Socio-Economic Planning Sciences 91 (2024) 101780

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

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

Implications of trust, preparedness, risk perceptions, and local context on deprivation costs and disaster relief planning

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ARTICLE INFO

Keywords:
Humanitarian logistics
Deprivation costs
Hybrid choice models
Trust
Preparedness
Risk perception

ABSTRACT

Deprivation Costs Functions (DCFs) are key to designing effective relief distribution operations after disasters. In this paper, data are collected in Colombia and Ecuador to estimate DCFs for water and food, considering the influence of individuals' attitudes on preparedness, risk perception, and trust in response agents. Hybrid Choice Models are used to analyze and compare the estimated DCFs. The analyses confirm that DCFs differ by commodity. Additionally, socioeconomic characteristics of individuals influence their willingness to pay for critical supplies to reduce their own suffering. Preparedness, risk perceptions and trust in response agents impact individuals' behavior in disaster situations. The results also show that community and religious groups are considered the most trusted response agents in both countries. As a result, their involvement in official relief efforts should be more articulated. Colombia and Ecuador show significant differences in their estimated DCFs, confirming that deprivation costs are context-specific by nature. As such, DCFs should not be directly transferred among disaster locations. The findings from this study will support decision-makers in designing effective preparedness and response plans that are based on trust relationships that serve as foundations for community resilience.

1. Introduction

The impacts of disasters, especially catastrophes, constitute a significant concern for relief organizations and decision-makers. There is a need to develop tools to enhance community resilience, both in terms of preparation for, and recovery from disasters. As the frequency and impacts of extreme events increase, especially in the Global South, it is common to see damaged infrastructure, minimal local inventories available, and private-sector supply chains disrupted or non-operational, leaving communities in desperate need of external support. These conditions require relief organizations to bring supplies from outside the impacted area, and to put in place distribution plans to minimize suffering. However, having the active participation of the locals, and enhancing their preparedness and risk perception could make the response stage easier to complete, with sustained benefits for a faster and more effective recovery. These considerations are aligned with the Sustainable Development Goals (SDGs) proposed by the United Nations [1], especially with the goal of making cities and human settlements inclusive, safe, resilient, and sustainable (SDG #11). The overall goal is to promote the adoption and implementation of integrated policies and plans towards more efficient use of resources that would help communities mitigate, adapt to, and recover from potential disasters, making them more disaster resilient.

Resilient recovery requires careful planning of preparedness and response operations to enhance their timeliness and effectiveness in the event of disasters. This requires the development of relief distribution plans that are activated when disasters strike. Such plans need to include equity metrics that would consider human suffering in the design process. In this context, deprivation cost functions (DCFs) have been proposed as a metric of human suffering that gives a monetary value to the lack of access to a good or service [2]. Using these functions, together with logistics costs, allows for the minimization of *social costs* when designing the optimal distribution of relief aid.

One of the challenges of estimating DCFs is that they are good/

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https://doi.org/10.1016/j.seps.2023.101780
Received 10 September 2022; Received in revised form 1 October 2023; Accepted 2 December 2023
Available online 12 December 2023

service specific, as the deprivation varies with the type of good or service the individual lacks. Suffering accrues in the absence of each product or service until it is received again. That is, deprivation costs (DCs) increase as deprivation time passes and may be reset once the product is received. Several estimations of deprivation costs have been proposed. Some depend on deprivation time (DT) [3,4], while others include—in addition to deprivation time—the socioeconomic characteristics of the individuals involved [5]. More recently, the estimation of DCFs considers the perceptions of the individuals to the response system [6]. Most of the efforts in DCF estimations concentrate on one commodity (i.e., water) using data collected in a single location (i.e., Colombia), increasing concerns about the transferability of results and the role played by the local context [7].

Deprivation Cost Functions (DCFs) could vary based on observed and unobserved heterogeneity. Observed heterogeneity is accounted for by factors such as the supply type, deprivation time, and individual characteristics. On the other hand, unobserved heterogeneity refers to unseen differences, such as individual differences in perceptions and attitudes. We can gain insights into the specific contextual factors that shape DCs by considering and analyzing observed heterogeneities such as differences in the type of supply, and individual characteristics such as age, gender and income level, all of which are commonly studied. We can also gain insights by studying unobserved heterogeneity, such as individuals' differences in trust towards response agents, attitudes about the importance of preparedness, or perceptions of the likeliness of their being impacted by a disaster (risk), all of which are relevant to extreme events. Not much is currently known about the influence of such unobserved heterogeneity on deprivation cost functions.

Shao et al. [8] completed a comprehensive review of deprivation cost functions, including the state-of-the-art and the state-of-the-practice. One of the gaps that needs to be filled is precisely investigating "*DCFs from affected populations from multiple countries, analyzing and comparing the trends of these data, and summarizing general features to verify the universality of deprivation theory.*" The only study considering two countries and two commodities is Fernandez Pernett et al. [9]. Yet, they studied multiple heuristics for DCF estimations, without accounting for the impacts of the socioeconomic characteristics of the individuals involved, or the role of their attitudes and perceptions.

In this paper, we fill this gap by analyzing the role played by individuals' trust in response agents, preparedness, and risk perception in their willingness to pay to reduce their suffering after a disaster, together with the influence of these unobserved factors on deprivation cost functions. Our research aims to explore the influence of the unobserved variables—individuals perceptions of Trust, Preparedness, and Risk Perception—on deprivation costs (DCs). We examine whether such variables and, consequently DCs, are affected by local conditions, socioeconomic characteristics, and issue-specific factors. By conducting this investigation, we seek to gain insight into the intricate relationships among these observed and unobserved variables and their impact on DCs. While DCs are typically determined by observable factors such as the type of supply/service (e.g., water or food), deprivation time, and individual characteristics, we analyze if DCs are also influenced by certain unobserved factors represented by individuals' attitudes and perceptions. Doing so allows us to empirically evaluate the impact of socioeconomic and issue-specific characteristics on deprivation costs (DCs) and to confirm the need to ensure the limited transferability of estimates. Implications of the analyses will facilitate more targeted interventions, which are needed to develop more resilient responses to reduce the suffering of those impacted by extreme events.

To reach the goal of understanding the implications of trust, preparedness and risk perception on deprivation costs, the research analyzes data collected in Colombia and Ecuador using stated preferences to estimate and compare DCFs for water and food in disaster conditions. The observed and observed factors are assessed by estimating Hybrid Choice Models (HCMs). To the best of our knowledge, this is the first study that empirically and simultaneously analyzes data for different products, from different geographic locations, considering the influence of individuals' attitudes on preparedness, risk perception, and trust in several response agents for the estimation of DCFs.

With the analyses conducted here, we test hypotheses to elucidate the causal relationship between the unobserved variables—Trust, Preparedness, and Risk Perception— on deprivation costs. Furthermore, we seek to explore whether the relationship between deprivation costs and these attitudes and perceptions is contingent upon the specific local context. We aim to estimate DCFs from multiple countries (Colombia and Ecuador), analyze similarities and differences, and compare their trends using empirical data. The differences between the estimated DCFs come from the observed and unobserved heterogeneity—explained by the type of supply (water or food), characteristics of the individuals (age, gender income level, etc.), and perceptions/attitudes such as preparedness, trust, and risk perception—that are captured in the model. Disaster managers and decision-makers will be able to use the estimated functions to develop relief distribution plans that consider community perceptions, which could also include the participation of trusted response agents. Thus, this research is important to ensure that the official response is aligned with, and acts according to the community being responded to, and not based on unrealistic assumptions. Individuals differ in their attitudes toward the potential for extreme events in their area, the extent to which they prepare for such events, and the level of trust they have in those tasked with responding to extreme events. This research confirms those differences, and clarifies how such unobserved heterogeneity also affects deprivations costs and the relative suffering of individuals in response to extreme events. Reducing disaster losses, encouraging the participation of the locals, and reducing suffering due to disaster impacts are crucial sustainable development goals for developing countries, especially in the Global South.

2. Literature review and hypotheses development

2.1. Relevant literature on deprivation costs

Deprivation costs were first defined by Holguín-Veras et al. [10] as " … *the economic value of the human suffering caused by a lack of access to a good or service* … " This cost component arises from the need to explicitly consider an equity measure in the objective function to model relief distribution operations, so response stage decisions aim at minimizing the suffering of those impacted. Holguín-Veras et al. [10] conclude that using DCFs instead of proxy measures of human suffering provides superior solutions for more equitable distribution of resources and minimized levels of suffering. Another concept used to measure human suffering is a numerical rating scale. This technique evaluates the degree of human suffering caused by a lack of access to a good or service using deprivation level functions (DLFs) [11]. Given the difference in units, these have not been widely adopted in modeling efforts.

In terms of the implementation of DCFs, there is a gap between state-of-the-art and state-of-the-practice. Practitioners use optimization models mainly based on logistics costs (private costs), while researchers and academics have been working on quantifying human suffering in the form of deprivation costs in recent approaches [8]. One of the main challenges to introducing DCFs in humanitarian logistics models is the non-linear, convex shape of these functions. This brings complex and demanding analytical capabilities to bear to solve such models.

Although quantifying human suffering is required when the objective function is based on social costs, a limited number of studies have estimated DCFs. Holguín-Veras et al. [3] used contingent valuation to estimate the first deprivation cost function for water using data collected in Colombia. In their research, individuals stated their willingness to pay for water in a post-disaster situation according to deprivation time values. Macea et al. [4] and Cantillo et al. [5] estimated deprivation cost functions using discrete choice models (DCMs) based on stated preferences data. Both studies proposed discrete choice techniques to estimate DCFs based on changes in consumer surplus that individuals experienced due to changes in water shortages [4] and a kit of necessary supplies [5]. On the other hand, Macea et al. [4] used a multinomial logit (MNL) model without systematic taste variations to evaluate water deprivation. Their model has restrictive assumptions, such as the absence of preference heterogeneity. Meanwhile, Cantillo et al. [5] estimated a mixed logit (ML) model to evaluate the need for a kit of basic supplies. The presence of socioeconomic attributes in the model allowed for capturing systematic and random taste variations among individuals.

Previous literature reports that age, gender, having children or elderly at home, and having been previously impacted by a disaster influence the deprivation cost functions [5]. Furthermore, Delgado-Lindeman et al. [12] estimated DCFs for emergency medical services, considering patient conditions and income level. The results indicate that deprivation costs of medical services are higher than prior estimations for water and food kits. Recently, Fernandez Pernett et al. [9] compared multiple heuristics for DCF estimation. They used Random Utility Maximization (RUM), Random Regret Minimization (RRM), and a combined method that considers both Regret and Utility-based decision rules. In their study, utility functions are explained by deprivation time, budget, and unit price of water and food.

Although DCFs have been estimated using multiple modeling approaches, flooding is the most common disaster considered. Just one study has collected data in two geographic locations. A gap in the literature is the estimation of DCFs to empirically test if attitudes and perceptions influence DCFs, enhancing their context-specific nature. In particular, the influence of risk perception, safety culture, and confidence on deprivation costs has been studied. However, since individuals' perceptions and attitudes are greatly affected by local conditions, other attitudes and perceptions should be taken into account. This study considers individuals' trust in response agents, risk perception, and level of preparedness. Table 1 summarizes the available literature on deprivation cost functions, including the description of this research at the end. To the best of our knowledge, this is the first study that empirically and simultaneously analyzes data for different supplies, from different geographic locations, considering the influence of individuals' attitudes on trust in several response agents, preparedness, risk perception, and local context for the estimation of DCFs.

2.2. Hypotheses development

When disasters strike, relief agencies and organizations mobilize resources to help those affected. Hence, the suffering of those impacted depends largely on the effectiveness of the distribution of basic supplies by the relief groups [13]. How relief agencies and organizations handle the event can affect survivors' recovery [14]. This is critical, as disasters may have major and lasting impacts on the affected communities and the relationships between survivors and institutions [15].

Lack of trust in response agents creates the perception that when terrible things happen, institutions cannot be trusted to provide the necessary resources to ensure the wellbeing of the impacted population [16]. This supports the need to study how individuals' level of trust in these agents could influence their suffering and ability to return to normalcy after disasters. We conjecture that when people believe that response agencies can do their job effectively, they will expect to get back to their normal situation faster, and as such, their suffering will be lower. However, trust in the response agents is one of the least studied factors in disaster operations contexts, particularly in the Global South. Trust in these agents contributes significantly to adopting risk mitigation and preparedness measures, especially when the community cooperates and has confidence in their agencies [17]. Understanding individuals' perceptions concerning response agents is key to developing relief distribution plans. Therefore, including such a latent construct as an influencing factor on willingness to pay for goods after disasters provides a holistic framework for estimating DCFs. Based on these considerations, we propose our first hypothesis.

H1. *Deprivation costs are negatively influenced by the level of trust individuals have in response agents. As individuals believe that response agents would do their job effectively, they expect to suffer less.*

Risk Perception, another factor that affects individuals' behavior during disasters, is a subjective variable that refers to an individual's assessment of the perceived likelihood of their being affected by an extreme event [18]. Risk perception can affect an individual's attitudes, expectations for future impacts, factors influencing hazard identification, and preparedness levels [19]. Under this perception, individuals make decisions according to their perspectives concerning hazards [20]. Risk perception plays a vital role in creating awareness regarding potential risks and the need for preparedness. If individuals have a high perception of the risks associated with the lack of critical supplies, they are more likely to take proactive measures to prepare for and mitigate those risks. The estimated models demonstrate this reasoning. Furthermore, risk perception influences individuals' decision-making when faced with scarcity conditions. People with an elevated risk perception may prioritize actions that address their immediate needs, such as seeking access to limited resources or participating in relief efforts. In sum, by recognizing and effectively addressing risk perception, relief

Table 1
Summary of available DCFs[a].

Article	Method/ Model Type	Goods or services	Main variables	Socioeconomic variables	Attitudes and perceptions	Disaster type/Case study
Holguín-Veras et al. [3]	CV/MLR	Water	DT	–	–	Flooding/Colombia
Macea et al. [4]	SC/MNL	Water	DT, AB, UP	–	–	Flooding/Colombia
Cantillo et al. [5]	SC/ML	A kit of basic supplies	DT, AB, UP, disaster type	Gender, age, and children	–	Flooding and Earthquake/ Colombia
Macea et al. [6]	SC/HCM	A kit of basic supplies	DT, AB, UP	Gender, age, children, previous experience, employment, education, household size, income	Risk perception, safety culture, confidence in ERSs	Flooding and Earthquake/ Colombia
Delgado-Lindeman et al. [12]	SC/MNL-ML	Medical services	DT, UP, patient's condition	Income	–	———/Colombia
Fernandez-Pernett et al. [9]	MNL/RUM, RRM, RMU	Water and food	DT, AB, UP	–	–	Flooding and Earthquake/ Colombia and Ecuador
This study	*SC/HCM*	*Water and food*	*DT, AB, UP*	Macea et al. [4] + *religious, supply & cash reserves, knowledge on emergency steps.*	*Trust in response agents, preparedness, risk perception,*	*Flooding and Earthquake/ Colombia and Ecuador*

[a] CV: Contingent valuation; SC: Stated choice; MLR: Multiple Linear Regression; MNL: Multinomial Logit; ML: Mixed Logit; HCM: Hybrid Latent Variable-Discrete Choice Model; DT: Deprivation time; AB: available budget, UP: unit price; RUM: Random Utility Maximization; RRM: Random Regret Minimization; RMU: Random Modified Utility; ERS: Emergency Response System.

efforts can be tailored to mitigate suffering, promote preparedness, and foster community resilience.

By assessing risk perception, planners can gain valuable insights into community perspectives to better anticipate their likely behaviors in the event of a disaster. Those who have a perception of risk before an event tend to prepare for potential events, and in so doing, are better able to withstand or deal with the effects of an event after one occurs. Risk perception serves as a valuable tool in understanding a person's level of risk awareness and can act as a mediator between knowledge and behavioral factors. Individuals typically assess and evaluate risks, making decisions that impact their overall wellbeing. Recognizing the significance of risk perception is particularly important in the context of human suffering after disasters. By understanding how individuals perceive risks, developed plans could better serve their needs and mitigate potential negative consequences in disaster contexts. Risk perception has been previously identified as an important variable in DCFs studies (See Macea et al. [4].

Researchers have explored various determinants of risk perception, concluding that it is affected by socioeconomic features such as gender, age, education, income, disaster type, and previous experience with disasters [21]. For instance, less educated and religious people may relate to natural disasters as a divine action and believe that the unfortunate consequences of disasters cannot be avoided. This behavior affects community awareness, preparedness, and the ability to cope with future events and, ultimately, the perception of risk [22]. Thus, assessing risk perception helps provide insight into community perspectives and likely responses to disasters. Individuals usually assess risks and make decisions accordingly. We expect that individuals with higher risk perceptions will be more willing to pay to reduce their deprivation—and suffering—under scenarios of limited access to goods. In other words, individuals' risk perception may also influence deprivation costs. This allows us to propose our second hypothesis.

H2. *Deprivation costs are positively influenced by the level of risk perception individuals have. Individuals with high levels of risk perception are willing to pay more to reduce their deprivation—and suffering—under disaster conditions.*

Preparedness is a crucial element in mitigating the impacts brought by disasters. Nonetheless, ensuring community preparedness is complicated. Understanding individuals' preparedness for disasters can be difficult if the perceptions and behavior of the community to be served are unknown. The objective of previous research has centered on identifying the elements that influence preparedness, and how different characteristics of the population influence their behavior in the presence of disasters. Characteristics such as education, previous experience with a disaster, employment, age, and having children living at home have been identified as positively increasing preparedness [23,24]. If we look at community perceptions, we will be able to unveil what is needed to improve preparedness, which goes beyond responding to that community once disaster has struck, and the various phases of disaster management. Furthermore, efforts to foster disaster preparedness will also foster better interactions between the responding parties, and improve the overall engagement of the community served.

While prior studies have primarily focused on identifying the factors affecting preparedness, there remains a notable gap in empirical research when it comes to evaluating the impact of preparedness on deprivation costs. Macea et al. [6] proposed "Safety culture" as a proxy for Preparedness, to assess the attitudes that people share about safety in an organization. They found that the probability of purchasing critical supplies to cover immediate needs increases when safety culture also increases. In our research, we examine the Preparedness attitudes of individuals in relation to disaster conditions by capturing more components in addition to safety culture, such as the availability of first aid equipment, training to overcome emergencies and safety behaviors. Since the goal of deprivation cost estimations is to reduce suffering, we hypothesize that individuals who are more prepared to act in the event ofdisasters are willing to pay more (are more sensitive) to reduce their deprivation of critical supplies. Thus, the following hypothesis proposes Preparedness as a possible influencing factor in the estimation of DCFs.

H3. *Individuals prepared for disasters are more sensitive to deprivation time and are willing to pay more to reduce their deprivation—and suffering—under disaster conditions. Thus, deprivation costs are positively influenced by the level of preparedness individuals have..*

The literature also shows that preparedness is related to risk perception and trust [25,26]. The correlation of preparedness and risk perception has shown mixed results as it varies across cultures and countries, depending on regional attributes [25,27]. Trust in the government and assistance groups also presents intricate effects on disaster preparedness, according to such contextual aspects as the disaster category, culture, and geographical frameworks [26]. Trust in organizations plays a role in determining risk perceptions [17], as communication about risks is more successful when the public trusts the source of information. Likewise, when relief institutions are trusted to apply preventive initiatives, the community more readily adopts self-preparedness behavior [28]. These three factors associated with individuals' behavior and perceptions are relevant to the value of deprivation costs.

Furthermore, researchers have found that two sets of variables primarily influence individuals' disaster preparedness, trust in various response agents, and risk perception [29]. The first set of variables is socioeconomic characteristics. Previous studies have reported the influence of socioeconomic factors on these attitudes/perceptions. For example, age [23,30]; gender [31,32]; household income [33]; and education [34,35] have been found to be significant. Moreover, individuals tend to be more prepared when there are children and the elderly in their households [36,37]. The second set of variables is issue-specific characteristics [29]. These variables commonly consist of individuals' previous experience, awareness concerning disasters, awareness or understanding of the hazard(s), degree of affiliation with faith [38] and training to cope with disasters, among others [39]. For instance, being impacted by disasters affects how individuals implement risk mitigation measures in the future, based on their knowledge and prior training [40].

Given the relations above, our last hypothesis examines the context-specific nature of deprivation costs, as individuals' attitudes and perceptions influence these functions. This hypothesis explores whether the relationship between deprivation costs and attitudes/perceptions varies based on the local context.

H4. *The relationship between deprivation costs and attitudes and perceptions—towards trust, preparedness, and risk perception—is contingent upon the local context of the community being served.*

Fig. 1 presents the conceptual framework of this research, illustrating the contribution of both observed and unobserved factors on DCFs. The ellipses in the figure represent unobserved factors, specifically Trust, Risk Perception, and Preparedness. At the same time, the rectangles denote observable descriptive variables such as socioeconomics, issue-specific characteristics, type of supply, and deprivation time. These observed factors are considered non-context specific. On the other hand, the unobserved heterogeneity represented by perceptions and attitudes is context-specific. These unobserved factors play a crucial role in differentiating DCs across contexts. By considering and analyzing these unobserved heterogeneities, we can gain valuable insight into the specific factors that shape DCs. Confirmation of the proposed hypotheses will help us understand the influence of Trust, Preparedness, and Risk Perception on deprivation costs (DCs) and the role played by the local context.

The available literature on DCFs is still too limited to respond to these hypotheses, and it fails to consider complex features such as the attitudes and perceptions of the impacted communities. No research has yet evaluated the influence of latent variables on deprivation cost

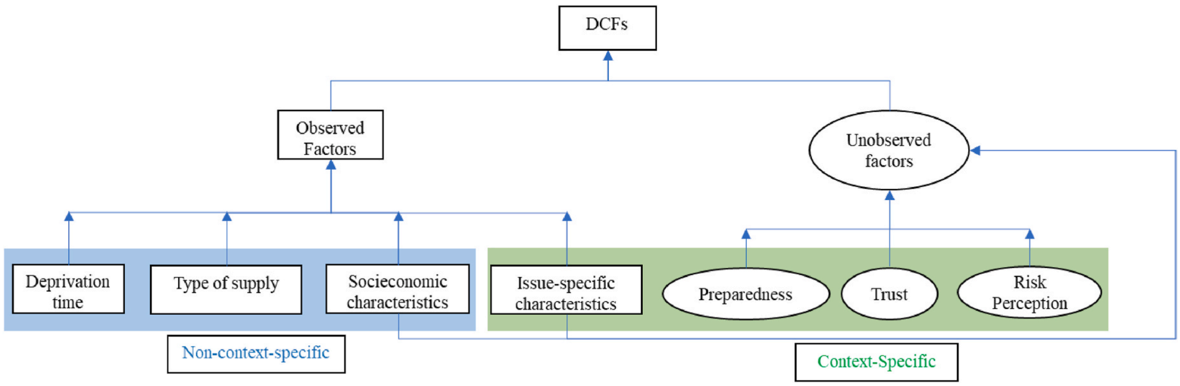

Fig. 1. Conceptual framework to DCs.

functions considering multiple locations and multiple supplies. This paper helps to fill these gaps.

3. Methodology

This section describes the methodology used in this study and the theoretical foundation that supports it.

3.1. Econometric approach

A random utility-based Discrete Choice Model (DCM) is used to estimate the deprivation cost function. The utility $U_{njt} = V_{njt} + \varepsilon_{njt}$ is assumed to be assigned by an individual n to alternative j in choice situation t, available from a set of critical supplies in this context, where V_{njt} is the systematic (representative) utility and the error term ε_{njt} captures the effects of observational or measurement errors. The specification of the systematic utility function (V_{njt}) is frequently assumed to be linear in the parameters in the generic form, i.e., $V_{nj} = ASC_j + \sum_j \beta_{njk} X_{njk}$ [41]. However, it is not appropriate for our modeling contexts. 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 (DT). The modeler uses some attributes *k* of the supply (X_{njkt}), characteristics of the individuals (S_n) and the deprivation time (*DT*) caused by the lack of access to the supplies. The traditional assumption is that preferences vary among individuals, and the alternative with the highest utility is chosen [42]. Equation (1) represents the utility function used in this research. ASC_j is the alternative specific constant. To correlate the observations from the same individual, an additional error component ξ_{nj}, called the panel effect, is specified. It will follow a normal distribution with mean zero and variance σ_ξ^2, which is $\xi_{nj} \sim Normal\,(0, \sigma_\xi^2)$. The β_s are the parameters to be estimated.

$$U_{njt} = ASC_j + \sum_k \beta_{njk} X_{njkt} + \beta_{njDT} f(DT_{njt}) + \xi_n + \varepsilon_{njt} \tag{1}$$

As mentioned, we specified a functional transformation (*f*) of the attribute associated with *DT* to model the non-linear form of the DCF. Specifically, we used the Box-Cox transformation (Equation (2)), which returns the non-linear effect of deprivation time on the deprivation cost, i.e, $\varphi > 1$. The Box-Cox transformation is continuous for all values of φ. Note that if $\varphi = 1$, it reduces to the linear form; furthermore, if $\varphi = 0$ we obtain the logarithmic form:

$$f(DT_{njt}) = \begin{cases} \dfrac{DT_{njt}{}^{\varphi-1}}{\varphi}, if\ \varphi \neq 0 \\ \log(DT_{njt}), if\ \varphi = 0 \end{cases} \tag{2}$$

On the other hand, including attitudes/perceptions in the utility function requires estimating Latent Variables (LVs) [43]. The LVs are estimated with the Multiple Indicators Multiple Causes (MIMIC) model, using a structure of two components. The first is the structural equations (Equation (3)), which associate the *s* characteristics of the individuals (S_n) with the *l* latent variables. The second is the measurement equations, which associate the *m* indicators of perceptions (I_{nm}) with the latent variable (LV) *l* (Equation (4)). When the indicators are categorical, ordinal variables $(\tilde{I}_{nm})$, the measurement equations are specified as ordered logit models [44]. The vector of thresholds (τ) is specified, within which a continuous latent variable will take some value from the categorical indicator (Equation (5)). For each indicator, if there are i categories, there are $i - 1$ thresholds. The error components follow a normal distribution: $\delta_{nl} \sim Normal\,(0, \sigma_\delta^2)$ and $\vartheta_{nl} \sim Normal\,(0, \sigma_\vartheta^2)$; λ *and* γ are parameters to be estimated.

$$LV_{nl} = \sum_s \lambda_{sl} S_{sn} + \delta_{nl} \tag{3}$$

$$I_{nm} = \sum_m \gamma_{lm} LV_{nl} + \vartheta_{nm} \tag{4}$$

$$\tilde{I}_{nm} = \begin{cases} 1\ if\ \tau_0 < I_{nm} < \tau_1 \\ 2\ if\ \tau_1 < I_{nm} < \tau_2 \\ \dots \\ i\ if\ \tau_{i-1} < I_{nm} < \tau_i \end{cases} \tag{5}$$

The LVs effects on the *DT* were modeled by the inclusion of systematic taste variations between the *DT* parameter (β_{njDT}) and the LVs, as represented in equation (6). In this way, the modeler can estimate different valuations of the *DT* according to the LV valuated.

$$\beta_{njDT} = \beta_{DT+} \sum_l \beta_{l-DT} LV_{nl} \tag{6}$$

The integration of DCM and MIMIC leads the way to estimate the HCM used in this research [45]. Combining Equation (1) and Equation (6) allows the incorporation of LVs into the utility function U_{nj} as presented in Equation (7). The unknown parameters are estimated using simultaneous estimation by the simulated maximum likelihood technique, building a combined likelihood function that includes the MIMIC model and the DCM [45]. Equation (7) is the specific functional form to estimate DCFs using the discrete choice model in the specific modeling context of disasters.

$$U_{njt} = ASC_j + \sum_k \beta_{njk} X_{njkt} + \left(\beta_{DT+} \sum_l \beta_{l-DT} LV_{nl}\right) f(DT_{njt}) + \xi_{nj} + \varepsilon_{njt} \tag{7}$$

When using discrete choice models, the marginal willingness to pay (WTP) is given by the marginal substitution rate between attribute k and income *I*, derived from the assumption that individuals choose under compensatory type mechanisms [46]. The marginal subjective value of deprivation time (*SVDT*) is the ratio of the marginal utility of *DT* to the marginal utility of income [5] (Equation (8)). The marginal utility of