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Discrete choice approach for assessing deprivation cost in humanitarian relief operations

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ABSTRACT

One of the key objectives of humanitarian logistics is to guarantee the timely delivery of supplies to people affected by disasters during the response phase. In this regard, it is fundamental to design appropriate models to minimize the social costs of response operations to distribute essential supplies to populations in need. In addition to merely cover logistics cost, social costs include deprivations costs, which are an increasing function of deprivation time, derived from the human suffering caused by the lack of access to a good or a service. This research uses the theory of discrete choices to assess deprivation costs due to the time spent waiting for the delivery of a basket of basic supplies, defined as the changes in the welfare of people affected by disasters. To this end, we designed a stated choice survey, applied to people living in areas affected by floods and earthquakes in Colombia. The estimated models consider the influence of individual's socioeconomic characteristics and random effects on the deprivation cost functions. The functions have a nonlinear structure, strictly increasing, and convex on the deprivation time. The results are useful for estimating the social costs of humanitarian relief operations.

1. Introduction

Natural disasters affect thousands of people each year in many countries around the world. Most of them have the potential to cause catastrophic loss of life and physical destruction. They affect people differently and at a variety of scales, impacting the most vulnerable groups (i.e. the poor, infants, women and the elderly) the most. Disasters such as the South-East Asia earthquake and tsunami that occurred in 2004 and the 2010 earthquake in Haiti give a dimension of the effect on these different segments of the population. In the first disaster, more than 220.000 people lost their lives [40], being most of them women. In countries such as Sri Lanka and Indonesia, one-third of the casualties were children, and thousands of others were registered as orphans [43]. The second disaster killed over 220.000 Haitians and caused the displacement of 2.3 million people [42]. It is estimated that 1.5 million children were affected while another 38.000 died. There were 103.000 registered cases of infants unprotected by relatives or family [44]. According to Unicef [44] moments after the earthquake, just 5% of the poorest women in the country had access to medical supplies.

These statistics illustrate the vulnerability of modern societies and the challenges faced by first responders. Moreover, they reflect how impact varies according to socio-economic characteristics. It implies that each group experiment diverse needs and assistance. In this sense, a proper and efficient humanitarian assistance process should respond in a differentiated way considering the specific requirements of each group, especially the most vulnerable, as social inequities exacerbate suffering. Nevertheless, there are common repercussions in all of the affected that must be considered, as the absence of critical supplies (e.g. food, water, shelter, medicine). This kind of suffering induces anxiety and depression as well as psychosocial problems. In all cases, affected people depend on a proper and efficient humanitarian assistance process [33].

Operations management research has created logistical humanitarian models to decide how to allocate scarce resources best. However, current methodologies typically use approaches based on commercial logistics, which are inappropriate for humanitarian logistics purposes. According to Holguín-Veras et al. [17] the main goal of humanitarian logistics is the timely assistance of affected people in a disaster situation, beyond the private costs that this

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could represent. In consequence, appropriated models must be based on social costs minimization, thus allowing a socially optimal level of distribution of scarce available resources.

Social costs are the summation of the impacts of each logistical decision over all sectors of society affected by the relief operation [45]. They include the logistics costs carried out by the relief groups (e.g., inventory, transportation, delivering and distribution), but also the direct impact on the population affected, which is the economic value of the deprivation of essential goods and/or services. This measure of suffering is known as “deprivation costs,” which are externalities associated with the aid distribution after disasters [18]. In most post-disaster environments, the relief supplies available are frequently not sufficient to meet the needs of all those affected. Then, aid agencies must decide on how best to allocate the scarce resources available while, at the same time, account for their logistic costs. Thus, the trade-offs between impacts on beneficiaries and logistic costs ought to be considered.

In response to this necessity, new approaches have proposed humanitarian logistics models based on social costs. Such is the case of Gutjahr and Nolz [13], who present the term “distress” as “psychological or social costs.” On the other hand, Hu and Sheu [20], and Sheu [36] include feelings like stress, anxiety, grief and depression as social costs. Meanwhile, Holguín-Veras et al. [17,18], Khayal et al. [23], Rivera-Royero et al. [35], and Balza-Franco et al. [2] emphasize that humanitarian logistics models must be based on approaches that incorporate the cost associated with human suffering in the delivery process of humanitarian aid. If the humanitarian logistics models do not include such externalities in the decision-making process of aid distribution, social optimum will not be reached. However, including such cost in humanitarian logistics models requires estimating proper Deprivation Cost Functions (DCFs) for critical supplies and services. These DCFs represent the economic value of human suffering derived from the lack of a critical supply, such as water, food, and medicine, among others.

Despite the difficulties in estimating appropriate DCFs, some efforts have been developed. Holguín-Veras et al. [16] estimated DCFs using the Contingent Valuation (CV) method. In the same sense [7], proposed a microeconomic approach based on the classical consumer theory to estimate DCFs. In both research papers, the results evinced the high magnitude of the social costs and the importance of their estimation in order to obtain logistic models sensitive to human suffering. Nevertheless, the econometric approaches presented above did not include socioeconomic variables on individuals. This entails considering affected people as a homogeneous population. Consequently, the deprivation costs are expressed only in terms of deprivation time without any consideration of the socioeconomic or demographic aspects of the affected people, which limits their use. It evokes the debate about equity measurement in humanitarian logistics involving social costs.

For Gutjahr and Nolz [13] equity is referred as providing fair treatment to all social groups. In emergency contexts, this means an equitable process of humanitarian aid distribution which should not affect or bring prerogatives to some social groups over others. In this sense, an interesting academic discussion about components of efficiency, effectiveness, and equity arises in the humanitarian aid distribution process [21]. Nevertheless, it is worth mentioning that this kind of events have different consequences on social groups, according to their socioeconomic characteristics. Factors such as age, gender or previous experience in emergency situations determine vulnerabilities during the occurrence of a natural disaster. PAHO [33] states that children, adults and the elderly experiment dissimilar repercussions. Children are more exposed to risks due to their limited possibilities of surviving by themselves. They are more susceptible to developing conditions such as anxiety, loss or increase of appetite and fears about environmental conditions. The NSWIP [30] has concluded that the elderly face reduced mobility, and limited abilities to see and hear. These conditions directly affect their capacity to evacuate, to follow emergency protocols or to look for help in a disaster context.

In the case of women, they are more vulnerable in countries where gender discrimination is practiced. In addition to some physical limitations -in comparison to males-, in discriminatory societies, women count with fewer tools and mechanisms to survive in disaster contexts. For instance, females have reduced access to information, which increases their vulnerability. After analyzing information from 141 countries affected by natural catastrophic events during the period 1981–2002, the UNDP [42] concluded that disaster situations diminish women's life expectancy more than men's and that females and children are 14 times more susceptible to perish than men during the occurrence of a natural disaster. Besides, pregnancy and fertility are biological aspects that increase their vulnerability [33]. This is due to their higher nutritional needs and limited mobility during the gestation period.

Given these remarkable dissimilarities between social groups and their suffering, it is mandatory for humanitarian logistic models to respond to the different needs of each socio-economic group. In this way, the humanitarian delivery process will bring proper assistance to the affected population in a more equitable manner.

To this effect, this paper uses discrete choice models, based on the random utility theory, to estimate DCFs that consider systematic and random heterogeneity over individual preferences and responses. To accomplish this objective, a stated choice survey was designed and applied to people living in areas affected by floods and earthquakes in Colombia. As a result, two different kinds of family models were specified with socio-economic variables and random variations in order to include specific measures equity over the population. The resulting DCFs can be used to evaluate the monetary value of deprivation due to lack of access to essential supplies in the immediacy of a disaster. Such DCFs can also be incorporated into comprehensive humanitarian logistics models to perform risk analysis as well as to conduct an economic evaluation of humanitarian aid operations.

2. Econometric approach and theoretical background

The environmental and socioeconomic impacts of natural disasters and their increasingly frequent occurrence have led governments and relief organizations to spend significant resources in prevention, planning, attention, and mitigation. A key aspect is identifying and assessing the economic value of real losses associated with disasters.

Affected populations experience deprivation and suffering due to lack of essential goods and services. Markets, where people can buy, sell or trade goods and services, disappear [18]. As a result, the demand for critical supplies rises as well as the population's suffering, forcing to an almost immediate action from relief agencies in a race against time [39]. The more the response is delayed, the lower the welfare of the beneficiaries [9]. In consequence, relief agencies must design a prioritized plan to provide life-saving emergency assistance for people in need, which must be based on social costs minimization as the objective function, [16–18,34].

Social costs include the logistics cost associated with the relief distribution and the deprivation costs perceived by the beneficiaries in the relief effort. The latter can be approximated by econometric models that allow estimating the utility change (in monetary terms) due to an increase in the deprivation time. In this paper, we use the change in the consumer surplus as an econometric approximation to the DCFs, expressed as a monetary measure of the externality derived from the delay of supplies in humanitarian operations. In general terms, the DCF can be denoted as a function of the type of good, the deprivation time and the socioeconomic characteristics of the individual. According to the theory, it is expected that this function should be strictly increasing and convex with respect to time [18].

This section provides an overview of the main economic valuation methods available to estimate externalities, as well as the discrete choice literature used in this paper to estimate DCFs, considering observed and unobserved heterogeneity.

2.1. Economic evaluation methods

Economic evaluation refers to the process of assigning monetary values to goods and services that are not part of a formal tradable market [4]. Methods used to approach the social evaluation of externalities may be classified into three groups: direct methods, indirect methods of market and questionnaire methods. The direct methods let you quantify the change in the value of a specific product regarding the impact on the social or individual productivity, which is known in the literature as the social accounting or shadow price approach. The indirect methods, also called revealed preferences (RP) techniques, use information of related markets to establish values to goods that are not of the market [31]. Meanwhile, the questionnaire techniques allow for the Willingness to Pay (WTP) to be deduced through choice situations using hypothetical scenarios (Stated Preference SP surveys). In this group, three methods stand out: Contingent Valuation (CV) [27], Conjoint Analysis (CA) and Stated Choice Methods (SC) [25,32]. Because they are based on surveys with hypothetical choice scenarios, the SP techniques can be used in more applications than the RP ones, taking into account that these last techniques require market information related to the goods and services that we wish to evaluate. In the case of natural disasters, given their infrequent occurrence and the collapse of the tradable system of products and services, it is not possible to obtain precise market information, which is why using RP data in this context is very limited.

The SC techniques have been used mostly to estimate intangible goods, such as changes in the risk of home loss [11], road closings [24], people's WTP for earthquake early warning systems [1] among others. Its properties enable an economic valuation of those aspects that are adjacent to a natural disaster, such as post-traumatic stress and its associated effects, changes in the quality of the environment and the reduction of risk, among others. Recently, Holguín-Veras et al. [16] used CV to estimate DCF through a hypothetical disaster scenario presented in a stated preference survey. In this case, individuals expressed their willingness to pay (WTP) for water consumption in a disaster context after different examples of deprivation time. They used Ordinary Least Squares, including a fixed factor, to account for the correlation introduced by using multiple observations from the same individual.

Unlike the contingent valuation, the discrete choice models using SC data are increasingly used for the economic valuation of goods and services. Although both methodologies, CV and SC, share significant similarities on the use of hypothetical scenarios, this last methodology provides more information about the valuation of goods, and it is possible to determine the subjective value for each attribute of the choice set. The discrete choice models focus on the compensating variation of attributes, which can be transferred between different contexts of modeling scenarios [28]. Thus selection of the preferred alternative is psychologically consistent across respondents and simulates a typical task in real markets. However, all of these advantages imply the development of more complex questionnaires that require the definition of appropriate levels for the attributes of the choice alternatives.

In sum, the use of SC techniques is an appropriate alternative to measuring externalities, including those generated in disaster situations. Next, we will formally present the proposed modeling approach.

2.2. Modeling approach

The discrete choice models (DCM) based on the random utility theory hypothesize that an individual n assigns each alternative j a utility U_{nj}. The traditional assumption is that the alternative with the maximum utility is chosen. The modeler observes some attributes of the alternatives ($\mathbf{X_{nj}}$) and characteristics of the individuals ($\mathbf{S_n}$) [41], and postulates that U_{nj} can be represented as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

where V_{nj} is the systematic or representative utility function, which is a function of $\mathbf{X_{nj}}$ and $\mathbf{S_n}$, and ε_{nj} is a random variable that captures the effects of idiosyncrasies, particular tastes of an individual, and any measurement or observational errors that are not captured nor included in V_{nj}[32]. The modeler assumes a probability distribution for the random variable. For instance, if the error terms are independently and identically distributed (IID) Gumbel, the Multinomial Logit model (*MNL*) arises. In such case the probability that the individual n chooses the alternative j within a set of alternatives $A(n)$ is given by equation (2), in which the scale parameter of the Gumbel distribution was normalized to one.

$$P_{nj} = \frac{e^{(V_{nj})}}{\sum_{A_i \in A(n)} e^{(V_{ni})}} \tag{2}$$

The specification of the systematic utility function is frequently assumed to be linear in the parameters as shown in equation (3); however, it is not always appropriate for all of the modeling contexts.

$$V_{nj} = ASC_j + \sum_k \beta_{njk} x_{njk} \tag{3}$$

In the systematic utility function presented above, the term x_{njk} represents the attribute k of the alternative j that the individual n observes, whereas β_{njk} is the parameter to be estimated, which may differ among the individuals. In such specification, these parameters represent the marginal utility that is derived from the characteristics of the alternatives (for example costs, time, among others). ASC_j stands for the specific constant that captures the average effect of all factors that have not been observed on the utility, and the alternatives that are not included in the model. The maximum likelihood method is used to estimate the utility model.

2.2.1. Influence of socioeconomics variables

Although *MNL* is the most popular discrete choice model, it is limited by certain restrictive assumptions, such as the total absence of heterogeneity in the preferences; consequently, the implicit assumption is that preferences are identical among all individuals ($\beta_{njk} = \beta_{jk}$). This restriction does not permit knowing variations in tastes, including the influence that socioeconomic characteristics have on the *WTP* of an individual. However, with a correct specification, it is possible to represent systematic variation of preferences, which is defined as the valuation that people who share certain characteristics observed by the modeler make about certain attributes of the choice set. Some of these socioeconomic characteristics could be gender, level of income, age, and family size, among others. In order to include this type of variations in the model, it is necessary to parameterize the β_{njk} coefficients, defining them in interaction with the individual socioeconomic characteristics $\mathbf{S_n}$ (normally defined as binary or binary categorical variables) with their respective coefficients δ_{jkl} to be estimated as presented in Equation (4):

$$V_{nj} = ASC_j + \sum_k \left(\beta_{jk} + \sum_l \delta_{jkl} s_{nl} \right) x_{njk} \tag{4}$$

As individuals differ on their socioeconomic characteristics, each coefficient δ_{jkl} will represent the mean valuation of the attribute (k) of those that have certain socioeconomic characteristics compared to those that do not. In this way, we are able to estimate different valuations of the same attributes according to the socioeconomic segment.

2.2.2. Functional form and transformations

Considering the convex and nonlinear shape of the DCF, it is necessary to specify a functional transformation (f) on the attribute related to deprivation time, as expressed in equation (5).

$$V_{nj} = ASC_j + \sum_k \left(\beta_{jk} + \sum_l \delta_{jkl} s_{nl} \right) f\left(x_{njk} \right) \tag{5}$$

This mathematical treatment will allow the variations on the *WTP* associated to the deprivation time to be captured. The use of mathematical transformations, such as the Box-Cox type, "lets the data decide" in an appropriate way the functional form [12]. The Box-Cox transformation of a positive variable x given by:

$$x^{(\tau)} = \begin{cases} \dfrac{(x^{\tau} - 1)}{\tau}, & \text{if } \tau \neq 0 \\ \log(x), & \text{if } \tau = 0 \end{cases} \tag{6}$$

The Box-Cox transformation is continuous for all values of τ. Note that if $\tau = 1$, it reduces to the linear form; furthermore, if all $\tau = 0$ we obtain the log-linear form [32]. Exponential functions, as proposed by Holguín-Veras et al. [16] are also appropriated for representing the non-linear behavior, strictly increasing and convex form of DCF.

By using specifications of the utility functions as presented in equation (5), it is possible to obtain a model including systematic variation in tastes involving the socioeconomic characteristics of individuals. However, random unobserved heterogeneity may exist among people with similar socioeconomic conditions. Discrete choice models make the proposal of flexible specifications that allow defining a broader behavior pattern possible, including heterogeneity within the target population.

2.2.3. Considering random variations among individuals

In addition to the systematic variation in the preferences among homogenous segments of the population, preferences can also vary randomly. Then, it is necessary to propose more flexible models that allow for non-observed heterogeneities by the modeler in the choice experiment.

The mixed logit model (*ML*) [26] permits more flexible error structures. For instance, the ML model facilitates the consideration of a random coefficients structure, in which the coefficients β's associated to the attributes vary among individuals in a random way with a function of density of probability $f(\beta|\theta)$, where θ represents the parameters that define the distribution. This specification of random parameters is proposed by adding a term η_{jkn} on the coefficients within the utility function presented in Equation (5). That, and superimposing it with the systematic variations, enables the estimation of the variance with respect to the mean valuation of an attribute, among the individuals who have certain socioeconomic characteristics compared to those who do not have them. This approach finally permits the obtention of a model that includes systematic, as well as random, variations, as presented in equation (7)

$$V_{nj} = ASC_j + \sum_k \left(\beta_{jk} + \sum_l \delta_{jkl}\, s_{nl} + \eta_{jkn} \right) f\left(x_{njk} \right) \tag{7}$$

The term η_{jkn} represents the deviation with respect to the mean that the individual n perceives of certain attribute k for alternative j. When estimating the model, we will be able to obtain the parameters of the statistical distributions ofβ; the mean β_{jk} and the variance $\sigma^2_{j\eta_k}$. In equation (7), it is established that those individuals who share certain socioeconomic characteristic have a valuation of the attribute k with mean $(\beta_{jk} + \sum \delta_{jkl} s_{nl})$ and the individual deviation values η_{jkn} distributed in the population with a typical deviation σ_{jk}. If the socioeconomic attributes are specified as binary variables, it is possible to compare whether such variations are equal for different socioeconomic segments of the population.

The parameters of the model (i.e. β, δ, τ) can be calibrated using data from SC surveys. Regarding the parameter estimation process, the maximum likelihood method is typically used [41]. Such method is based on the idea that although a sample could originate from several populations, a particular sample has a higher probability of having been drawn from a certain population than from others. Therefore, the maximum likelihood estimates are the set of parameters that makes the observed data the most probable.

2.2.4. Estimating DCF from DCM

Discrete choice models are widely used for economic evaluation. In the context of a disaster, a method for assessing the benefits (or costs) derived from the providing basic supplies during humanitarian relief operations is the traditional measurements of the change in the consumer surplus derived from changes in individual's utility caused by variations in the attributes of alternatives. When using logit models, the consumer surplus, CS_n, is given by the maximum expected utility perceived within the choice set [41]:

$$CS_n = \frac{1}{\alpha_n} \left[\max_j U_{nj} \right] \tag{8}$$

In equation (8), $\alpha_n = \partial U_n / \partial I_n$ is the marginal utility of income, which converts the utility in monetary terms. Typically a price or cost variable enters the representative utility, in which case the negative of its coefficient is α_n.

Under the establishment of some assumptions, it is possible to have a closed expression for estimating the consumer surplus using logit models. The first assumption consists of the non-observed component ε_{nj} having an IID Gumbel distribution such as it has been proposed for logit type models. The second one is absence of income effect [45] which is why the marginal utility (α_n) remains constant before and after change. Under such assumptions, the expected consumer surplus is given by [38,46]:

$$E(CS_n) = \frac{1}{\alpha_n} \ln \left(\sum_{A_j \in A(n)} e^{(V_{nj})} \right) + C \tag{9}$$

In equation (9), C is an unknown constant derived from the fact that the absolute level of utility is unknown by the modeler. The expression is commonly called *logsum*. The change in consumer surplus is calculated as the difference between the consumer surplus before (^{0}) and after (^{1}) the variation [41], as expressed in equation (10).

$$\Delta \mathrm{E}(\mathrm{CS_n}) = \frac{1}{\alpha_n}\left[\ln\left(\sum_{A_{j^1}\in A(n)} e^{(V_{nj}^1)}\right) - \ln\left(\sum_{A_{j^0}\in A(n)} e^{(V_{nj}^0)}\right)\right] \quad (10)$$

Since the marginal utility of deprivation time is negative, if (^{0}) is the initial condition and (^{1}) is the condition in which a certain deprivation time has elapsed then, ceteris paribus, the utility in (^{1}) is less than the utility in (^{0}). Consequently, the change in the consumer's surplus will be negative, which implies a loss of benefit. The absolute value of this loss of benefit is the deprivation cost.

When considering more flexible models that have random variability in the preferences, such as the case of the *ML* models, equation (10) applies as long as the parameters are known at the individual level. In the case where they are not known, and these are variables in the population, McFadden [27] proposes a methodology based on techniques simulations, which solves this problem without any need of recovering the individual parameters. The method consists of carrying out random extractions of the parameters from the estimated probability distribution and calculating for each extraction the change in the consumer surplus. An unbiased value of $\Delta E(CS_n)$ is obtained averaging the extractions of each individual and then the entire sample's.

An equivalent approach for estimating the changes in consumer surplus arises from the assumption that individuals choose under compensatory type mechanisms [5]. In this sense, the *WTP* is given by the marginal rate of substitution between the attribute *k* and the income *I* [27]. In particular, if the deprivation time, (T_n), is one of the model attributes, then the subjective value of deprivation time (*SVDT*), defined as how willing is the individual to pay for saving deprivation time if utility remains constant, will be obtained as:

$$\mathrm{SVDT_n} = \frac{\partial \mathrm{V_n}/\partial \mathrm{T_n}}{\partial \mathrm{V_n}/\partial \mathrm{I_n}} \quad (11)$$

As explained beforehand, under the proposed microeconomic models, the marginal utility of the income is the negative of the marginal utility of the cost coefficient, as cost attribute is specified in an additive and linear way and constant across individuals, then $\alpha_n = -\beta_C$ [41].

The change in consumer surplus expressed in monetary terms, which represents the deprivation costs due to the lack of basic supplies, could be calculated as the product of the *SVDT* and the variation in the attribute of the deprivation time. It is defined as the difference between the time at the beginning (T_0) and the end (T_1) of the deprivation period, as expressed in equation (12):

$$\Delta \mathrm{E}(\mathrm{CS_n}) = (\mathrm{SVTS_n})\left(\mathrm{T^0} - \mathrm{T^1}\right) \quad (12)$$

However, when the *SVDT* is not constant over time, as occurs in non-linear models, it is necessary to evaluate each unit in its marginal measurement, integrating the *SVDT*, from T^0 to T^1 as follows:

$$\Delta \mathrm{E}(\mathrm{CS_n}) = \int_{\mathrm{To}}^{\mathrm{T1}} \mathrm{SVTS_n(t)dt} \quad (13)$$

A good approximation for the integral presented in equation (13) is obtained by treating time as discrete and calculate the sum of the marginal loss of benefits each hour of the period of deprivation, such as proposed in equation (14):

$$\Delta \mathrm{E}(\mathrm{CS_n}) = \sum_{\mathrm{t=To}}^{\mathrm{T1}} \mathrm{SVTS_n(t)} \quad (14)$$

Estimation of the loss of benefits for an individual with Equation (14) using *ML* models requires simulation techniques. In such case, it is necessary to extract on a random basis the time coefficients (β_T) of its probability distribution $f(\beta|\theta)$, and calculate the *SVDT* for each extraction. This will enable the subsequent calculation of the mean on all of the extractions to obtain unbiased value of change in benefits. This method has been applied by Refs. [14,37] in order to derive *WTP* values with *ML* models.

Using equations (10) and (14) enables the evaluation of the loss of benefits in monetary terms when faced with an increase of deprivation time of basic supplies in the context of a disaster, that is, the deprivation costs. Likewise, this research aims to analyze the influence of the socioeconomic characteristics on the valuation of the deprivation time and to determine if there are random variations among individuals using the specification of utility functions with systematic and random variations in the preferences.

3. Data

The data employed in this paper to estimate the models were collected from a stated preference (SP) survey that was applied to independent people and heads of families from different areas of Colombia that have been affected by natural disasters. The surveys were conducted from September 2014 to November of the same year. In most cases, the respondents were inhabitants of small towns affected by the winter emergency that occurred in Colombia during 2010 (Sahagún, Caimito, Suan, Candelaria, Santa Lucía and Campo de la Cruz) [19] and by the Armenia-Colombia earthquake occurred in 1999. Data also included people from the two largest capitals of the Colombian North Coast (Barranquilla and Cartagena). The breakdown of the sample by location was: Armenia (29%), Barranquilla (11%), Cartagena (10%), Sahagún (11%), Caimito (11%), Suan (8%), Candelaria (6%), Santa Lucía (7%) and Campo de la Cruz (7%). Fig. 1 presents the Colombian map, pointing out the cities where the SP survey was applied. It also shows the areas affected by the floods during 2010 and the earthquake during 1999.

The survey gathered data from (1) socioeconomic information at household and individual level (e.g. age, gender, household size, family income level, occupation, educational levels, number of children and adolescents at home and if respondents have or not previous experiences in natural disaster events); (2) the choice preferences of respondents according to the SC experiment next presented, which allows the generation of a hypothetical market. As the SC experiment was based in a natural disaster context, it was hypothesized that individuals who have experienced the devastation of natural disasters, or who have seen first-hand their devastating impact, would be able to provide better SP data than those who did not have such experience.

As it is known, a set of critical supplies is required by affected people after a disaster occurrence (e.g. water, fuel, medicines, food, first-aid kit, personal hygiene kit, and clothing, among others). However, for the purpose of this paper and its analyses, a basic food kit (including water) was considered since it is a common supply in the international humanitarian logistics processes. Moreover, all affected people need access to this kind of supplies to stay alive. If the affected people are deprived of water and food for an extended period, they can suffer permanent damage and even die [16]. Additionally, previous disaster experiences show that water and food are essential supplies in the initial days of a response. In this sense, the SC experiment presented to respondents allowed us to collect their preferences about nine hypothetical choice scenarios of being a disaster survivor, where they had two options to handle the local scarcity of critical supplies: to purchase (p) a basic food kit to cover their immediate needs considering their budget restriction, or to wait (w) longer for free humanitarian aid to arrive, which