vehicle utilization and must be taken into account. Consequently, we specified vehicle usage variation through a separate equation, Eq. (7).

$$Uvar_i = \zeta_0 + \zeta_1 Dvar_i + \zeta_2 FreqMnt_i + \zeta_3 Age_i + \zeta_4 Mission_i + \zeta_5 Model_i + \zeta_6 Accid_i + \zeta_7 Qinf_i + \zeta_8 Conf_i + u_{i7}. \quad (7)$$

Hypothesis 4a (the existence of a trade-off between utilization and residual value) was tested by examining the coefficient α_1 in Eq. (2). Nevertheless, to assess the conditions in which a utilization versus residual value trade-off was most likely to occur, we ran another test inspired by the procedure developed by Lapre and Scudder (2004). We defined TO_i as the binary variable indicating the existence of a trade-off. To compute TO_i, we proceeded as follows. First, we computed $\overline{TM}_j$ as the mean of the total distance traveled by all vehicles in country j and $\overline{PD}_j$ as the mean of percentage of price decline of all vehicles in the same country. In the second stage, we computed the difference between individual vehicles' price decline and utilization and the average price decline and utilization in the country of operations. That is, we set $TM_{ij} = TM_i - \overline{TM}_j$ and $PD_{ij} = PD_i - \overline{PD}_j$. We called these factors "relative price decline" and "relative utilization." Then, for every vehicle observation (vehicle i in country j), we determined whether (i) the relative price decline was less than the average while relative utilization was higher than the average ($TM_{ij} > 0$ and $PD_{ij} < 0$), (ii) a trade-off occurred ($TM_{ij} > 0$ and $PD_{ij} > 0$ or $TM_{ij} < 0$ and $PD_{ij} < 0$), or (iii) the relative price decline was higher than the average and the relative utilization for vehicle i was less than the average ($TM_{ij} < 0$ and $PD_{ij} > 0$). If a trade-off for vehicle i occurred, we set $TO_i = 1$; otherwise, we set $TO_i = 0$. Since we were interested in simultaneous improvement, we removed 197 observations where both $TM_{ij} < 0$ and $PD_{ij} > 0$ and estimated Eq. (8) using a probit regression[13]:

$$TO_i = \theta_0 + \theta_1 Age_i + \theta_2 TM_i + \theta_3 Mission_i + \theta_4 Accid_i + u_{i8}. \quad (8)$$

5. Results, discussion, and managerial insights

All models were estimated using STATA 13.1. Results are illustrated in Tables 3–5. Table 3, which displays the coefficient estimates for Eq. (1), suggests some counterintuitive results. The coefficient estimate of the variable $Model_i$ is negative and significant; contrary to our initial assumption and to HumOrg's recommendation, this indicates that more reliable and specially equipped vehicles are allocated to light-duty missions instead of heavy-duty ones. The results show that about 95% of normal vehicles were assigned to heavy-duty missions even if a sufficient number of specially equipped vehicles were available. On the other hand, as expected, specially equipped vehicles had a smaller chance of accident compared to normal vehicles ($\delta_3 \approx -1.97$), while these vehicles did not receive more maintenance services. Therefore, standard vehicle-mission assignment policy, if implemented in the field, might fulfill HumOrg's primary goal. Nevertheless, such a mismatch may be due to a lack of communication and incentive misalignment between the HQ and delegations. Such a counterintuitive allocation policy has implications for the other relationship tested as well.

Table 3
Probit regression estimates for vehicle-mission assignment.

Constant (η_0)	1.316** (0.454)
$Model_i(\eta_1)$	−1.390** (0.447)
$FreqMnt_i(\eta_2)$	0.025*** (0.006)
Model $\chi^2(2)$	34.31***
Log likelihood	−220.17
Pseudo R^2	0.07
Number of observations	367

Note: *10%, **5%, and ***1% statistical significance.
Numbers in parentheses show standard deviation.

The second column of Table 4 displays the results of the price decline analysis. As hypothesized, vehicles used for administrative duties, on average, lose less value than vehicles used for field missions. An interesting post hoc finding from Eq. (2) is that specially equipped vehicles lose more value than normal vehicles, while on average, their mileage upon sale is about 17,000 km less than that of the normal vehicles. Surprisingly, the magnitude of this effect is even larger than that of mission type on vehicle resale value. We discussed our findings with some field managers who provided interesting insights and helped us to understand the drivers of such an unexpected allocation policy. Specially equipped vehicles have stronger suspensions and more sophisticated electronic devices. However, precisely because their suspensions are stiffer, these vehicles are not as comfortable for long trips as normal vehicles and are therefore preferred for short city trips. For the same reason, normal vehicles have a better reputation in the local market and therefore sell at a higher price. Furthermore, the superior electronic and communications capabilities of specially equipped vehicles make them particularly appealing for transporting heads of delegations and other senior staff members. As such staff members rarely perform field missions, specially equipped vehicles end up being used primarily for city trips.

Taken together, the results of Eqs. (1)–(3) suggest that while the effect of vehicle-mission mismatch on vehicle utilization is insignificant, its effect on price decline is considerable. The results summarized in Fig. 3 show that normal vehicles, on average, lose 63% of their value if they are assigned to heavy-duty missions, while they only lose 34% of their initial value if they are assigned to appropriate missions (i.e., light-duty).

As HOs currently do not follow the HQ's recommendation, we conclude that HQ should either change its current purchasing policy and provide all delegations with only normal vehicles, or introduce appropriate incentives to make sure its recommendation is properly followed. We estimate that a different vehicle-mission assignment policy would save over US$ 8000 per normal vehicle, while a different procurement policy whereby only normal vehicles are purchased could save up to US$ 4200 per vehicle. Given the size of most HOs' fleets, the total savings resulting from such a policy could easily amount to several million US dollars.

The impact of usage trend on vehicle utilization and residual value is not completely in line with what was hypothesized (Hypotheses 3a and 3b). In analyzing the impact of usage trend on vehicle residual value, the parameters of interest are those that can be used to compute the direct and indirect effects of usage trend on a vehicle's price decline. The coefficient α_5 in Eq. (2) is the direct effect of usage trend on the average price decline. As shown in the second column of Table 4, this parameter estimate is insignificant. However, estimating the indirect effect of usage trend on price decline involves estimation of two components, as follows: the effect of usage trend on sold age (i.e., ξ_3 in Eq. (6)) and the effect of sold age on price decline (i.e., α_2 in Eq. (2)). Combining the two

[13] We identified 236 vehicles with $TM_{ij} > 0$ and $PD_{ij} < 0$, 207 with $TM_{ij} > 0$ and $PD_{ij} > 0$, 192 with $TM_{ij} < 0$ and $PD_{ij} < 0$, and 197 with $TM_{ij} < 0$ and $PD_{ij} > 0$.

Table 4
Regression estimates—seemingly unrelated regression.

Independent variable	Dependent variable					
	Colm. 2 % of Price decline	Colm. 3 Utilization	Colm. 4 Maintenance Freq.	Colm. 5 Accident	Colm. 6 Age	Colm. 7 Usage variation
TM_i	−0.000*** (0.000)		0.000* (0.000)			
Age_i	0.650*** (0.067)	397.953*** (114.728)	0.323*** (0.035)	−0.016*** (0.003)		−11.008*** (2.068)
$Model_i$	13.543** (4.281)	2427.722 (29697.160)	12.088 (9.960)	−1.977* (1.124)	−5.651 (4.250)	282.244** (121.980)
$Accid_i$	5.930*** (0.736)				−3.767*** (0.888)	25.431 (28.843)
$FreqMnt_i$		676.584*** (163.607)		0.071*** (0.006)	1.263*** (0.099)	4.907 (3.613)
$Utrend_i$	0.070 (2.595)	−3479.403 (6450.630)	−1.817 (1.543)	−0.199 (0.159)	7.133** (2.564)	
$Mission_i$	10.115*** (2.492)	−53488.810 (45704.950)	19.943** (10.067)	−1.062 (1.143)	−12.036*** (2.572)	−83.472 (90.602)
$Conf_i$		−2061.840*** (325.069)				−40.328*** (5.765)
$Qinf_i$		−3197.666 (15795.600)	6.301* (3.452)	−1.693*** (0.307)		−584.563** (263.338)
$Uvar_i$		13.997*** (3.134)				
$Dvar_i$						−0.005 (0.049)
$Mission_i \times Qinf_i$		29474.860* (15327.790)				
$Mission_i \times Utrend_i$		15147.370* (8079.288)				
$Mission_i \times Model_i$		1186.222 (30253.950)	−12.401 (10.098)	1.123 (1.148)		
Sudan	−17.885*** (3.577)					
Ethiopia	−30.340*** (3.667)					
Georgia	−30.183*** (5.129)					
Intercept	37.259*** (6.900)	96738.590* (55996.680)	−36.240** (12.693)	5.661*** (1.342)	63.033*** (4.873)	3763.527*** (745.076)
Chi-Squared	594.52***	546.97***	179.67***	181.25***	184.04***	107.40***
R-Squared	0.63	0.66	0.17	0.35	0.15	0.28
Obs	270	270	270	270	270	270

Note: *10%, **5%, and ***1% statistical significance. Numbers in parentheses show standard deviation.

Table 5
Probability of observing a trade-off: probit regression estimates.

Constant (θ_0)	2.207*** (0.529)
$Age_i(\theta_1)$	0.013** (0.005)
$TM_i(\theta_2)$	−0.000*** (0.000)
$Mission_i(\theta_3)$	0.376* (0.221)
$Accid_i(\theta_4)$	0.885** (0.330)
Model χ^2	161.39***
Log likelihood	−112.66
Pseudo R^2	0.41
Number of observations	306

Note: *10%, **5%, and ***1% statistical significance. Numbers in parentheses show standard deviation.

	Utilization (km)	Residual value (CHF)	Sold age (months)
Decreasing usage trend	98,095	6,677	82.2
Non-decreasing usage trend	85,369	9,905	70.8

Fig. 4. Impact of usage trend on the utilization and residual value of field vehicles.

	Heavy-duty mission	Light-duty mission
Specially equipped	71%	70%
Normal	63%	34%

Fig. 3. Vehicle price decline.

coefficients as $\alpha_2\xi_3$ provides the estimate of the indirect effect of usage trend on price decline. Therefore, we can conclude that overall, a decreasing usage trend negatively affects the resale value of used vehicles. This suggests that, ceteris paribus, following a decreasing usage trend does not enable HOs to sell vehicles at a higher price. Therefore, Hypothesis 3a cannot be accepted.

Conversely, the third column of Table 4 indicates that Hypothesis 3b is supported. Our result shows that indirectly and through vehicle age, a decreasing usage trend increases vehicle total mileage, regardless of the vehicle mission type. Nevertheless, the direct impact on utilization is positive and statistically significant only for vehicles used in heavy-duty missions. Yet, the positive effect is rooted in vehicles' sold age; it only increases utilization if a vehicle is kept for a longer time in fleet. Fig. 4 summarizes the average utilization, sold age, and residual value of heavy-duty vehicles used following a decreasing usage versus non-decreasing usage pattern.

Recall that HumOrg recommends a decreasing usage trend, primarily for safety reasons. Our result, however, illustrates that a decreasing usage trend does not minimize the chance of accident during a vehicle's operational life cycle (coefficient δ_5). It shows that vehicles are sold far below the critical odometer threshold. Therefore, using vehicles according to a decreasing usage trend does not improve the safety of humanitarian workers because it does not decrease the likelihood of accidents or mechanical failures.

The analysis of the utilization–price decline trade-off (Table 4, column 2) provides interesting insights. The insignificant impact of utilization on vehicle residual value suggests that, on average, there is no simple trade-off between utilization and residual value. However, and in accordance with Hypothesis 4b, the occurrence of such a trade-off strongly depends on vehicle age, mission, and accident history (see Table 5). While the probability of observing a trade-off increases with the age of a vehicle (i.e., 0.3%), it is almost independent of its mileage. Note that the impact of age on total mileage is very small; on average, for each additional month a vehicle is kept, its cumulative mileage might increase by about 400 km. These opposite effects are driven by the different approach used to replace vehicles. The mean of total distance traveled by all vehicles in our dataset is only 103,526 km. This is close to the optimal replacement threshold (100,000 km) recommended by Pedraza Martinez and Van Wassenhove (2013), but still far below the critical odometer threshold indicated by the manufacturer. Note that over 91% of the vehicles in our sample were sold before their total mileage became large enough to cause wear-out failures and generate a trade-off. Conversely, unless used intensively, vehicles were kept in the fleet for a long time (almost 7 years on average), well beyond the recommended replacement age indicated by HumOrg's standard replacement policy (5 years). This is also beyond the age threshold after which obsolescence starts to increase the failure rate, thereby generating a trade-off.

The marginal effect of age on trade-off is small compared to the effect of accident and heavy-duty missions. On average, each accident increases the chance of trade-off by about 18.1%. In addition, the probability of avoiding the trade-off for light-duty missions, on average, is 7.7% greater than that for heavy-duty vehicles. Undoubtedly, one way to avoid the trade-off is to minimize the accident rate. Although we show that an optimal vehicle-mission assignment might decrease the chance of accident and consequently decrease price decline, our dataset does not provide related information to investigate the causes of accident or how HumOrg can decrease its occurrence. Taken together, the results suggest that another way to avoid a utilization–residual value trade-off is to use vehicles more intensively and replace them sooner. The findings demonstrate that using a vehicle more intensively does not affect price decline or maintenance cost. Hence, this policy would allow HOs to both minimize maintenance costs and maximize residual value. It is worth noting that such a recommendation applies to all vehicles, regardless of their mission type. Yet, we should make this recommendation cautiously as there might be other issues, such as the workload limitation, nature of missions in the field, and level of conflict, that prevent delegations from following this policy.

The impact of age, utilization, and mission type on price decline and maintenance frequency reported in Table 4 indicate that HOs should reconsider their current vehicle replacement policy. The results suggest that an optimal replacement policy must take both age and mileage into account. In addition, the large and negative impact of mission type on residual value and its effect on frequency of maintenance suggest that HumOrg should have distinct vehicle replacement policies based on mission type; a general policy to replace vehicles after 5 years or 150,000 km may not be effective for all vehicles. Our result consistent with that of Brosh et al. (1975), which takes both age and mileage into account, while it contrasts with that of Pedraza Martinez and Van Wassenhove (2013), wherein the findings lead to the recommendation that the optimal replacement threshold should be set based on vehicle total mileage alone.

An interesting post hoc finding is that maintenance services are not based on vehicle model. This is in sharp contrast with Conlon et al.'s (2001) argument that the initial quality of a vehicle significantly affects the user's decisions when it comes to determining how to maintain vehicle quality over time. With respect to their argument, if HumOrg has expended more for the initial quality of specially equipped vehicles, it is rational for the organization to protect initial investment through better maintenance. Furthermore, HumOrg purchases specially equipped vehicles because of their reliability, which can be beneficial for heavy-duty missions. It is therefore a reasonable assumption that delegations will engage in maintenance activities consistent with that purpose. In contrast to this rationale, looking at coefficients γ_2 and γ_6 in Eq. (4), vehicles receive maintenance services based on mission type and age.

Finally, the results reveal that, on average, normal vehicles are used more consistently than specially equipped vehicles. It is worth noting that the usage variation of all vehicles, regardless of their mission type does not depend on an increase in demand variation. This observation makes apparent that, in many delegations, fleet size might be larger than the actual need.

6. Limitations

By providing a more comprehensive and more nuanced picture of humanitarian fleet management at the field level, this paper makes a contribution to the literature on fleet management in humanitarian development programs. At the field level, where data availability is extremely limited, and where most HOs do not even have good visibility of their operations in remote areas, this is one of the first empirical studies to use objective measures in order to examine the performance of fleet management policies. Insights resulting from our analysis can also be a useful input for further modeling-based research. Yet, similar to many empirical studies, this research has also some limitations. One limitation of this study stems from the use of data from a single humanitarian organization, although it is very large. Researchers do not necessarily consider this as a drawback (Fisher, 2007), however, and some similar studies, such as Pedraza Martinez and Van Wassenhove (2013) and Conlon et al. (2001), are also based on single-firm data. On one hand, restricting the scope of our study was useful in eliminating confounding firm-level effects; at the same time, it was also a necessary compromise because HOs usually do not have appropriate systems to collect and register data on their fleets. On the other hand, although the data used in this study have the virtue of high reliability and validity, some variables might have been understated. Second, due to the lack of previous literature related to the questions discussed in this paper, following Fisher (2007), Flynn et al. (1990) and Meredith (1998), we developed our hypotheses based on interviews with practitioners and the literature on commercial fleet management whenever humanitarian literature did not cover the topic. Third, the purpose of this study is to improve the performance of fleet through maximizing vehicle utilization while minimizing asset price decline. Nevertheless, as there are no *true* performance measures related to humanitarian fleet management, we had to employ vehicle utilization as a proxy for demand coverage. Other proxies to evaluate performance of fleet management that take humanitarian aspects, such as mission criticality, into account could be very beneficial. These indicators can still be inspired by those normally used to evaluate commercial fleet management such as vehicle loading, transportation schedules, and percentage of empty running. Furthermore, as indicated by Guide and Ketokivi (2015), we should ideally use a panel data analysis to understand the actual magnitude of the effect of one variable on another. Due to the limitation of our dataset (for example, the absence of data showing vehicles' monthly residual value), we had to convert our data to a cross sectional format, and therefore, we could not benefit of using a panel data analysis. This has also led a sacrifice in data granularity: for instance, we lost the richness of conflict fluctuations over time. One may address these limitations in future research in order to examine whether the phenomena we have discussed remain valid in different operational contexts and for humanitarian organizations with different fleet management and organizational models.

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