Journal of Operations Management 45 (2016) 44–56

Contents lists available at ScienceDirect

Journal of Operations Management

journal homepage: www.elsevier.com/locate/jom

Econometric estimation of deprivation cost functions: A contingent valuation experiment

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ARTICLE INFO

Article history:
Accepted 4 May 2016
Available online 30 June 2016
Accepted by: Mikko Ketokivi

ABSTRACT

This paper details research to design an estimation process for Deprivation Cost Functions (DCF) using Contingent Valuation, and to apply it econometrically to obtain a DCF for drinkable water. The paper describes both the process and results obtained. The results indicate that deprivation costs for drinkable water have a non-linear relation with deprivation times. The estimated DCFs provide a consistent metric that could be incorporated into humanitarian logistic mathematical models, eliminating the need to use proxy metrics, and providing a better way to assess the impacts of delivery options and actions. The research reported in this paper is the first attempt in the literature to produce estimates of the economic value of human suffering created by the deprivation of a critical supply or service.

1. Introduction

The growing social and economic impacts of disasters add tremendous urgency to the development of effective disaster preparation and response procedures. These pressures are expected to intensify with the growing urbanization of the world population, which is resulting in increasingly large and complex metropolitan areas. Many of these population centers—rarely well prepared to respond to large disasters—are located in coastal areas, or in proximity to earthquake fault lines, increasing their vulnerability. The size and complexity of these emerging megalopolises dramatically complicate disaster response procedures. In such a context, the humanitarian logistics (HL) system will play an even more important role, having to transport and deliver larger amounts of supplies for longer distances, and in more complex and congested transportation networks. There is a wide spectrum of HL operations, from regularly programmed efforts to fight malnutrition in chronic regions to the extremely challenging operations in post-disaster environments (Holguín-Veras et al., 2012).

The common thread across all variants of HL is the desire to minimize the suffering brought about by the deprivation of critical supplies and services. This insight has been recognized by HL practitioners and researchers, who must consider alternative strategies for allocating scarce resources. In this context, relief groups strive to find the most effective way to help the population in need, while using their assets efficiently. In most cases, they make such important decisions on the basis of intuition and experience, without the assistance of analytical tools. As in other fields—such as health care policy and medical triage—these gut-wrenching decisions determine who gets help and who does not (Moskop and Iserson, 2007). For instance, the arrival of a new expensive lifesaving drug leads to difficult decisions about whether large amounts of money should be paid to save a few individuals, or whether the money is better used to improve the lives of many (New York Times, 2014). There are no easy answers to these questions. However, for the purposes of this research, it is

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http://dx.doi.org/10.1016/j.jom.2016.05.008
0272-6963/

important to separate ethical and philosophical debates about the allocation of resources from the practical imperatives, and the development of mathematical models primarily designed to assist decision-making. These models, as simplifications of reality, are not designed to weigh philosophical and ethical considerations (Le Menestrel and Van Wassenhove, 2004), which can only be done by the decision makers who must allocate scarce resources. Models can only provide guidance to the decision makers tasked with the many facets of response operations.

The chief role of HL mathematical modeling is to develop support tools to provide decision-makers with unbiased, reliable, and robust information to help them allocate scarce resources, often under difficult and time-critical conditions. In recent years there has been increasing interest in the development of such models. In creating any mathematical model it is crucial to ensure that the objective functions are appropriate. In terms of HL mathematical modeling, this necessitates proper consideration of human suffering and the impacts of delivery strategies. By any account, this is a very challenging proposition, with no universal consensus about the best ways to formulate the objective functions in HL models. The first worthy attempts to account for human suffering extended commercial logistic techniques to humanitarian cases. This has led to the use of penalties for late deliveries, the minimization of unmet demands, and the specification of equity constraints. Regrettably, the validity of such approaches has been called into question because they cannot correctly account for the complex non-linear effects associated with human suffering over time (Holguín-Veras et al., 2013).

Recognizing the limitations of these approaches, researchers have attempted to define and formulate novel objective functions for use in HL modeling. Gralla et al. (2014) used Conjoint Analysis of experts' preferences to define an objective function able to assess the trade-offs among the goals to be pursued when deciding on relief distribution strategies. Sheu (2014) assessed psychological impacts on beneficiaries, and proposed a disaster relief distribution model from the perspective of the survivors. Holguín-Veras et al. (2013) conducted a comprehensive analysis of the objective functions and proxy measures of human suffering reported in the literature. Because of its relevance to this paper, Holguín-Veras et al. (2013) is discussed in detail.

Holguín-Veras et al. (2013) analyzed the methodological alternatives, and concluded that welfare economics—the branch of economics that studies the economic impacts of the allocation of resources—provides the most appropriate framework to decide on the allocation of relief supplies. The use of welfare economics led Holguín-Veras et al. (2013) to suggest the use of minimization of social costs—the summation of the impacts of logistical decisions on all sectors of the society affected by the relief operation—as the objective function. Using social costs is important because the impacts on the beneficiaries cannot be assessed using private costs as the economic markets where supplies and services are normally traded are not likely to be functioning. Disasters could paralyze or destroy the local suppliers, the ability of sellers to bring goods to the market, or the ability of buyers to generate income to purchase goods or services. In such conditions, humanitarian aid becomes the only alternative. As a result, the impacts of the transactions involving relief supplies become externalities that must be captured in social costs (Varian, 1992; Holguín-Veras et al., 2013).

The implication is that proper HL modeling must ensure that the models account for the impacts of the delivery strategy on all involved. Three groups stand out among those impacted by a HL operation: the relief group itself; the individuals who receive aid at a given delivery-epoch; and the individuals who do not receive aid and must wait for future relief. In the social cost objective function defined in Holguín-Veras et al. (2013), the effects on these groups are measured in economic terms. The impacts on the relief group are the logistical costs associated with procuring, transporting, storing, and delivering the aid. The direct impact on the individuals who receive aid at a delivery-epoch is the reduction in their Deprivation Cost (DC)—the economic value of the deprivation of a good or service—brought about by the arrival of the supply or service. The computation of the impacts on beneficiaries necessitates translating the human suffering into a DC. It is also important to consider the impacts on the individuals who do not receive aid, because their DCs will increase as they wait for another delivery. These additional costs are the opportunity costs of the delivery strategy, which are important because in the days after a large disaster the supplies of critical items typically do not meet all demands. Thus, the number of individuals who do not receive relief aid typically outnumbers those who receive some. Sound HL decision-making boils down to judicious management of scarcity and human suffering. The use of welfare economics highlights the inadequacy of the proxy measures and approximate objective functions widely used in HL modeling (Holguín-Veras et al., 2013). At the same time, the use of social costs leads to models that, though computationally more complex, produce conceptually solid results. For instance, Pérez-Rodríguez and Holguín-Veras (2015) developed a social cost inventory-allocation model that produced compelling insight into the benefits of supply rationing. The mathematical models based on the alternative objective functions used in the literature are unable to reach such conclusions.

Although HL models based on social costs are a very promising approach, there are obstacles to their use. Foremost among them is the challenge of how to valuate, and incorporate into a social cost objective function, the human suffering produced by the deprivation of a critical supply or service. This is a complex undertaking that has to balance multiple considerations: accuracy and robustness of the valuations of deprivation, the level of difficulty associated with gathering the input data needed to estimate and use the resulting model, and mathematical tractability, among others. Methodological alternatives that perform the best in a single criterion are not necessarily the most appropriate for inclusion in a social cost model. In terms of assessment of the physiological impacts of deprivation, for instance, medical exams by well-trained physicians are the most precise mechanism to assess the health of individuals, in order to allocate resources to mitigate suffering. However, these assessments may not be practical in post-disaster environments where there are, lack of data about the impacted populations, and where rapid deployment of medical teams is difficult. Similarly, the most tractable metrics of human suffering, or the ones that use the least data, are not necessarily the most appropriate either because they may lead to formulations that cannot capture the complexities of the problem. The key is to identify a methodology that captures the essence of the phenomenon, and which requires data that could be readily obtained, and could lead to computable models. Adding to this already complex challenge, there are no publications that estimate anything that resembles DCFs.

The alternative considered in this paper uses Contingent Valuation techniques to collect stated preference data and econometrically estimate Deprivation Cost Functions (DCFs) that capture the DCs as a function of the Deprivation Time (DT). The proposed DCFs offer a good compromise solution. To start, they could be estimated using standard techniques of economic valuation and econometric modeling. Second, some of the inputs required to use these DCFs, e.g., number of individuals in the impacted areas, could be obtained from Geographic Information Systems (GIS), interviews with local responders, and the initial rapid-needs-assessments conducted by relief groups. Third, these DCFs can be readily incorporated into computable models, e.g., Pérez-Rodríguez and Holguín-Veras

(2015). In an environment where data and resources are scarce, techniques that provide order-of-magnitude estimates of social costs—based on relatively easy-to-get inputs—will be a welcome addition to the toolbox of disaster responders, particularly during the initial phases of the response.

The main goal of this research is to design and test a process—encompassing experimental design, data collection, and econometric modeling—to estimate DCFs for critical supplies and services. If successful, this research effort could have a transformative effect on HL modeling because it could open the door to the estimation of DCFs for other supplies and services. The availability of DCFs that provide a consistent and robust depiction of human suffering could obviate the need to use the kind of proxy metrics criticized by Holguín-Veras et al. (2013), and lead to more realistic mathematical models.

The paper contains six sections in addition to the introduction: Section 2 discusses relevant literature and provides background on DCFs; Section 3 discusses economic valuation techniques; Section 4 describes the experimental design and descriptive analyses of the data; Section 5 presents the modeling results; and Section 6 discusses their implications. The paper ends with conclusions in Section 7.

2. Relevant literature

This section provides an overview of the literature relevant to the estimation of the impacts of humanitarian efforts on beneficiaries, and provides background information about DC and DCFs.

2.1. Assessment of impacts on beneficiaries

There is a sizable and important literature that reports the research conducted on the health and nutrition impacts of humanitarian aid. A number of approaches have been developed to measure food deprivation and food insecurity, and to identify the most appropriate interventions. Gold et al. (2002) discusses the Health-Adjusted Life Years (HALYs) measures that are used to estimate the burden of disease, compare the relative impact of specific illnesses and conditions on communities, and conduct economic analyses. HALYs include two measures that could be used to prioritize the allocation of resources: Disability-Adjusted Life Years (DALYs) and Quality-Adjusted Life Years (QALYs). Gold et al. (2002) provide an overview of these measures, and discuss the key issues associated with their use in health-related decision making. QALYs, conceptually grounded in welfare economics, rely on the stated preferences of the impacted population to assess their valuations of health improvements. DALYs, in contrast, measure the gap between a population's health and an ideal health condition. In the opinion of Gold et al. (2002), major drawbacks of these measures are that they: fail to give priority to those who are worse off; discriminate against people with limited treatment potential; and fail to account for qualitative differences in outcomes (because of the way in which morbid and mortal outcomes are aggregated). Maxwell and Caldwell (2008) propose the Coping Strategies Index (CSI) as a tool for "rapid measurement of household food security and the impact of food aid programs in humanitarian emergencies." Rather than attempting to collect data on food consumption, the CSI focuses on the study of the behaviors that people adopt when they do not have access to enough food. The CSI can be determined by measuring the frequency in which coping strategies are implemented, as well as their level of severity. A downside is that it requires a significant effort during the initial setup. Analyzing the changes of the CSI over time can help determine the effectiveness of the aid efforts. As discussed in Yang et al. (2013), these measures are designed to evaluate long-term interventions leading to improved health and mortality rates. Another technique to assess the condition of children at risk of malnutrition during emergencies is the Mid-Upper Arm Circumference (MUAC) (World Health Organization (WHO), 1999; Brennan and Rimba, 2005).

Other approaches include food security assessment and its relation with market conditions. Young et al. (2001) describe the way some Non-Governmental-Organizations (NGOs) assess food security in slow onset emergencies. Their approach aims to support livelihoods by determining the need for interventions based on shifts in food entitlements, coping strategies, and nutritional status. Such assessment often means conducting in-depth interviews and analyses of the risk for the various population groups. Young et al. (2001) indicate that, in the early stages of an acute emergency, where people have obviously been cut off from their normal sources of food, measuring nutritional status is not a priority and is impractical. Darcy and Hofmann (2003) analyzed the link between needs assessment and decision-making in the humanitarian sector, and concluded that needs assessments play only a marginal role in the decision making of relief agencies and donors. As highlighted by Checchi et al. (2007), health interventions cannot be implemented without conducting detailed situation and needs assessments. In the absence of adequate information to support the decision-making process, "response analysis" has emerged to link ground information and response. Barrett et al. (2009) outline the rationale of this intermediate step between the needs assessment and the planning/implementation functions. Building on Barrett and Maxwell (2005), they introduce the Market Information and Food Insecurity Response Analysis (MIFIRA), as a tool to identify the conditions under which food aid is effective. As a "rule of thumb" they propose providing food aid in situations where there is a significant food availability deficit, and a market failure, which is the usual case in the aftermath of major disasters. Byrne and Albu (2009) and Brady (2012) analyze the benefits of the Emergency Market Mapping and Analysis Toolkit (EMMA), a tool designed to conduct market analysis in emergency situations. EMMA was designed to assess the functioning of the markets that people affected by emergencies depend on for income, food, and livelihoods. To complement the efforts resulting from response analysis, Ryckembusch et al. (2013) introduce an analytical tool for use before implementing initiatives targeting nutritional objectives, and to help identify the most cost-effective intervention.

The evidence clearly indicates that these approaches are effective in fostering health improvements in slow onset emergencies and chronic humanitarian crises. In most cases, they have been implemented during the recovery stage, when the conditions are stable, beneficiaries have been identified, and the fieldwork required could be conducted. New modeling approaches are needed. The approach developed in this paper could provide an important avenue for early decision making regarding how best to allocate scarce relief supplies.

2.2. Background on deprivation costs

The concept of deprivation cost (DC) was defined by Holguín-Veras et al. (2013) as: "… the economic value of the human suffering caused by a lack of access to a good or service. As such, the deprivation cost is likely to be a function of the deprivation time, and the socio-economic characteristics of the individual (e.g., age, gender, physical condition) …" Holguín-Veras et al. (2013) postulated that DCFs are "… expected to be: (1) monotonic, non-linear, and convex with respect to the deprivation time; and (2) associated with non-additive demands and, possibly, hysteretic effects that reflect residual damage to the beneficiaries …".

In general terms, DCFs could be denoted as $\gamma(\theta, \delta_{it}, Z)$, where θ is a parameter vector, δ_{it} is the DT of individual i at time t (the length of time the individual has been without access to a good or service), and Z is the vector of socio-economic characteristics of the individual (Holguín-Veras et al., 2013). The authors' conjecture is that the DCFs vary according to individual characteristics. For instance, the DCs of children and the elderly are likely to be different from those of healthy male adults. However, practical and philosophical considerations indicate that using a generic DCF that only depends on DT may be the best alternative. It is not likely that in the immediate aftermath of a large disaster relief groups will have accurate data about the socio-economic characteristics of the people in need. Thus, the consideration of socio-economic characteristics based on faulty data could lead to results that unfairly favor one group at the expense of others, which is questionable on ethical and moral grounds. Assuming that the individuals are observationally identical to outsiders is both practical and ethically sound (Holguín-Veras et al., 2013). As a result, the DCFs used in the paper reduce to a generic version $\gamma(\theta, \delta_{it})$ that only includes the deprivation time and the corresponding parameter.

The analyses of the impacts of deprivation led Holguín-Veras et al. (2013) to define two types of DCFs. In the hysteretic case, the deprivation creates permanent effects that do not disappear when the need is fulfilled; while in the non-hysteretic case, once the need is fulfilled there are no residual (permanent) effects on the individual. Given the state of knowledge on this subject, it is not possible to tackle the estimation of hysteretic DCFs, as the determination of residual effects can only be done with physiological studies, which are beyond the scope of this paper. This paper only considers the non-hysteretic case.

Conceptually, the DCFs for various critical supplies and services could be illustrated with the assistance of Fig. 1. The figure qualitatively illustrates three DCFs associated with supplies and services of differing levels of criticality. Case A exemplifies medical attention to injured individuals, where the lack of attention rapidly leads to death. Case B illustrates a critical supply like drinkable water, the deprivation of which, in a matter of days, could lead to a person's demise. Case C is an illustration of basic food supplies, the deprivation of which could cause death after longer periods of time. It is important to mention that these DCFs do not account for the interactions produced by deprivation of multiple supplies or services. For instance, an individual who is simultaneously deprived of both water and food is likely to experience DCs that are much higher than those produced by the deprivation of water or food alone.

The figure makes clear that the shapes of the DCFs are strongly influenced by what is defined in the paper as the Terminal Point (TP), the point at which death occurs. The need to cap the DCs at the point of death reflects the fact that the DC could only increase until it reaches the Value of Life (VOL). As shown, the TP is defined by the VOL, and the terminal DT. However, defining the values of these parameters is far from straightforward.

The selection of the VOL is one of the most controversial decisions in economics. There are multiple techniques to estimate VOL, including: the human capital approach that is based on lifetime earnings; CV methods that assess the WTP for reductions in the probability of death; actuarial methods that combine the human capital with demographic information to compute VOL; and techniques that use discrete choice models to compute VOLs as the trade-off between an extra unit of risk of death and an increase in wealth (Dore and Singh, 2013). The reliance of these techniques on individual data such as lifetime earnings, lead them to estimate VOLs that are different for each person. Philosophical and humanitarian principles suggest otherwise. The principle of impartiality, which requires that all individuals be treated in the same way implies that their needs be given equal weight by humanitarian groups. The latter implies that, by extension, the VOL must be the same for all individuals. Moreover, not ensuring that the DCF at the terminal DT is equal to a single value of VOL would lead to violations of humanitarian principles. For instance, data collected from different populations could lead, because of sampling errors, to different DCFs. This would lead relief groups to provide preferential treatment to some individuals at the expense of others. These considerations suggest that the best course of action is to assume that the VOL is the same for all individuals.

The terminal DT, the time at which the deprivation of supplies or services causes death, is equally difficult to estimate. Since different individuals have different capabilities to endure deprivation, terminal DTs could exhibit great variability. However, it is obvious that the terminal DT depends on how critical the supply or service is. While lack of medical attention could lead to a quick death, lack of food will cause death after weeks of deprivation. For the purposes of this paper, however, the terminal DT is assumed to be deterministic.

There are no easy or straightforward ways to estimate DCFs. One possibility is to conduct in-depth studies of the impacts of deprivation on the human body and mind. Regrettably, although there have been studies on the biology of deprivation, e.g., Keys (1950), assigning economic value to the various degrees of deprivation would require the calculation of costs associated with the restoration of an individual's health to the original state (if at all possible). Needless to say, this process would have to be conducted for a wide range of individuals and deprivation levels. Although technically possible, such an undertaking is outside the scope of this research. The literature on health economics is of no help in the estimation of DCFs.

These considerations led the authors to use economic valuation techniques to assess the economic value of the deprivation. These techniques, though approximate, are routinely used to assess the value of non-market goods (Bateman et al., 2002), which is appropriate as the beneficiaries' impacts are indeed externalities. Using economic valuation, however, could prompt concerns about the accuracy of the resulting DCFs because economic valuation is

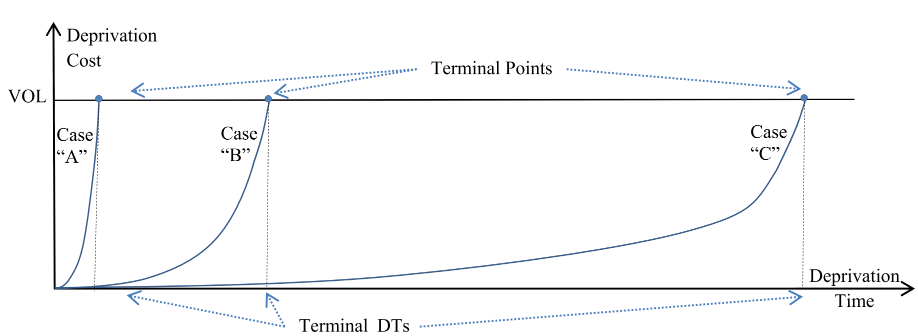


Fig. 1. Deprivation cost functions.

not an exact science, and frequently leads to diverging estimates. To keep things in perspective, one must remember that this paper is seeking to identify the most appropriate way to incorporate human suffering in the objective function of social cost models. The "most appropriate way" is not necessarily the "most accurate," as the latter may not be practical or feasible in post-disaster contexts. There are other reasons that support this position. The analytical evidence suggests that the social costs model would produce sound results, even if the DCFs are estimated with an error. Holguín-Veras et al. (2013) found that if the estimated DCF consistently overestimates the "true" but generally unknown DCF, the delivery patterns produced by the model are likely to be optimal or quasi-optimal, and undoubtedly better than solutions produced by the alternative methods. This result reduces the pressure to estimate "accurate" DCFs, making it worthwhile to estimate DCFs that are only approximate. Ultimately, the concerns about accuracy in the estimation of DCFs must be weighed against the benefits of using a more realistic objective function based on social costs. A brief review of economic valuation techniques is presented next.

3. Review of economic valuation techniques

This section provides a succinct overview of valuation techniques, the process of estimating the economic value of non-market goods and services (Bateman et al., 2002). Valuation techniques are essential for cost-benefit analyses to consider impacts that are not traded in normal markets. Central to valuation is the insight that the value of a good or service is an expression of consumer preferences and needs. Eliciting preferences could provide an indication of the value of a good or service in a given choice situation. Economic valuation uses the interrelated concepts of willingness-to-pay (WTP) and willingness-to-accept (WTA). WTP is the amount of money that a decision maker is willing to part with to procure a good or service, or to achieve a higher level of welfare; while WTA is the amount that a decision maker is willing to accept to give up using a good or service, or to put up with a decrease in welfare. In other words, WTP measures the economic value of an improvement with respect to the status quo (if change is preferred), while WTA assesses the value of a detrimental change (if status quo is preferred) (Bateman et al., 2002). The techniques that could be used for economic valuation (Button, 1994; Pearce and Howarth, 2000; Weisbrod et al., 2009), include:

- **Damage (restoration) costs.** These approaches quantify the value of the impacts as the cost required to repair the damage, and restore things to their original condition. A key limitation is that it is not always possible to restore an impacted system to its original condition, or to quantify the corresponding costs. Thus, this technique is limited to situations where it is possible to do so.
- **Control or prevention costs, averting behavior.** The basis for this technique is that market goods could be considered substitutes for other goods, implicitly assuming that it is possible to quantify the economic value of externalities in terms of the avoidance costs of implementing actions that prevent the damage produced, e.g., installing noise mitigation devices to eliminate airport-related night noise. The amount of resources spent to avoid damage thus estimates the intrinsic value of the external effect. However, this technique could lead to odd results because they could be influenced by the perception of risk, or other factors that determine WTP to prevent a negative outcome. For instance, since the air industry spends more money than the automobile industry to prevent fatalities, one could erroneously conclude that the same individual could have two different values of life depending on the transport used (Button, 1994).
- **Hedonic prices.** This technique studies existing markets where an externality influences price to estimate the value of externalities. For instance, comparing the prices of similar houses in different areas of a city could provide estimates of the impacts of airport noise on housing values. Although useful, these techniques can only be applied in cases where an externality produces a noticeable impact on price and appropriate comparable goods exist, to measure the economic impact of the externality. Moreover, the analyst does not have any control of the experimental factors, which limits the validity of the conclusions to the cases, and extent of impacts, observed in real life.
- **Stated preference (SP) techniques.** The approaches in this group—Contingent Valuation, Choice Scenarios, and Conjoint Analysis—try to assess the economic value of an externality by collecting preference data from decision makers. In Contingent Valuation (CV) scenarios, after defining a hypothetical market and a decision context, users are asked to state how much they would pay to improve a condition that affects them (WTP), or how much they would be willing to accept to allow a decrease in their welfare (WTA). In Choice Scenarios, users are presented with multiple alternatives that exhibit tradeoffs between costs and a negative externality. "Conjoint Analysis" refers to techniques that involve asking individuals to rank alternatives rather than to explicitly express a WTP or WTA. The inclusion of prices in the alternatives enables the conversion to monetary values (Pearce and Howarth, 2000). Frequently, econometric techniques are used to estimate the average value of the externality of interest.

In pondering advantages and disadvantages of valuation techniques, the authors concluded that SP techniques are the only feasible alternative. Quite simply, the other techniques rely on actual observations and data that either do not exist, or may not be practical to collect in this particular context. The selection of SP techniques leads to the question of which approach to use, and while there are numerous pros and cons to each, there is no clear best approach (Bateman et al., 2002). Conjoint Analysis was discarded because, given the lack of experience with its application to estimate DCFs, it may require a large number of pair-wise comparisons. Two worthy alternative methodologies remain: stated choice experiments combined with discrete choice modeling, and CV paired with least squares estimation. However, for modeling purposes, the econometric models that could be obtained from a CV exercise (e.g., polynomial and exponential functions that express WTP/WTA as a function of DT) are easier to incorporate in HL models than the results from choice modeling (a log sum of the exponential of the utilities). These considerations tilted the balance towards CV.

The selection of CV is not without concerns. Some believe that asking a person to guess how much he/she would be willing to pay for a good or service, in an environment of deprivation, is a cognitive challenge. In particular, researchers have noticed significant differences between the stated and revealed WTPs, a phenomenon that is referred to as "hypothetical bias" (Cummings et al., 1986). Hensher (2010) reviewed previous efforts to identify and correct for hypothetical bias, and noted that the inclusion of a well-scripted presentation that explains the objectives of the choice experiment (including cheap-talk scripts), could be effective. Bosworth and Taylor (2012) assessed the effectiveness of the cheap-talk script and found that it appears to reduce the problem, though the size and direction of the bias is sensitive to study design and context. This result is also supported by Fifer et al. (2014), who found that the mitigation techniques, including cheap-talk scripts, could ameliorate the problem. Loomis (2014) reviewed ex-ante and ex-post strategies to correct for hypothetical bias, and concluded that in the majority of studies (six out of eight) cheap-talk either eliminated or reduced hypothetical bias, overcorrected in one case, and had no effect on the other.

Using CV to estimate DCFs involves a unique challenge in that WTP depends on ability to pay. Although WTA does not have the exact same limitation, it is also susceptible to distortion by income, though more subtly. WTA is likely to be influenced by the differences in the marginal utility of income (a unit of monetary compensation is more valuable to a low-income individual than to a wealthy one). Thus, the WTA for a low-income person is likely to be lower than that for a wealthy individual. Moreover, asking a person to guess the compensation that they would need to receive to be willing to subject himself/herself to deprivation of critical supplies seems to be a more challenging cognitive exercise than asking the same person to estimate how much they would be willing to pay for that good or service. Further research is needed to assess the potential role of WTA techniques. Given that this is the first research to tackle the complex task of estimating the economic value of suffering created by the deprivation of a critical supply or service, the authors decided to use the simpler of the two techniques, WTP, in combination with a cheap-talk script and randomization of scenarios. This approach provides a good combination of practicality and conceptual correctness.

4. Experimental design and descriptive analysis

As illustrated earlier in the paper, DCFs are good-specific (or service-specific) and therefore a choice must be made for the focus of this paper and its analyses. The choice is not trivial; there are several hundred unique items that need to be transported to disaster sites, though a much smaller set represent the bulk of critical needs. For instance, Holguín-Veras and Jaller (2012) found that in the days after Katrina, twenty commodities accounted for approximately 30% of all requests for critical supplies. After considering several alternatives, the authors decided to focus on drinkable water, for a number of reasons. First, water is a critically important, life-sustaining item, as individuals suffer permanent damage and even die if they are deprived of water for a long period of time. Second, lack of water is typically a major issue in the initial days of a response. Ironically, once the response starts in earnest, so much water arrives in excess of needs that it seriously complicates the response (Holguín-Veras et al., 2014). Third, since all respondents are familiar with water consumption, they will be more likely to provide solid estimates of WTP. Fourth, because water is so critical to human life, the water DCF will provide an upper bound for other high-priority supplies. The estimation of DCFs for other supplies and services should be tackled in future research.

The data used in the paper were collected at seven towns in the Colombian Caribbean Region that are subject to periodic flooding and mudslides (see Fig. 2). Almost every year the area is officially declared in a state of disaster. The sample included individuals representing a wide range of socio-economic conditions. The breakdown of the sample by location was: Barranquilla (46.02%), Santa Lucia (15.92%), Campo de la Cruz (13.68%), Manatí (11.69%), Piñón (10.95%), Soledad (1.49%), and Chinu (0.25%). Among them, the most severely impacted (with more than 70% of its area affected) were Campo de la Cruz, Santa Lucia and Piñón. Chinu was only partially impacted (20% of its territory); Barranquilla and Soledad had not been impacted.

The sample was selected from two different groups: (1) individuals who had been directly impacted by a disaster; and, (2) individuals who had not been impacted. The former were selected from a database from the Oficina de Prevención y Atención de Desastres (Office of Prevention and Disaster Response), the disaster response agency in the country. The conjecture was that individuals who have been impacted by a disaster, or who have seen the impacts of disaster firsthand, would be able to provide better SP data than those who did not have such experience. All interviews took place face-to-face. A total of 402 complete responses were collected.

The survey gathered data about: (1) the characteristics of the individual and household (e.g., occupation, gender and age distribution, number of family members, income); (2) characteristics of the respondent's house (type of structure, roof, and floors); (3) perception of risk of being impacted by a disaster; and (4) WTP for water given a hypothetical scenario of DT, and the amount of money available to the individual in the immediate aftermath of the disaster (the Budget). Two experimental variables were considered: (a) Deprivation Time (DT), and (b) the amount of money available to the individual right after the disaster (Budget). The reason to include DT is rather obvious, as this is the key variable that determines the DCs. The inclusion of Budget as an experimental variable is much less clear, and deserves further discussion.

Using WTP carries the challenge of removing the distorting effect of the individual's ability to pay. To this effect, it is useful to think of WTP as the summation of two factors: the “actual” DC, and the “ability to pay”. An individual who experiences deprivation would be willing to pay for the item the actual cost of the suffering plus an extra cost that is determined by the individual's ability to pay. Under the assumption that all humans are equal, for individuals with the same physiology, the “actual DC” would be the same. However, the ability to pay is different because it depends on income, and attitude towards risk, among other factors. Wealthy individuals are able to pay more than low-income individuals. This does not mean that their DCs are higher; only their ability to pay. Not removing the effect of ability-to-pay would lead to an incorrect valuation of DCs and DCFs.

Treating Budget as an experimental variable helps separate ability-to-pay from the DCs in two different ways. First, it removes the role of income, because the scenario makes clear that the only money available to the respondent is the Budget specified in the scenario. Second, using Budget as an experimental variable enables the econometric model to capture its effects. This is possible because of the ability of least square models to separate the contributions of the different variables, as long as they are independent. Since an orthogonal design was used, the experimental variables are guaranteed to be independent. To disentangle the effects of ability to pay and DC, the combined use of experimental design and econometric modeling is key.

The selection of the range of the values of the experimental variables is also very important. In the case of Budget, the values ought to be significantly lower than the household income, but higher than the potential values of WTP. Selecting values in this range removes the effect of household income, without imposing a constraint on the reported values of WTP. The possible values of DT could theoretically range from zero (no deprivation) to the Terminal Point (TP) or the moment at which the individual dies. The terminal DT for water—assumed to be deterministically equal to 120 h—was selected on the basis of Packer (2002) and Piantadosi (2003). However, attempting to collect data for the entire range of DT may not be advisable, or practical.

Experience clearly shows that SP techniques can provide great insight into behavior, as long as the respondents understand, and are able/willing to put themselves in the decision scenario. The latter is more easily accomplished if the scenarios are designed as variations (a “pivot”) from a condition known to the respondent. In the context of this research, it makes sense to pivot from the condition that is best known to all respondents: normal

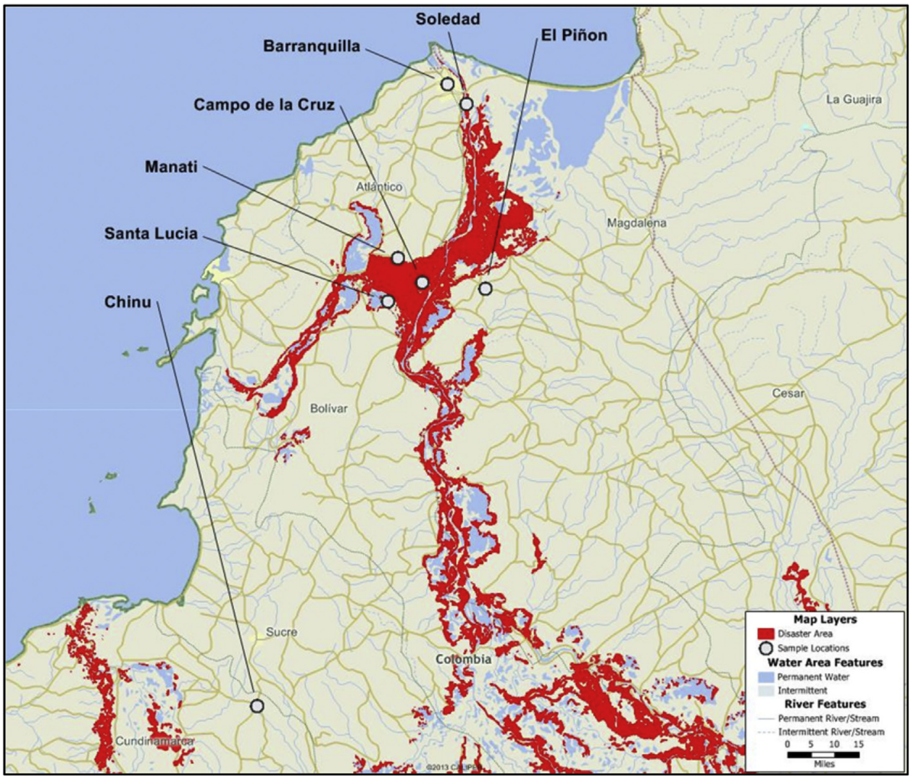


Fig. 2. Disaster area after 2010 Floods.

conditions without scarcity. However, doing so creates a challenge because the respondents' ability to provide solid estimates of WTP is not the same across the possible range of DTs. The shorter the DT, the better able the respondent is to provide good estimates of WTP. The longer the DT, the more difficult it becomes for the respondent to imagine the realities of the scenarios, and the less reliable their responses become. If they are not able to imagine the scenario, they cannot provide solid estimates of their WTP. This poses a dilemma.

Collecting data from the entire range of DTs could potentially improve the quality of the econometric models estimated, because the computation of the parameters can account for the data patterns across the entire range of values. The downside is that the quality of the data for the upper range of DTs is likely to be suspect. Restricting the data collection to the lower range of DT values—within the respondents' ability to imagine the scenarios—would collect better data, though for only a portion of the DTs of interest. There are other important considerations to ponder. The first has to do with the increasing risk of hysteretic effects. After the initial stages of water deprivation, a point will be reached at which permanent damage starts to accrue. Only highly specialized medical professionals may know what these effects would be and when they would occur. The second consideration, a relatively minor one, is that widening the range of DT values to be considered increases the number of interviews necessary to collect data with a sufficient level of detail. Yet, the additional expense in time, effort, and money would yield data of questionable quality. After pondering the alternatives, the authors decided that the most appropriate course of action would be to restrict the data collection to the range of DT values for which the data collected could be expected to be of reasonable quality. To a great extent, this decision was a judgment call. However, the decision benefitted from experience in the first round of data collection that indicated that respondents could provide responses for DTs up to 48 h.

The scenarios considered a large water bottle (900 ml), because that is the size typically consumed in Colombia. The respondent, typically one of the heads of the household, was presented with the following scenario:

> "Imagine that a disaster has occurred in the city where you live, and that you lost your possessions. No water or food is available, and the crisis is expected to continue for at least several days. A few hours have elapsed and you have some money in your pockets. We are going to show you nine scenarios where you have to decide how much you would pay for water. Assuming that the water is only for your own use, how much would you be willing to pay for one bottle of water (900ml) if you drank water for the last time ____ hours ago, and you have only ____ Colombian Pesos (COP) in your pockets?"

In addition, the respondents were read a statement stressing the importance of getting accurate data to enhance disaster preparation and response efforts. Such statements, referred to as "cheap-talk" (Cummings and Taylor, 1999) have been found to sharpen the focus of respondents, and to help them provide better estimates of what they would actually do if faced with a situation like the one in the scenario. The text included was:

> "The experience with other similar surveys indicates that people generally respond in one way but, in real life, may do something else. It is very common for a respondent to state their willingness-to-pay for water, but exhibit a different willingness-to-pay in real life. Please, when responding to the scenarios, try to guess what you would actually pay. Please help us develop better response procedures by closely paying attention to the scenarios presented before giving an answer."

The range of values considered was: Budget (B) from \$15.92

(COP 30,000) to $106.12 (COP 200,000), and DT from 2 to 48 h (the exchange rate used was $1 equal to COP 1,884.63). The treatment levels used were: (1) Budget (COP): 30,000, 50,000, 80,000, 120,000, 150,000, and 200,000; and (2) DT (hours): 2, 4, 8, 16, 24, and 48. The SP scenarios were structured around nine sets, using a fractional factorial design with four blocks. Trained staff conducted the interviews.

The survey was pilot tested and the team proceeded to collect the data. Unfortunately, econometric modeling of the data revealed that the experimental design failed to produce sound estimates of DCFs. During this initial effort, sensing that WTP is influenced by the respondent's expectation of a solution to the problem that produces the deprivation (Expectation), the authors decided to treat Expectation as an experimental variable. The hope was that treating Expectation as an experimental variable could facilitate its econometric removal from the DCFs. In reality, the inclusion of Expectation had a very different effect. The resulting data, though interesting, were not very useful for estimation of DCFs because the WTPs were dominated by the influence of Expectation. It seems that by mentioning Expectation, the survey inadvertently alerted the respondents of a key factor (the Expectation) that they ought to consider. Once that awareness was raised, it was difficult for respondents to focus on the DCs, and the role played by DTs (the key variable of interest). Upon realizing this, the authors discarded the data for use in estimation of DCFs, modified the experimental design and conducted a second round of SP experiments with a new set of respondents. The revised experimental design—which does not mention Expectation—worked much better, and produced the data used in the paper. This experience illustrates the complexity of the behavioral determinants that influence WTP, and the need to conduct further behavior research to design standard procedures that could be routinely used by practitioners to estimate DCFs.

The resulting data were post-processed, coded in an electronic data set, cleaned, and reviewed to ensure they represented the respondents' answers. The WTPs provided by the respondents, originally in Colombian Pesos (COP), were converted to US dollars ($) using an exchange rate of COP 1,884 per $1 (Banco Central de Colombia, 2014); the DTs were expressed in hours. The final step was to ensure that all observations had WTPs lower than the Budget. Using Budget as an experimental variable was intended to remove the income effect without constraining the ability of the respondents to indicate their actual WTPs. This design worked well, as most WTPs were well below the Budget. However, in three out of more than 400 responses, the respondents provided WTPs equal to the Budget. These observations were removed to eliminate the possibility of negatively affecting the results. A descriptive analysis was conducted to characterize the sample. See Table 1.

Table 1
Sample statistics.

Gender		**Income**		**Age**	
Male	44.28%	< $ 265	46.77%	≤25	25.87%
Female	55.72%	$265–$371	18.66%	26–30	18.16%
Household size		$371–$531	15.17%	31–36	16.17%
1–2	10.95%	$531–$796	3.73%	37–45	19.40%
3–4	41.29%	$796–$1,061	2.74%	46–55	12.19%
5–6	34.58%	$1,061–$1,327	2.49%	>55	8.21%
7–9	10.95%	$1,327–$1,592	1.24%		
≥10	2.24%	>$1,592	9.20%		
Number of children		**Occupation**		**Previously impacted**	
0	43.03%	Student	19.90%	Yes	59.45%
1	22.89%	Employee	19.15%	No	40.55%
2	22.64%	Independent	24.88%	**Probability being impacted**	
3	9.45%	Housewife	31.09%	High	36.82%
4	1.24%	Unemployed	4.73%	Medium	37.06%
>5	0.50%	Other	0.25%	Low	26.12%

The data show that the majority of participants were housewives between the ages of 18 and 25, with no children (43%), living in households of four people. The median household monthly income was between $265 and $371 (COP 500,000 to 700,000). About 59% of respondents had been impacted by disasters. About 63% of the respondents consider that they either have low or medium probability to be impacted by a disaster, while 37% believe that they have a high probability of being impacted. The sample is consistent with the population of the country. Household size is also similar to the general population (3.9 individuals per household). However, 5% of the sample are unemployed, whereas this rate was 9.4% in the general population in 2013 (DANE, 2014).

As discussed earlier, a consequence of the decision to limit the data collection to the first 48 h is that there are no data between 48 and 120 h. This is potentially problematic, as this is the range within which the DCs are expected to be highest. Estimating DCFs with only the data for less than 48 h will lead to DCFs that underestimate the DCs for the rest of the DTs, because of the non-linear nature of suffering. To ensure consistency with the estimate of Value of Life (VOL), and mitigate for the lack of data in the upper range of DTs, the authors added a "Terminal Point" (TP) to the data. The decision to add the TP leads to the question of what VOL to use, as the authors could not find estimates of VOL for Colombia. To account for the uncertainty in the estimate of VOL, the authors assumed three different VOL (i.e., $200,000, $1,000,000, and $5,000,000) and conducted sensitivity analyses. These values are in-line with the estimates of Rizzi and Ortuzar (2003), that places the VOL in Chile between $650,000 and $1.3 million dollars; and those of Larsen (2004), who, based on a meta-analysis conducted by Mrozek and Taylor (2002), concluded that the VOL in Colombia is between $1.5 and $2.5 million dollars (in 2001 dollars). The next section discusses the results.

5. Modeling results

The models were estimated using Ordinary Least Squares (OLS) (Gujarati, 2003). To account for the correlation introduced by using multiple observations from the same individual, models with fixed factors were used. Multiple functional forms were tried, including: linear, power, logarithmic, and 2nd order Taylor series. Statistical significance was assessed using t-tests, while conceptual validity was evaluated on the basis of the authors' expectations of the sign and magnitude of the parameters. Tests were performed to ensure that the data and model results conformed to the assumptions embedded in OLS; in all cases the assumptions held. The models were screened out to ensure that their estimates are strictly positive, which led to the rejection of the Taylor series models because they produced negative values of DCs for the low range of DTs. The models presented in the paper are conceptually valid, statistically significant, and strictly positive.

Two different groups of models were estimated: WTP models and DCFs. The WTP models, as the name implies, estimate how much an individual would be willing to pay for water for a given DT. WTP is determined by two factors: the DC experienced by the individual, and the individual's ability to pay. The latter is defined as the inclination of an individual to pay, in excess of the DC, for a good or service. This implies that the WTP models must consider the role of socio-economic characteristics of the individual, such as household income, that influence WTP, as well as those variables that determine DCs. The DCFs, in contrast, must remove the distorting effect of the ability-to-pay so that only the DC is reflected in the model. As an intrinsic characteristic of the individual, the DC is only a function of the physiological traits of the person. These

Table 2
Econometric results without the terminal point.

WTP Model

$$WTP = 0.3445B^{0.2722}e^{0.0189DT}$$
$$(-18.05) \quad (19.58) \quad (27.73)$$
$$F = 488.21 \quad R^2 = 0.7406 \quad \text{Adjusted } R^2 = 0.7081$$

Deprivation Cost Function (DCF)

$$\gamma'(\hat{\delta}) = 0.9814e^{0.0188DT}$$
$$(-11.14) \quad (26.06)$$
$$F = 679.33 \quad R^2 = 0.7029 \quad \text{Adjusted } R^2 = 0.6658$$

Note: t-values are in parenthesis. Sample size: 402.

considerations lead to the classification of the independent variables into two groups: determinants of *ability to pay*; and determinants of *deprivation costs*. While the WTP models consider all variables, the DCFs only consider the second group. These classifications are not always clear-cut, because there are variables such as gender and age that could influence both ability-to-pay and the DC. Variables like Income and Budget clearly impact the ability-to-pay and not the DCs; while variables such as DT influence the DCs, but have no impact on ability to pay. The variables included in each group are: (1) **Determinants of ability to pay**: Household Income, Budget, Occupation, Gender, Age, Characteristics of the House, Experience with previous disasters, Perception of Risk of being impacted by a disaster, and Level of Preparedness (of the individual and the corresponding city government); and (2) **Determinants of deprivation cost**: Deprivation Time, Age, and Gender.

These variables were used to estimate the WTP models and DCFs. After a comprehensive estimation process, the authors obtained the final WTP models and DCFs. As a reference, the WTP models and DCFs without the TPs are shown in Table 2. Although these models should not be used for HL modeling, because they are not consistent with the VOL, they illustrate that DCs are non-linear even without the addition of the TP. The models selected are those that provide the best combination of statistical significance and conceptual validity.

The results are interesting in numerous respects. To start, the models have a fairly strong explanatory power, explaining 67%–71% of the total variance. This, in itself, is remarkable given the complexity of the subject matter. The independent variables are very significant, with t-values that exceed the minimum threshold (the constant in the DCF model must be retained, in spite of the low t-value, because it is needed to account for the fixed factors). The models confirm the non-linear nature of DCs. Taken together, these results are conceptually valid and statistically significant. The model estimates considering the TP are discussed next.

5.1. Willingness-to-pay (WTP) models with a terminal point (TP)

Table 3 shows the best WTP models for the three different VOLs considered. As shown, the models explain between 85.4% and 85.9% of the variance. In all cases, both DT and Budget are statistically significant and conceptually valid. The longer the DT, the higher the individual's WTP for water. Reflecting the role of ability to pay, the WTP increases with Budget. It should be highlighted that none of the variables that represent the socio-economic characteristics of the respondents, such as Income and Gender, were found to be statistically significant. The fact that Income was not statistically significant is very important because it suggests that the experimental design succeeded in removing the effects of Income. The responses provided by individuals who had been impacted by a disaster were statistically similar to those of the individuals who had not been impacted.

The point elasticities of WTP with respect to the variable show that the contributions of DT and Budget are different. The results, shown in Table 4, indicate that the elasticity of DC with respect to DT is linear with DT; while the one for Budget is constant. This implies that for DT values of less than 3.2 h (0.4104/0.1252), the Budget has a larger impact on WTP than the DT. After that time, DT becomes dominant. Conceptually speaking, this result makes sense, as it reflects the growing importance of the DT.

5.2. Deprivation cost functions (DCFs) with a terminal point (TP)

The DCFs estimated are shown in Table 5 and Fig. 3. The figure shows the DCF without the TP, labeled “DC,” and the three DCFs with a TP corresponding to the various VOLs. As expected, the net effect of adding the TP is an increase in the slope of the DCFs. The models have a number of interesting features, consistent with those already discussed in relation to the WTP models. The DCFs are non-linear, as hypothesized in Holguín-Veras et al. (2013). Also, the models' explanatory power is about the same as the WTP models, as the removal of the ability-to-pay variables did not have an appreciable impact on statistical quality. As in the WTP models, the different assumptions of VOL lead to different DCFs.

As expected, the coefficients of DT are the same as in the WTP models. Not surprisingly, the constants of the DCF models are different from those in the WTP models. These results indicate that the experimental design succeeded in isolating the effect of DT on DCFs. It is worth noting that the parameters of the DT are similar to those estimated with a small sample collected with a parameter value of 0.1172 (Holguín-Veras et al., 2013).

It is important to check if the estimated DCFs provide estimates that are consistent with (normal) market conditions. Ensuring that the DCFs reproduce both the price of water in normal conditions without deprivation and the VOL is reached at the terminal DT helps ensure that they produce sound results. If the models were perfect, their estimates of DC for the time at which a healthy individual would buy water to satisfy thirst would be just below the

Table 3
willingness-to-pay models.

Value of Life	WTP Model
\$200,000	$WTP1 = 0.0682B^{0.3774}e^{0.0991DT}$ $(-18.86) \quad (10.39) \quad (126.6)$ $F = 8265.92 \quad R^2 = 0.873 \quad \text{Adjusted } R^2 = 0.859$
\$1,000,000	$WTP2 = 0.0525B^{0.3939}e^{0.1121DT}$ $(-18.22) \quad (9.53) \quad (125.81)$ $F = 8164.83 \quad R^2 = 0.871 \quad \text{Adjusted } R^2 = 0.856$
\$5,000,000	$WTP3 = 0.0405B^{0.4104}e^{0.1252DT}$ $(-17.68) \quad (8.84) \quad (124.97)$ $F = 8054.27 \quad R^2 = 0.868 \quad \text{Adjusted } R^2 = 0.854$

Note: t-values are in parenthesis. Sample size: 402.

Table 4
Elasticities of WTP with respect to key variables.

Value of Life	Deprivation Time	Budget
$200,000	0.0991 *DT*	0.3774
$1,000,000	0.1121 *DT*	0.3939
$5,000,000	0.1252 *DT*	0.4104

market price of the water, Pw, (to account for the effect of WTP, which increases the price above and beyond the actual cost). In cases where there is a significant difference between Pw and the DCF estimate, using a correction procedure may be warranted. Fig. 4 shows the DCFs estimated.

The procedure suggested by the authors compares the estimate of the DCF and the market value of a small bottle of water at the time individuals should drink 200 ml of water. The assumption is that, in normal conditions, at that time most individuals would pay the market price to purchase the 200 ml of water. Using the 900 ml bottle of water in the comparison would introduce distortions in the analysis because other elements— not accounted for during the estimation of the DCF such as the possibility of saving money—would be introduced. According to the Institute of Medicine, the adequate daily intake of liquids is about 3 L for men and 2.2 L for women (Mayo Clinic, 2014). Using an average of 2.6 L, and assuming that the water is consumed in 16 h, a person would need to consume 200 ml in about 1.25 h.

The suggested procedure modifies the DCFs as outlined below:

$$\gamma(\delta) = \gamma\prime(\delta) + [P_w - \gamma\prime(1.25)] \quad (1)$$

Where:

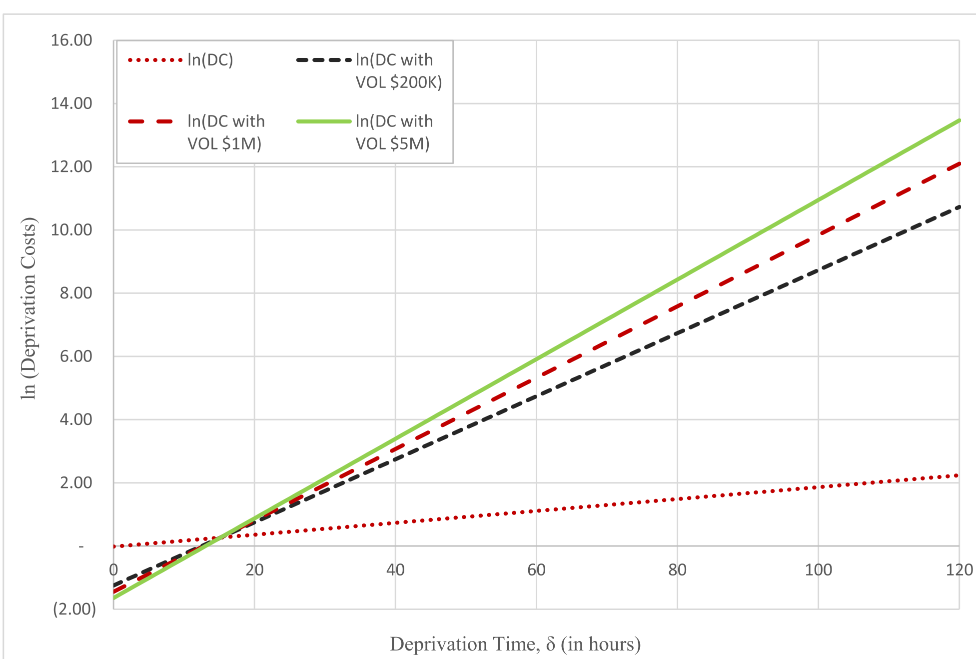
$\gamma(\delta)$ = Corrected DCF
$\gamma\prime(\delta)$ = Uncorrected DCF
P_w = Market price of a 200 ml bottle of water
$\gamma\prime(1.25) = \gamma\prime(\delta)$ evaluated at 1.25 h

The second term of equation (1) ensures that the DCF matches P_w at a DT of 1.25 h. After this time, the DC will increase above and beyond the market price in normal conditions. As shown in the figure, there is a small mismatch between the values estimated by the models, and the value of water in normal conditions. The DCFs of Table 4 estimate that the DC at 1.25 h is between $0.23 and $0.33. The market value of 200 ml bottle of water is $0.41, which indicates

Table 5
Deprivation Costs Functions.

Value of Life	Deprivation Cost Function (DCF)
$200,000	$\gamma_1'(\delta) = 0.2869e^{0.0998DT}$ (−52.18) (127.16) F = 16168.55 $R^2 = 0.869$ Adjusted $R^2 = 0.855$
$1,000,000	$\gamma_2'(\delta) = 0.2354e^{0.1129DT}$ (−53.76) (126.46) F = 15992.53 $R^2 = 0.867$ Adjusted $R^2 = 0.853$
$5,000,000	$\gamma_3'(\delta) = 0.1932e^{0.1259DT}$ (−54.85) (125.68) F = 15794.89 $R^2 = 0.865$ Adjusted $R^2 = 0.850$

Note: t-values are in parenthesis. Sample size: 402.



Note: VOL refers to value-of-life

Fig. 3. Estimated Deprivation Cost Functions. Note: VOL refers to value-of-life.

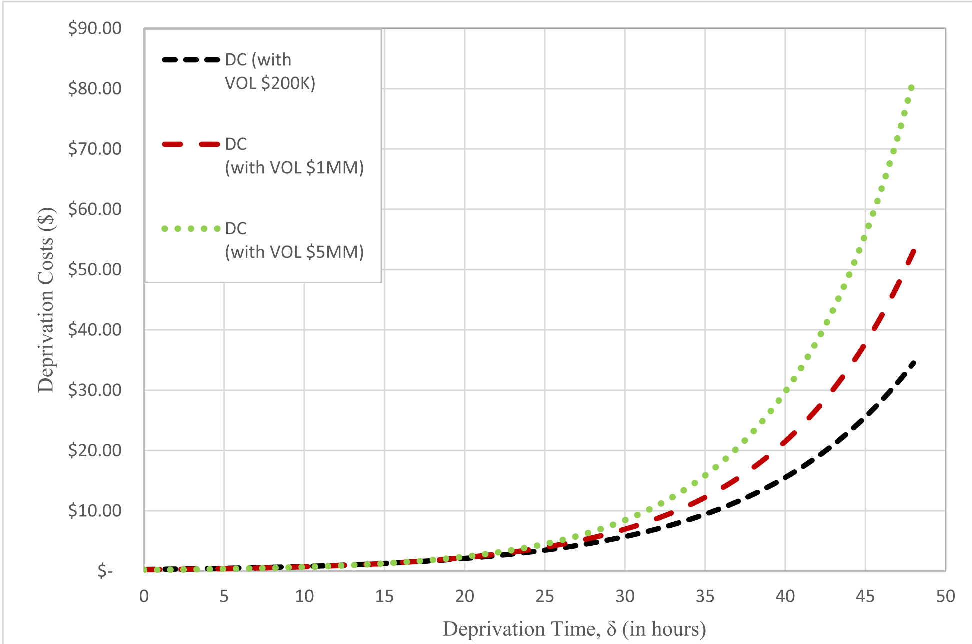


Fig. 4. Estimated deprivation cost functions for water.

that the DCFs only slightly underestimate the market price. Since the difference is small, and the role of ability to pay has not been accounted for, no correction was undertaken. The results presented in this section confirmed that the CV approach succeeded in estimating conceptually valid WTP models and DCFs. The implications of this finding are discussed next.

6. Implications and lessons

The econometric estimation of DCFs has important implications for HL modeling. The results clearly show that it is possible to estimate DCFs of a critical supply that are "consistent" with real life. Here, the emphasis is on "consistency," because the valuation of something as complex as human suffering cannot be expected to be done with "accuracy". The DCFs are also unbiased, as they only consider the variables that, as a matter of physiology, influence DCs. The combination of consistency and unbiasedness exhibited by the models suggest that it is practically possible to estimate DCFs for at least some of the critical supplies and services needed after disasters and emergencies. These DCFs provide a conceptually solid way to assess the complex tradeoffs that are routinely and frequently made in the conditions of scarcity that prevail in the aftermath of large disasters. Among other potential uses, the availability of suitable DCFs for the key relief supplies would allow relief organizations to determine the optimal way to allocate these scarce supplies, to minimize the total social costs. The chief implication is that there is no need to use proxy measures, such as the ones criticized in Holguín-Veras et al. (2013), that cannot account for the effects of deprivation. Granted, the mathematical models based on social costs may be more complex than those that use simpler objective functions. However, complexity is a small price to pay for more realistic models that lead to better allocation of scarce resources.

There are other aspects that deserve discussion. First on the list is the transferability of the DCFs to conditions other than those captured in the calibration data. Obviously, without large comparative studies that collect similar data in different socio-economic environments and countries, it is not possible to reach definite conclusions about transferability. The heart of the issue is that, though the human suffering produced by deprivation could be expected to be the same for all individuals with similar physiological conditions, its economic valuation (the DC) may be influenced by culture and level of socio-economic development. In environments where living conditions are harsh and suffering pervasive, one may expect a lower valuation of deprivation than that which may be encountered in wealthier areas where suffering is less frequent.

However, a counterargument could be made. The assumption that all individuals are equal, or observationally identical to the relief groups, leads to the conclusion that the valuation of deprivation and the VOL must be the same for all people. Obviously, the data collected as part of this research is far from being representative of the entire human race. Collecting a large dataset, from multiple countries, combined with the adoption of an internationally accepted VOL could lead to DCFs that represent the world population. Comparative studies are needed to address the challenge of producing widely accepted DCFs. In addition to helping improve decision support systems, DCFs may provide relief groups with potent tools to convince donors to invest in disaster preparation and response procedures. Estimates of the economic value of efforts to reduce human suffering could prove influential in increasing funding for relief efforts.

The research conducted has provided numerous lessons that offer guidance to future efforts of estimation of DCFs using CV approaches. The experience gained in this research was used to produce an outline for the application of CV to the estimation of DCFs. It is important to stress that the outline presented below is only a general description of the process, and not a substitute for the vast literature in the subject:

1. Decide on whether to use WTP or WTA as the metric. Although the paper used WTP, WTA is a valid metric though it may be impacted by differences in marginal utility of income across incomes.
2. Design an experimental setup that allows the removal of ability to pay. Including the experimental variable "Budget" worked

well with WTP, and is likely to work well with WTA. Obviously, the DT must be one of the experimental variables.

3. Decide on the range of values the experimental variables would take in the experiments. One of the key lessons of this research is that it is important to collect data for scenarios within the cognitive grasp of responders. Collecting data beyond this point is counterproductive and expensive. Obviously, the range of values of interest depend on the type of supply or service being studied.
4. Decide on the values of the experimental variables (treatment levels) and the specific combinations to be used in the scenarios. The number of treatment levels determine the number of combinations, while the way in which they are combined determines the type of models that could be estimated. For technical publications see (Louviere, 1988; Louviere and Lancsar, 2009).
5. Pilot test the survey. Pilot testing a survey in a realistic setting could help improve the framing and language in the questions, though it would not necessarily identify issues in the experimental design that are only revealed when the entire data have been collected, as demonstrated by the failure of the first round of data collection in this paper.
6. Collect data and econometrically estimate the DCFs. This stage of the process is when the inadequacies in the experimental design are revealed. For this reason, it is extremely important to take all necessary steps to carefully design the experimental effort. It is also important to estimate DCFs without the TP (to get a sense of the data quality), and with the TP (to produce DCFs that are consistent with the VOL).

The authors' hope is that this outline will help researchers tackle the estimation of DCFs using CV techniques. Obviously, the outline is no replacement for the huge technical literature in CV, stated preference methods, experimental design, and the like.

7. Conclusions

The paper designed a process, comprised of experimental design and econometric modeling, to produce econometric estimates of deprivation cost functions (DCFs) for use in social cost models. The process was applied to obtain DCFs for drinkable water. To this effect, the authors designed and conducted a Contingent Valuation experiment, where a sample of respondents provided data about their willingness-to-pay (WTP) for water under various scenarios of deprivation. To ensure consistency between the DCFs and the value-of-life, and to account for the role of the high range of values of deprivation costs (DCs)—which take place at the upper range of Deprivation Times (DTs)—the authors added a Terminal-Point (TP) to the data. The TP represents the point of death of an individual due to deprivation, which for water was assumed to take place at 120 h, at a DC equal to the value-of-life. Three different value-of-life estimates were used to assess the sensitivity of the results with respect to changes in value-of-life. The resulting stated preference data were used to econometrically estimate WTP and DCF models. The first group of models expressed WTP as a function of the socioeconomic variables that influence both ability to pay and DCs. The second group of models, DCFs, only considered the variables that influence DCs, providing insight into the time-dependent nature of human suffering.

The results indicate that both DCFs and WTP models are non-linear functions of DT. In most cases, exponential functions provided the best agreement with the data. The resulting models also indicate that the assumption of value-of-life, though having an impact on the DCFs, leads to parameter values in the same order of magnitude. In general terms, the DCFs provide conceptually valid estimates that are in line with expectations. For the low range of DTs, the models estimate values similar to the market price of water. However, after 10 h the deprivation costs rapidly increase, reflecting the increased level of suffering produced by water deprivation, until they reach the value-of-life at the point of death.

The successful estimation of DCFs has important implications for mathematical modeling of humanitarian logistics, as it clearly shows that it is indeed possible to obtain reasonable estimates of the economic value of deprivation. The availability of DCFs reduces the need to use proxy metrics and approximate objective functions that, by their mathematical construction, cannot account for the non-linear nature of deprivation.

There are limitations that should be acknowledged. As extensively discussed in Holguín-Veras et al. (2013), there are serious philosophical objections to the valuation of human suffering and life, and particularly, to the aggregation of utilities. There are also questions about the ability of respondents to provide solid estimates of WTP for conditions they have not previously experienced. The authors recognize these concerns, and have taken all steps possible to mitigate them. However, in subjects like this one—at the intersection of economic, philosophical, ethical, and humanitarian considerations—it is not always possible to satisfactorily address the multitude of conflicting views that arise from these disciplines. It is important to mention that the use of DCFs should not prevent the use of more precise techniques to assess the condition of the impacted population. After all, social cost models are intended to support rapid decision-making in the early stages of the response.

In spite of these concerns, for a decision support system to fulfill its mission, it has to provide a meaningful representation of reality. The authors' conclusion is that achieving this important objective is best done with DCFs. As argued, the estimation of DCFs and its incorporation in mathematical models does not address or bypass the need to consider the complex philosophical and ethical issues related to the allocation of resources in conditions of scarcity. More than ever, it is important for decision makers to consider the philosophical and ethical implications of these decisions. No one should expect that simplified mathematical models of the kind used in HL could be made to ponder the fine points of distributive justice. At most, these models provide the basic information that decision makers need to make sound decisions in extremely critical decision making environments. After all, it is up to qualified decision makers to select the most appropriate course of action. The authors hope that this paper is a step towards realistic HL mathematical models that support relief efforts consistent with humanitarian principles.

Acknowledgements

This research has been funded by the National Science Foundation's project “Cyber Enabled Discovery System for Advanced Multidisciplinary Study of Humanitarian Logistics for Disaster Response” (NSF-IIS 1124827) and by the Partnerships for Enhanced Engagement in Research (PEER) Science's project “Integrated Humanitarian Logistics System for Developing Countries” (PGA-2000003441).

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