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Measuring the Benefits of a Morbidity and Mortality Risk Reduction Project Evaluated by a Binary Response Model with Sample Selection

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Abstract

This paper presents a theoretical and statistical framework for measuring the benefits of a morbidity and mortality risk reduction project. To consider the mechanisms by which the project changes the probability of death or injury/illness, we extend the basic standard model defining the value of a statistical life (VSL) or the value of a statistical injury (VSI). The extension is done by introducing the probability of occurrence of events that cause death or injury/illness and the conditional probability of survival or recovery to the basic standard model. Since the project's benefits are defined by the extended model and are associated with VSL and VSI, the benefit transfer approach can be applied to measure them. Moreover, assuming that individual data on the death or injury/illness of individuals who have experienced a disaster or accident are available, we provide a statistical approach for deriving their conditional probabilities of survival and recovery based on a binary response model by considering sample selection. Furthermore, a case of out-of-hospital cardiopulmonary arrest and emergency medical services (EMS) transport was chosen as a specific event that could cause death or injury/illness. The proposed binary response model approach was applied to this case using Japanese Utstein-style data. Using the estimation results, we predicted the changes in the probabilities of survival and recovery when the time between ambulance call and arrival at the patient's side was reduced by one minute, and the benefits of the project were measured.

Keywords: Benefit-cost analysis, Morbidity and mortality risk, Value of a statistical life, Sample selection, Binary response model, Utstein-style data

JEL Classification: D61, J17, C54, I18

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1. Introduction

Saving lives is an essential objective of the public sector. For example, some projects or policies in areas such as health care, environment, and transportation are public goods that reduce morbidity and mortality risks and benefit a large number of people. It is well known that a cost-benefit analysis is required to ensure efficient projects or policies. This analysis is a crucial element in evaluating projects or policies, especially in Organisation for Economic Co-operation and Development (OECD) member countries and is a significant target for projects or policies related to human life (OECD, 2012). In recent years, since human lives have been exposed to various risks, such as frequent natural disasters, the spread of new viruses, and an outbreak of international conflicts, it is necessary to devote more effort to valuing and efficiently implementing morbidity and mortality risk reduction projects or policies.

To measure the benefits of morbidity and mortality risk reduction, the marginal willingness to pay (MWTP) for reduction in the probability of death or injury/illness can be employed as a shadow price. The MWTP for reduction in the probability of death is called the value of a statistical life (VSL). There is a large body of research on its theory and estimation (Hammitt, 2000; Viscusi and Aldy, 2003). The MWTP for reduction in the probability of nonfatal injury/illness is called the value of a statistical injury (VSI) and it is subject to the same framework as the VSL. VSL and VSI are based on the standard model originating from Schelling (1968), Jones-Lee (1974), Viscusi (1978), and Weinstein et al. (1980), which are defined by the von Neumann-Morgenstern expected utility. Approaches for estimating them are roughly classified into revealed and stated preference methods. The revealed preference method uses data observed in the actual market, such as industrial and traffic accidents, for which results are considered reliable. This is because they reflect the trade-offs that individuals face in practice with respect to morbidity and mortality risk, and many policy analyses in the United States support this method (Kniesner and Viscusi, 2019). The stated preference method is a direct questionnaire about the trade-off between the probability of death or injury/illness and wealth or money. Although this method can estimate the VSL for risks that are not captured by the revealed preference method, there is no guarantee that the hypothetical choices reflect the trade-offs that would take place in the real market. Therefore, it is necessary to check the reliability of the estimation results by validity tests such as a scope test (e.g., Viscusi, 2014). Many studies have been conducted to improve the generality and reliability of both estimation approaches. For example, Viscusi and Gentry (2015) showed that the VSL estimated from revealed preference data in the labor market is rea-sonable for a benefit transfer to transportation policy. Corso et al. (2001) illustrated the effectiveness of visual aids in making respondents more accurately aware of changes in mortality risk in the stated preference methods. Recently, Alberini and Ščasný (2021) proposed a VSL estimation method for cancer mortality risk based on the contingent valuation method, showing the respondents the probability of getting and surviving cancer. They also evaluated its reliability and validity. Herrera-Araujo et al. (2022) provided a method to remove bias in the VSL estimates obtained from hypothetical non-marginal risk reduction in questionnaires.

When measuring the actual benefits of a project or policy that reduces morbidity and mortality risk, it is necessary to estimate the VSL, VSI, and the changes in the probability of death and injury/illness associated with the project or policy. People face a variety of events that cause death and injury/illness on a daily basis; thus, the project or policy can affect the morbidity and mortality risk in the ex-ante or ex-post state of such events. For instance, a project such as vaccination to prevent viral infections and road maintenance to minimize traffic accidents will reduce the probability of an event causing death and injury/illness. Further, projects such as providing emergency medical care and developing viral therapeutics will change the conditional probability of survival under the condition that an event caused death or injury/illness occurs, as well as the conditional probability of recovery under the condition of survival from that event. Both projects will change the probabilities of death and injury/illness, but the mechanisms are indubitably different. In particular, it is implausible to ignore changes in the probability of recovery or rehabilitation due to a project or policy because of the remarkable technological advances in emergency medical services (EMS). For example, Kitamura et al. (2010) reported that using an automated external defibrillator (AED) in the early stages of ventricular fibrillation improves survival and rehabilitation in patients with out-of-hospital cardiopulmonary arrest. Accordingly, to measure the benefits of a project or policy that reduces morbidity and mortality risk, it is necessary to develop a methodology that considers the VSL, VSI and the mechanism by which the project or policy changes the probability of death and injury/illness. However, to our knowledge, no study has proposed such a methodology, and most studies have aimed to provide more reliable VSL and VSI estimates. Nonetheless, some studies have measured the benefits of pro-jects or policies by employing VSL and VSI. Sund et al. (2012) evaluated the benefits of improving the probability of survival by providing defibrillation in both ambulances and fire services for out-of-hospital cardiopulmonary arrest in Stockholm, Sweden, based on VSL estimates. Echazu and Nocetti (2020) used VSL and VSI estimates to measure the social willingness to pay to reduce the morbidity and mortality risk from the spread of novel coronaviruses in the United States. However, both studies can be regarded as the practical utilization of VSL and VSI to measure the benefits of specific projects or policies and did not aim to provide a general methodology for measuring the benefits by employing them.

Therefore, this study presents a theoretical framework for measuring the benefits of projects and policies that aim to reduce morbidity and mortality risk, explicitly considering the mechanisms by which they change the probability of death or injury/illness. The basic standard model defining VSL depends only on whether the utility is death or survival and not on the cause of death. Carthy et al. (1999) built one of the models in which utility depends on death and injury. By combining the contingent valuation method and the standard gamble method, an approach to reliably measure VSL was proposed, but the causes of death and injury were not considered. Scotton and Taylor (2011) extended the model to one in which utility depends on events that cause death and estimated hedonic wage functions relying on it. However, nonfatal injuries and illnesses were not included. Hence, we introduce not only death and injury/illness but also the multiple events that cause them to the standard model, thus formulating the probability of occurrence of an event causing death or injury/illness, the conditional probability of survival, and the probability of recovery under the condition that the event occurred. Consequently, it becomes clear how a project or policy affects these three probabilities and produces benefits. Furthermore, we relate the benefits of projects and policies to VSL and VSI using first-order approximations with respect to these three probabilities. This allows for the benefit transfer of VSL and VSI estimates in other studies. Such a benefit transfer approach is widely used in cost-benefit analyses for projects or policy evaluations (e.g., Hammitt and Robinson, 2011; Johnston et al., 2015; Smith et al., 2022). We also provide theoretical evidence on how VSL and VSI differ across events that cause death and injury and discuss the validity of benefit transfers.

In addition, since there has been significant development in information and communication technology in recent years, which has increased the rapid accumulation and easy accessibility of individual data, this paper also proposes a statistical framework for obtaining the estimated change in the conditional probability of survival and the conditional probability of recovery by the project from individual data on people who encountered a disaster or accident. More specifically, some projects can affect the probability of a specific event causing death or injury/illness, while others can affect the conditional probability of survival and recovery under the event's occurrence. Thus, we focus on the latter and propose an appropriate approach for estimating changes in conditional survival probabilities and conditional recovery probabilities using a binary response model from the individual data by adapting a sample selection mechanism to represent a two-step process in which it is first observed whether the individuals survived or not, and then whether the survivors recovered or not. This implies that the state of recovery can be observable only for the survivor, and we should not presume that the individual's survival and recovery are uncorrelated. Here, it is implicitly assumed that there exists data on individuals who faced a specific event that caused death and injury/illness and that they consist of some individual attributes, including the status that changes depending on the project, as well as items that allow us to check whether the individuals survived and recovered. As the related literature, Jaldell et al. (2014) analyzed the effect of EMS transport time on the probabilities of death, severe injury, and slight injury by estimating a logit model for each of the injuries from the emergency medical data of Thailand. In addition, Swan and Baumstark (2021) estimated the probabilities of death and severe injuries as a function of EMS transport time from French individual data related to EMS using a multinomial logit model. However, both studies ignored the two-step process that determines whether an individual survived and only then makes it possible to observe the degree of injury/illness, as already pointed out, which may lead to the so-called sample selection bias problem in terms of statistical analysis. In contrast, the binary response model with sample selection employed in this study is thus characterized by explicitly describing such a process as its mechanism, thereby avoiding potential bias in the estimation of parameters.

Furthermore, in this study, the event of EMS transport due to cardiopulmonary arrest is taken up as a specific event that causes death or injury, and Utstein-style data consisting of individuals who faced this event are adopted as the individual data assumed above. Thus, we derive the change in the conditional probabilities of survival and recovery due to the reduction in the EMS transport time from these data by estimating the above binary response model by considering sample selection, as already mentioned, and then measure the benefits of this reduction by benefit transfer. Utstein-style data are collected by international standards for out-of-hospital cardiopulmonary arrest patients. In Japan, for example, the number of out-of-hospital cardiac arrest patients has recently increased to over 100,000. No previous study has utilized such internationally standardized large-scale data to estimate the changes in the survival and recovery probabilities due to a reduction in EMS transport time and measured that benefit using the MWTP approach.

However, some related studies have evaluated the medical or monetary benefits of reducing EMS transport times. For example, although Mashiko et al. (2002), Nishiuchi et al. (2008), Rea et al. (2010), and Gold et al. (2010) statistically analyzed the relationship between the time from patient collapse to ambulance arrival, CPR, and defibrillation, and the probability of survival until discharge, they discussed changes in the survival and recovery probabilities, focusing on the medical rather than the economic evaluation. On the other hand, Sund et al. (2012) examined the benefit of defibrillation in both ambulances and fire services by VSL but, unfortunately, did not consider the change in the probability of recovery or return to society. Jaldell et al. (2014) estimated the benefit of reduced transport time by evaluating the change in the probability of death, severe injury, and slight injury with a one-minute reduction in EMS transport time in Thailand. However, the cost-of-illness approach was used in this study because there are no VSI estimates for severe and slight injuries in Thailand. In this study, we estimated the increase in the conditional probability of survival and the conditional probability of recovery by shortening the EMS transport time for patients with cardiopulmonary arrest in Japan using Utstein-style data, from which we measured its benefit by transfer-ring the existing VSL and VSI estimates.

Thus, this study not only provides a theoretical framework for evaluating the benefits of projects that change the probability of death and injury but also proposes a statistical approach using individual data, especially Utstein-style data, to estimate the change in the probability of death and injury, which is essential for deriving their benefits. To the best of our knowledge, no previous study has attempted to use this approach. The remainder of this paper is organized as follows. Section 2 develops a theoretical framework that generalizes the standard models required to measure the benefits of projects that reduce the probability of death and injury. Section 3 presents a statistical approach incorporating sample selection to estimate the probabilities indicated by the theoretical model from individual data containing binary variables on whether an individual facing an event that can cause death or injury/illness survives or recovers. Section 4 provides an overview of the Utstein-style data and variables in Japan used in this study and the results of applying the estimation method in Section 3. Section 5 proposes a method for estimating the changes in the probabilities of death and injury based on Sections 3 and 4, respectively, for a hypothetical project to reduce the EMS transport time in Japan and measure the actual benefits. Finally, Section 6 presents conclusions and future research topics.

2. Theoretical framework

The basic standard model underlying VSL and VSI assumes that individuals face the risk of either death or a nonfatal injury/illness. In this paper, we generalize the standard model by assuming that death and multiple nonfatal injuries and illnesses can occur due to multiple events. This generalized model provides the derivation of different VSLs and VSIs for each event that causes death or injury/illness, clarifies how a project generates the benefits by reducing the risk of death or nonfatal injury/illness, and facilitates the interpretation of benefit transfers of VSLs and VSIs to be adapted to measure the benefits of such a project. Furthermore, we induce an approximate expression to measure the benefits of a project that changes not only the probability of an event that may cause death or injury/illness but also the probabilities of survival and recovery when such an event occurs.

We consider a model in which an individual lives for only a single period. There are two categories of events that can occur in an individual. The first category consists of health-related events $S_0, S_1, \cdots, S_H$, which are exclusive of one another. Specifically, S_0 is the event that the individual dies, and $S_1, \cdots, S_{H-1}$ are the events that the individual suffers the injury/illness $1, \cdots, H-1$ respectively. S_H is an event that the individual does not die or suffer any injury/illness; that is, the individual is in good health. The second category consists of the hazardous events $X_1, \cdots, X_J$ that can cause death and injury/illness medically as natural disasters or the spread of new viruses, which are mutually exclusive for simplicity but not so for $S_0, S_1, \cdots, S_H$. That is, if X_j occurs, S_h can also occur $(j = 1, \cdots, J; h = 0,1, \cdots, H)$.

The individual has the same income or wealth w independent of events, but its utility is assumed to be event-dependent. If the product event $X_j \cap S_h$ occurs, the individual will have utility $u_{jh}(w)$. On the other hand, if event S_H occurs, the individual will have utility $u_H(w)$, regardless of the event that causes death or injury/illness. We assume that each utility is twice differentiable with respect to income and satisfies the following inequalities:

$$u_{j0}(w) < u_{jk}(w) < u_H(w), \tag{1}$$

$$0 \leq u'_{j0}(w) < u'_{jk}(w) < u'_H(w), \tag{2}$$

$$u''_{j0}(w) \leq 0, \ \ u''_{jk}(w) \leq 0, \ \ u''_H(w) \leq 0, \tag{3}$$

where $j = 1, \cdots, J$ and $k = 1, \cdots, H-1$.

The basic standard model with only death and survival events assumes that the utility and marginal utility of income are higher at survival than at death and that the marginal utility of income at survival or death is weakly decreasing. Eqs. (1)–(3) are natural extensions of these assumptions. These equations indicate that the utility and marginal utility of income are higher at injury/illness than at death but lower at injury/illness than at survival and that the marginal utility of income at in-jury/illness is also weakly decreasing.

Let $\alpha_{jh} = P(X_j \cap S_h)$ be the joint probability of the product event $X_j \cap S_h$. Then, because the probability of event S_H is given by $\sum_{j=1}^{J} \alpha_{jH} = 1 - \sum_{j=1}^{J} \sum_{h=0}^{H-1} \alpha_{jh}$, the expected utility function of the individual is

$$EU(\boldsymbol{\alpha}, w) = \sum_{j=1}^{J} \sum_{h=0}^{H-1} \alpha_{jh} u_{jh}(w) + \left(1 - \sum_{j=1}^{J} \sum_{h=0}^{H-1} \alpha_{jh}\right) u_H(w), \tag{4}$$

where $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_j, \overline{\boldsymbol{\alpha}}_j)$, $\boldsymbol{\alpha}_j = (\alpha_{j0}, \alpha_{j1}, \cdots, \alpha_{jH-1})$, and $\overline{\boldsymbol{\alpha}}_j = (\boldsymbol{\alpha}_0, \cdots, \boldsymbol{\alpha}_{j-1}, \boldsymbol{\alpha}_{j+1}, \cdots, \boldsymbol{\alpha}_J)$.

Suppose that the individual is offered a change in the joint probability of the product event $X_j \cap S_0$, i.e., the probability of death when the event X_j occurs, from α_{j0}^0 to α_{j0}. Subsequently, the compensating variation for this change, CV_{j0}, satisfies

$$EU(\alpha_{j0}^0, \alpha_{j1}^0, \cdots, \alpha_{jH-1}^0, \overline{\boldsymbol{\alpha}}_j^0, w^0) = EU(\alpha_{j0}, \alpha_{j1}^0, \cdots, \alpha_{jH-1}^0, \overline{\boldsymbol{\alpha}}_j^0, w^0 - \mathrm{CV}_{j0}), \tag{5}$$

where $\overline{\boldsymbol{\alpha}}_j^0 = (\boldsymbol{\alpha}_0^0, \cdots, \boldsymbol{\alpha}_{j-1}^0, \boldsymbol{\alpha}_{j+1}^0, \cdots, \boldsymbol{\alpha}_J^0)$. VSL is commonly defined as the MWTP for the probability of death; thus, we define the VSL when the event X_j occurs as follows:

$$\mathrm{VSL}_j(\boldsymbol{\alpha}^0, w^0) \equiv - \left.\frac{d\mathrm{CV}_{j0}}{d\alpha_{j0}}\right|_{\alpha_{j0} = \alpha_{j0}^0} = \frac{u_H(w^0) - u_{j0}(w^0)}{\lambda(\boldsymbol{\alpha}^0, w^0)}, \tag{6}$$

where

$$\lambda(\boldsymbol{\alpha}^0, w^0) = \sum_{j=1}^{J} \sum_{h=0}^{H-1} \alpha_{jh} u'_{jh}(w^0) + \left(1 - \sum_{j=1}^{J} \sum_{h=0}^{H-1} \alpha_{jh}\right) u'_H(w^0) > 0. \tag{7}$$

Similarly, suppose that the individual is offered a change in the joint probability of the product event $X_j \cap S_k$, i.e., the probability of injury/illness k when the event X_j occurs, from α_{jk}^0 to α_{jk} ($k = 1, \cdots, H-1$). The compensating variation for this change, CV_{jk}, satisfies

$$\begin{aligned} &EU(\alpha_{j0}^0, \alpha_{j1}^0, \cdots, \alpha_{jk}^0, \cdots, \alpha_{jH-1}^0, \overline{\boldsymbol{\alpha}}_j^0, w^0) \\ &\quad = EU(\alpha_{j0}^0, \alpha_{j1}^0, \cdots, \alpha_{jk-1}^0, \alpha_{jk}, \alpha_{jk+1}^0, \cdots, \alpha_{jH-1}^0, \overline{\boldsymbol{\alpha}}_j^0, w^0 - \mathrm{CV}_{jk}). \end{aligned} \tag{8}$$

In the same manner as VSL, we define the VSI of injury/illness k when event X_j occurs as

$$\mathrm{VSI}_{jk}(\boldsymbol{\alpha}^0, w^0) \equiv -\frac{d\mathrm{CV}_{jk}}{d\alpha_{jk}}\bigg|_{\alpha_{jk}=\alpha_{jk}^0} = \frac{u_H(w^0) - u_{jk}(w^0)}{\lambda(\boldsymbol{\alpha}^0, w^0)}. \tag{9}$$

According to the concept of conditional probability, we describe the process of changes in the probability of death and injury/illness due to project implementation. First, let the probability of event X_j be represented as $p_j = P(X_j)$, the conditional probability of S_0^c with the condition that event X_j occurs as $s_j = P(S_0^c|X_j)$, and the conditional probability of event S_k^c with the condition that the product event $X_j \cap S_0^c$ occurs as $r_{jk} = P(S_k^c|X_j \cap S_0^c)$ $(k = 1, \cdots, H-1)$. These are referred to as the hazard probability, conditional probability of survival, and conditional probability of recovering from the injury/illness k in this study. Using these expressions, the probability of death and the probability of injury/illness when event X_j occurs can be expressed as

$$\alpha_{j0} = P(X_j)P(S_0|X_j) = p_j(1 - s_j), \tag{10}$$

$$\alpha_{jk} = P(X_j)P(S_0^c|X_j)P(S_k|X_j \cap S_0^c) = p_j s_j(1 - r_{jk}). \tag{11}$$

If $s_j = 1$, that is, the individual always survives when facing event X_j, then $\alpha_{j0} = 0$ and our model coinsides with a standard model with only injury/illness risk. On the other hand, if $r_{j1} = \cdots = r_{jH-1} = 1$, i.e., the individual always recovers from or does not suffer all the injuries and illnesses when surviving event X_j, then $\alpha_{jk} = 0$ and our model coincides with a standard model with only mortality risk.

Consider a change in probability from (p_j^0, s_j^0, r_j^0) to (p_j^1, s_j^1, r_j^1). Denoting the differences in each probability by $\Delta p_j = -(p_j^1 - p_j^0)$, $\Delta s_j = s_j^1 - s_j^0$, and $\Delta r_{jk} = r_{jk}^1 - r_{jk}^0$, the compensating variation $\mathrm{CV}(\boldsymbol{\delta}_j)$, is defined as

$$EU(\boldsymbol{\alpha}_j^0, \bar{\boldsymbol{\alpha}}_j^0, w) = EU(\boldsymbol{\alpha}_j^1, \bar{\boldsymbol{\alpha}}_j^0, w - \mathrm{CV}(\boldsymbol{\delta}_j)), \tag{12}$$

where $\boldsymbol{\delta}_j = (\Delta p_j, \Delta s_j, \Delta r_{j1}, \cdots, \Delta r_{jH-1})'$,

$$\alpha_{j0}^1 = (p_j^0 - \Delta p_j)(1 - s_j^0 - \Delta s_j), \tag{13}$$

$$\alpha_{jk}^1 = (p_j^0 - \Delta p_j)(s_j^0 + \Delta s_j)(1 - r_{jk}^0 - \Delta r_{jk}), \quad k = 1, \cdots, H-1, \tag{14}$$

$\boldsymbol{\alpha}_j^0 = (\alpha_{j0}^0, \alpha_{j1}^0, \cdots, \alpha_{jH-1}^0)$, and $\boldsymbol{\alpha}_j^1 = (\alpha_{j0}^1, \alpha_{j1}^1, \cdots, \alpha_{jH-1}^1)$. In addition, if and only if $\boldsymbol{\delta}_j = \mathbf{0}$, then $\alpha_{j0}^1 = \alpha_{j0}^0$ and $\alpha_{jk}^1 = \alpha_{jk}^0$ hold for all k.

The compensating variation based on the expected utility in Eq. (12) is often called the option price. Other welfare measures in the presence of risk include the expected surplus, defined as the expected value of the compensating variation in each state, and the option value, defined as the option price minus the expected surplus. For example, Graham (1981) presented a theoretical relationship between option prices, expected surplus, and option values, which was also introduced by Boardman et al. (2014). However, because we assume that the public project only affects the probability of death or injury/illness and does not affect the state-by-state utility, the expected surplus is zero, and the op-tion value is equal to the option price.

Lett b_j be the first-order approximation value of the compensating variation, defined in Eq. (12) with $\boldsymbol{\delta}_j = \mathbf{0}$, which explicitly includes VSL and VSI and depends on death and types of injuries/ill-nesses, as well as the event that causes them, we then have

$$b_j = \omega_j^p \Delta p_j + \omega_j^s p_j^0 \Delta s_j + \sum_{k=1}^{H-1} \omega_{jk}^r p_j^0 s_j^0 \Delta r_{jk}\,, \tag{15}$$

where

$$\omega_j^p = (1 - s_j^0)\mathrm{VSL}_j + \sum_{k=1}^{H-1} s_j^0 (1 - r_{jk}^0)\mathrm{VSI}_{jk}\,, \tag{16}$$

$$\omega_j^s = \mathrm{VSL}_j - \sum_{k=1}^{H-1} (1 - r_{jk}^0)\mathrm{VSI}_{jk}\,, \tag{17}$$

$$\omega_{jk}^r = \mathrm{VSI}_{jk}, \qquad k = 1, \cdots, H-1. \tag{18}$$

Eq. (15) expresses the private or per capita benefits of a project or policy. By using $\bar{N}$ to denote the number of people potentially enjoying the project or policy and defining $\Delta N_j^p \equiv \bar{N}\Delta p_j$, $\Delta N_j^s \equiv \bar{N} p_j^0 \Delta s_j$ and $\Delta N_j^r \equiv \bar{N} p_j^0 s_j^0 \Delta r_{jk}$, the total benefit B_j is represented as follows:

$$B_j \equiv \bar{N} b_j = \omega_j^p \Delta N_j^p + \omega_j^s \Delta N_j^s + \sum_{k=1}^{H-1} \omega_{jk}^r \Delta N_{jk}^r\,, \tag{19}$$

where ΔN_j^p is a decrease in the number of individuals facing event X_j, ΔN_j^s is an increase in the num-ber of individuals facing event X_j and surviving event X_j, and ΔN_{jk}^r is an increase in the number of individuals facing event X_j and recovering from the injury/illness k. Eqs. (16)–(18) can be regarded as the values for the unit benefits associated with those changes. First, ω_j^p denotes the benefits from one less individual facing event, X_j. If an individual was to face that event, the individual would not survive with probability $1 - s_j^0$. Furthermore, if an individual was to survive that event with probabil-ity s_j^0, the individual would suffer injury/illness k with probability $1 - r_{jk}^0$. That is, when an individual encounters event X_j, the individual may die, or the individual may survive event X_j and still suffer injuries or illnesses. One less individual facing event X_j generates benefits $(1 - s_j^0)\mathrm{VSL}_j$ from the for-mer risk reduction and benefits $s_j^0(1 - r_{jk}^0)\mathrm{VSI}_{jk}$ from the latter risk reduction. Consequently, the unit benefit of the one less individual facing event X_j depends on both VSL and VSI and is given by Eq. (16). Second, ω_j^s represents the benefit from one more individual surviving event X_j. If one more in-dividual survives on the condition that event X_j occurs, the conditional benefits increase by VSL_j but decrease by $(1 - r_{jk}^0)\mathrm{VSI}_{jk}$ because the individual is at risk of injury/illness after survival. Finally, ω_{jk}^r is the benefit from one more individual recovering from the injury/illness k on the condition that the individual faces event X_j and survives. The conditional benefits are equal to VSI_{jk}.

In the subsequent sections, we assume that individual data are available for individuals facing an event X_j with a given hazard probability and that $\Delta p_j = 0$, i.e., the project or policy does not affect the hazard probability. In addition, we consider the case where $H = 2$ and S_1 is the event in which the individual suffers from severe disability. Subsequently, the approximate value of the total benefit is

$$B_j = \omega_j^s \Delta N_j^s + \omega_{j1}^r \Delta N_{j1}^r. \tag{20}$$

To set ω_j^s and ω_j^r in the measurement of this benefit, it is necessary to obtain the estimates of VSL_j and VSI_{j1}. If these are not available, it is possible to adopt a benefit transfer from VSL_l and VSI_{l1} corresponding to event X_l different from event X_j. However, it should be noted that from Eqs. (6) and (9), such a transfer is valid if and only if $u_{j0}(w^0) = u_{l0}(w^0)$ and $u_{j1}(w^0) = u_{l1}(w^0)$ hold; that is, the utility of death and the utility of severe disability are the same regardless of events X_j and X_l, because we deduce that

$$\frac{\mathrm{VSL}_j(\boldsymbol{\alpha}^0, w^0)}{\mathrm{VSL}_l(\boldsymbol{\alpha}^0, w^0)} = \frac{u_H(w^0) - u_{j0}(w^0)}{u_H(w^0) - u_{l0}(w^0)}, \tag{21}$$

$$\frac{\mathrm{VSI}_{j1}(\boldsymbol{\alpha}^0, w^0)}{\mathrm{VSI}_{l1}(\boldsymbol{\alpha}^0, w^0)} = \frac{u_H(w^0) - u_{j1}(w^0)}{u_H(w^0) - u_{l1}(w^0)}. \tag{22}$$

Carthy et al. (1999) obtained a similar expression for estimating VSL using the contingent valuation method and the standard gamble method in a different context. Eqs. (21) and (22) imply that the event that causes greater utility loss results in greater VSL or VSI. Furthermore, to set ΔN_j^s and ΔN_j^r in Eq. (20), both s_j^0, r_{j1}^0 and s_j^1, r_{j1}^1 should also be estimated using the available individual data, so that the statistical analysis required for this purpose is described later, although it is implicitly assumed that p_j^0 can be replaced by the empirical probability of facing event X_j.

3. A binary response model with sample selection

Suppose that we have a large amount of individual data to determine whether an individual facing an event with a known probability of occurrence X_j survives or recovers, that is, rehabilitated, within a certain period. Since rehabilitation presupposes survival, these individual data have the property that survival and rehabilitation are not considered to be uncorrelated. Furthermore, because the state of rehabilitation is not formally observed for deceased individuals, the data for that part of the population can be missing. This study estimated a binary response model with survival and rehabilitation as binary response variables from individual data with these characteristics, whereby we predicted changes in the probability of survival and rehabilitation due to projects and policies.

In a case where there is a correlation between survival and rehabilitation, it is not plausible to take a simple approach, such as estimating whether the patient survived from the full sample, then estimating whether the patient returned to society from only the survival samples using a standard binary response model individually. If such a procedure is adopted without ensuring non-correlation, sample selection bias arises (Heckman, 1979), which incurs inconsistency in the estimators of parameters, and thus, the results of the analysis lose their reliability. To avoid this problem, it is necessary to incorporate a selection mechanism into the binary response model. In the following, we construct a sample selection model whose structure is also described by a binary response model.

First, the binary response variable that represents whether individual i survived after facing event X_j, is expressed as z_i. If event S_0 occurs in individual i who faced event X_j (i.e., if the individual i who faced event X_j died), then $z_i = 0$, and when event S_0^c occurs in individual i who faced event X_j (i.e., if the individual facing event X_j survived), then $z_i = 1$. Meanwhile, the binary response variable that indicates whether individual i facing event X_j was rehabilitated is represented as y_i. If event S_1 occurs in individual i who survived event X_j (i.e., the individual i who faced event X_j is severely disabled), then $y_i = 0$, and if event S_1^c occurs in individual i in the face of event X_j (i.e., when the individual i who survived in the face of event i returns to society), then $y_i = 1$. However, y_i is observed only when $z_i = 1$ and not when $z_i = 0$, so it is possible to consider that the y_i data when $z_i = 0$ are missing.

Based on the above, we formulated a binary response model in this study. If y_i^* and z_i^* are the latent continuous variables of y_i and z_i, respectively, and assuming that both are linearly specified, they are expressed as:

$$y_i^* = \mathbf{x}_i'\boldsymbol{\beta} + u_i, \quad y_i = I(y_i^* > 0)z_i, \tag{23}$$

$$z_i^* = \mathbf{w}_i'\boldsymbol{\gamma} + v_i, \quad z_i = I(z_i^* > 0), \tag{24}$$

$$\begin{bmatrix} u_i \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right), \tag{25}$$

where $\mathbf{x}_i$ and $\mathbf{w}_i$ are the covariate vectors of y_i^* and z_i^*, respectively, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the coefficient vectors of $\mathbf{x}_i$ and $\mathbf{w}_i$. $I(\cdot)$ denotes the indicator function, which is 1 if the parentheses are true and 0 otherwise. The error term vector $(u_i, v_i)'$ is assumed to be independent of $(\mathbf{x}_i', \mathbf{w}_i')'$ and follows a bivariate normal distribution with zero means, unit variances, and correlation coefficient ρ. In such modeling, if $\rho = 0$, implying that u_i and v_i are independent of each other, there is no sample-selection bias. It would also be possible to use a semi-nonparametric distribution that relaxes the normal distribution condition in Eq. (25) and does not assume a specific distribution in the above framework (see Gallant & Nychka, 1987; Melenberg & von Soest, 1996; Stewart, 2005). However, from the perspective of the statistical properties of the estimator and ease of handling in the predictor, that is, the predicted probability described later, we will only mention and not pursue it in this paper.

Next, since y_i represents the outcome of whether individual i who survived facing event X_j eventually rejoined society, Eq. (23) is called the outcome equation. Meanwhile, Eq. (24) is called a selection equation because it describes the selection process of whether the survival of individual i who faced event X_j is realized, which is a precondition for return to society. Considering the characteristics of objective individual data, a binary response model incorporating sample selection can be constructed and expressed as a bivariate probit model from Eq. (25). Although our modeling is, therefore, a two-equation system of binary response models, it has a useful property in numerical calculations that the conditional probability required for the likelihood function is relatively simplified, as will be clarified later. This point also plays an essential role in estimating the changes in the probabilities of rehabilitation and survival based on the above model, which is key to the theoretical framework described in the previous section.

From Eqs. (23)–(25), the probability of each event for individual i is derived as follows:

$$\pi_{11i}(\boldsymbol{\theta}) = \mathrm{P}(y_i = 1, z_i = 1 | \mathbf{x}_i, \mathbf{w}_i; \boldsymbol{\theta}) = \Phi_2(\mathbf{x}_i'\boldsymbol{\beta}, \mathbf{w}_i'\boldsymbol{\gamma}; \rho), \tag{26}$$

$$\pi_{10i}(\boldsymbol{\theta}) = \mathrm{P}(y_i = 1, z_i = 0 | \mathbf{x}_i, \mathbf{w}_i; \boldsymbol{\theta}) = \Phi_2(\mathbf{x}_i'\boldsymbol{\beta}, -\mathbf{w}_i'\boldsymbol{\gamma}; -\rho), \tag{27}$$

$$\pi_{01i}(\boldsymbol{\theta}) = \mathrm{P}(y_i = 0, z_i = 1 | \mathbf{x}_i, \mathbf{w}_i; \boldsymbol{\theta}) = \Phi_2(-\mathbf{x}_i'\boldsymbol{\beta}, \mathbf{w}_i'\boldsymbol{\gamma}; -\rho), \tag{28}$$

$$\pi_{00i}(\boldsymbol{\theta}) = \mathrm{P}(y_i = 0, z_i = 0 | \mathbf{x}_i, \mathbf{w}_i; \boldsymbol{\theta}) = \Phi_2(-\mathbf{x}_i'\boldsymbol{\beta}, -\mathbf{w}_i'\boldsymbol{\gamma}; \rho), \tag{29}$$

where $\Phi_2(\cdot)$ represents the cumulative distribution function (cdf) of the bivariate standard normal distribution, and $\boldsymbol{\theta} = (\boldsymbol{\beta}', \boldsymbol{\gamma}', \rho)'$ is the unknown parameter vector. Based on Eqs. (26)–(29), the log-likelihood function is

$$\ln L(\boldsymbol{\theta}) = \sum_{z_i=0} \ln\{\pi_{10i}(\boldsymbol{\theta}) + \pi_{00i}(\boldsymbol{\theta})\} + \sum_{z_i=1}\sum_{y_i=0} \ln \pi_{01i}(\boldsymbol{\theta}) + \sum_{z_i=1}\sum_{y_i=1} \ln \pi_{11i}(\boldsymbol{\theta}). \tag{30}$$

Given that $\Phi(\cdot)$ is the cdf of the univariate standard normal distribution, it is easily seen that the relation $\pi_{10i}(\boldsymbol{\theta}) + \pi_{00i}(\boldsymbol{\theta}) = \Phi(-\mathbf{w}_i'\boldsymbol{\gamma})$ holds. Hence, by maximizing Eq. (30), we derive the maximum likelihood estimator of $\boldsymbol{\theta}$; i.e., $\widehat{\boldsymbol{\theta}} = \arg\max \ln L(\boldsymbol{\theta})$. Then, using estimator $\widehat{\boldsymbol{\theta}}$, we can obtain the predictor (predicted probability) of Eqs. (26)–(29), which makes it possible to estimate the change in the probabilities of rehabilitation and survival from individual data. Further details about this will be discussed in Section 5.

However, because the system consisting of Eqs. (23)–(25) is nonlinear, the parameters can be identified even if appropriate so-called exclusion restrictions are not imposed; however, it is known that parameter estimates can be unstable and unreliable. As discussed in Wooldridge (2010), for example, it would thus be recommended that at least one variable in $\mathbf{w}_i$ should be excluded from $\mathbf{x}_i$. In addition, regarding further extensibility, it should be noted that the modeling was limited to two survival states. However, it can easily be generalized to an ordered response model applicable to the possible existence of multiple states, where the outcome equation is assumed to have an ordinal form. For example, since Eqs. (23) and (24) are reduced to a bivariate probit model, even as an ordered response-dependent variable, the likelihood function, as in Eq. (30), can be constructed from the probabilities corresponding to Eqs. (26)–(29) in the present context, using a similar procedure.

4. Estimation using Utstein style data

With this framework, this study considers event X_j, in which an individual with an out-of-hospital cardiopulmonary arrest is transported by ambulance. Individuals who experience this event face the risk of death or severe disability; therefore, Utstein-style data were used in the estimation of the binary response model in the previous section.

4.1 Data Description

The Utstein-style data are a collection of individual data on out-of-hospital cardiopulmonary arrest patients transported to the hospital by EMS based on international standards, which have been collected nationwide in Japan since 2004 by the Fire and Disaster Management Agency of the Ministry of Internal Affairs and Communications. These data can be divided into the following major categories: "Witness of cardiac arrest," "Bystander CPR," "Initial cardiac rhythm," "Details of emergency life-saving treatment," "Time interval," "Presumed causes of cardiac arrest," and "Outcome and prognosis." "Outcome and prognosis" is based on the Glasgow-Pittsburgh Cerebral and Overall Performance Categories, which are internationally used to evaluate the quality of life of patients with cardiopulmonary arrest. After one month, the patients' cerebral performance categories (CPC) and overall performance categories (OPC) were classified as good performance, moderate disability, severe disability, coma, and death or brain death. The Fire and Disaster Management Agency of the Ministry of Internal Affairs and Communications (2013) deems survival if the CPC and OPC after one month are good performance, moderate disability, severe disability, or coma, and rehabilitation if those after one month are either good performance or moderate disability. Therefore, in this paper, the period assumed in the theoretical model is one month, and if an individual is alive according to the above definition, we consider that a conditional event $\left(S_0^c|X_j\right)$ has occurred to them, and if the individual corresponds to rehabilitation, we consider that the conditional event $\left(S_1^c|X_j \cap S_0^c\right)$ has occurred.

Figure 1 shows the flow of the extraction process of the Utstein-style data, and we used data from 2012 in this study. The number of patients who were transported by ambulance due to out-of-hospital cardiopulmonary arrest, that is, the number of patients who experienced the event X_j, was 121,392 out of 126 million people in Japan. Of these, 6,210 were survivors, that is, they experienced the conditional event $\left(S_0^c|X_j\right)$. Moreover, 3,377 patients among the survivors returned to society, that is, they the experienced the event $\left(S_1^c|X_j \cap S_0^c\right)$. The 115,182 patients who did not survive were treated as having missing data on their rehabilitation status. Table 1 shows the description and summary statistics for

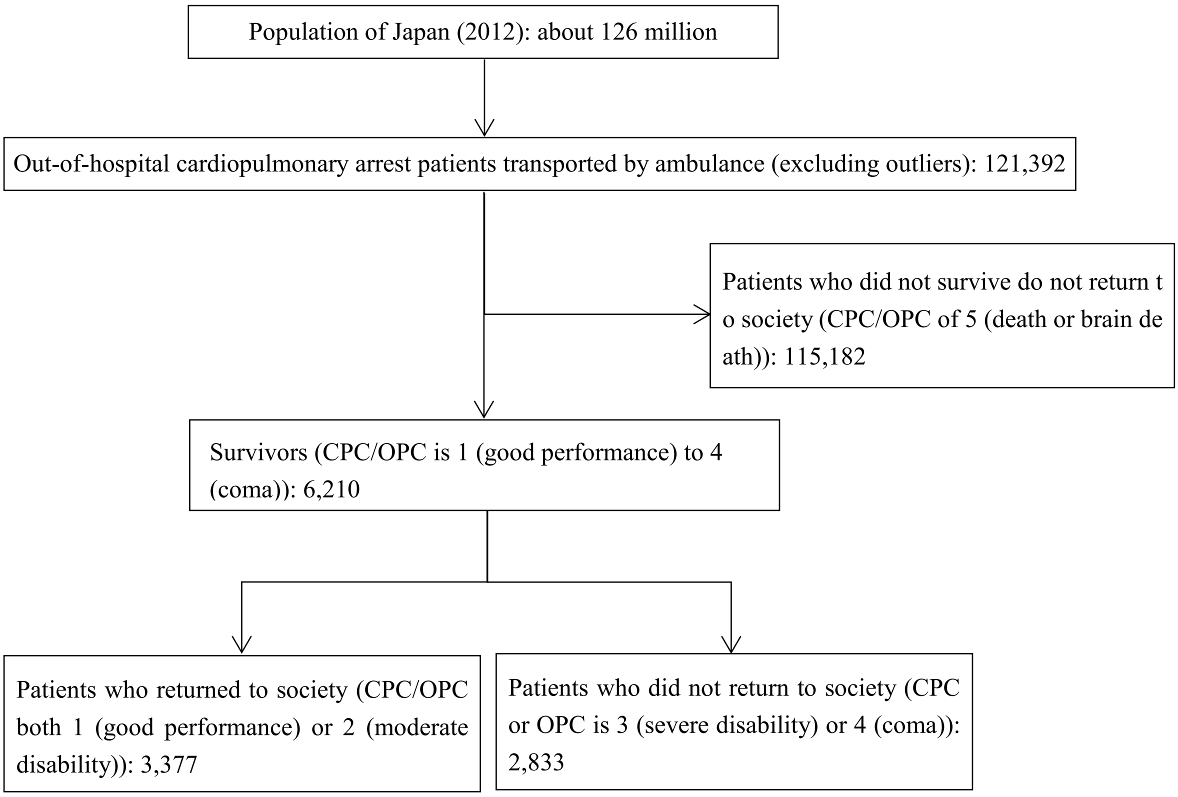

Figure 1: Flow diagram of data extraction process for analysis

variables generated from the Utstein-style data for analysis, the full sample, and the sample that survived for one month. First, 1MS and SR are the dependent variables in the binary response model. 1MS is a dummy variable for whether the patient survived for one month, and it corresponds to z_i. SR is a dummy variable for whether the one-month survivor returned to society and corresponds to y_i. In the following, we explain covariates $\mathbf{x}_i$ and $\mathbf{w}_i$ of the binary response model.

ETT1 and ETT2 are data related to the time intervals of the EMS transport. ETT1 is the time interval from ambulance call to arrival at the patient's side; the shorter the ETT1, the quicker the medical treatment started. In this study, we include ETT1 as a covariate $\mathbf{x}_i$ in the outcome equation, based on the hypothesis that early initiation of medical treatment facilitates patient rehabilitation. On the other hand, the covariate $\mathbf{w}_i$ in the selection equation is not ETT1 but ETT2, which represents the time interval from ambulance call to hospital arrival. This implies that the hypothesis is that early hospital admission promotes patient survival. However, because ETT2 is the time interval between ambulance call and hospital arrival added to ETT1, if this hypothesis is correct, the early start of medical treatment will also promote patient survival. In addition to the means and standard deviations in Table 1, the medians of ETT1 and ETT2 are 8 and 30 min, respectively, while the maximum values

Table 1 Variable descriptions and summary statistics

Variable	Description	Full sample		Survival sample	
		Mean	SD	Mean	SD
1MS	Dummy for 1-month survival after cardiac arrest	0.051	0.220	—	—
SR	Dummy for social rehabilitation among 1-month survivors	—	—	0.544	0.498
ETT 1	Time interval from ambulance call to patient's side arrival (min)	9.210	7.123	8.150	3.641
ETT 2	Time interval from ambulance call to hospital arrival (min)	34.27	17.35	34.20	18.17
Witness	Dummy for witnessed arrest by bystanders or EMS personnel	0.407	0.491	0.796	0.403
Sex	Dummy for male	0.432	0.495	0.334	0.472
Young	Dummy for age 18 years or younger	0.014	0.116	0.037	0.190
Old	Dummy for age 81 years or older	0.440	0.496	0.242	0.429
ELST	Dummy for emergency life-saving technicians in ambulance	0.976	0.152	0.980	0.139
Doctor	Dummy for medical doctors in ambulance	0.029	0.169	0.068	0.252
ACLS	Dummy for advanced cardiac life support by a medical doctor	0.075	0.263	0.100	0.300
CC	Dummy for chest compressions by a bystander	0.441	0.496	0.467	0.499
RB	Dummy for rescue breathing by a bystander	0.080	0.271	0.112	0.315
AED	Dummy for the use of an AED by a bystander	0.013	0.113	0.057	0.231
VF/VT	Dummy for ventricular fibrillation or pulseless ventricular tachycardia as initial cardiac rhythm	0.066	0.248	0.348	0.476
PEA	Dummy for pulseless electrical activity as initial cardiac rhythm	0.209	0.406	0.275	0.446
Asystole	Dummy for asystole as initial cardiac rhythm	0.682	0.466	0.139	0.346
DFEP	Dummy for defibrillation by EMS personnel	0.096	0.294	0.391	0.488
CO	Dummy for presumed cardiac origin	0.139	0.346	0.337	0.473
CVD	Dummy for cerebrovascular diseases	0.036	0.187	0.037	0.190
RD	Dummy for respiratory diseases	0.062	0.240	0.075	0.263
MT	Dummy for malignant tumors	0.035	0.184	0.004	0.066
EXC	Dummy for external causes	0.160	0.367	0.141	0.348
Other	Dummy for other non-cardiac origin	0.130	0.336	0.106	0.308
	Sample size	121392		6210	

are 1414 and 1423 min (the minimum values are both 0 min). These data are considered to have a rather distorted and long right-tailed distribution. To reduce the possible influence of skewness, the data were log-transformed by adding 1 to them, denoted as lnETT1 and lnETT2, respectively. However, the validity of using logarithmic transformation for the time variables is discussed in the next section from the model selection perspective. "Witness" is a dummy variable for whether a bystander witnessed the patient's cardiac arrest. The mean for the full sample was 0.407, while that for the survivors was 0.796, which was extremely high, indicating that a bystander witnessing a cardiac arrest is important for the patient's life. This is because if a bystander witnesses cardiac arrest, the patient is acknowledged soon after the incident without being neglected. "Sex," "Young," and "Old" are dummy variables for individual attributes. "Sex" is a dummy variable related to gender and is set to 1 if the subject is female. "Young" and "Old" are dummy variables related to age. Following Nishiuchi et al. (2008), we divided age into three categories: 18 years old or younger, 19 to 80 years old, and 81 years old or older. Then, dummy variables were set based on the age group between 19 and 80 years. "ELST" and "Doctor" are dummy variables related to the EMS system. "ELST" and "Doctor" are dummy variables for the presence of emergency life-saving technicians and medical doctors in the ambulance, respectively. In addition, "ACLS" is a dummy variable for whether a medical doctor provided advanced cardiac life support. "CC," "RB," and "AED" are dummy variables for the bystander's first aid treatment. CC and RB are dummy variables for whether the bystander performed chest compressions or rescue breathing, respectively. The AED is a dummy variable for whether the bystander used an AED. A dummy variable for whether EMS personnel performed defibrillation is denoted by "DFEP." "VF/VT," "PEA," and "Asystole" are dummy variables for the initial cardiac rhythm, indicating whether it showed ventricular fibrillation or pulseless ventricular tachycardia, pulseless electrical activity, or asystole, respectively. "CO," "CVD," "RD," "MT," "EXC," and "Other" are dummy variables for the presumed cause of cardiac arrest. Dummy variables were assigned to the presumed cardiac origin, cerebrovascular diseases, respiratory diseases, malignant tumors, external causes, and other non-cardiac causes, where cardiac origin by the exclusion diagnosis was regarded as the reference category.

As mentioned above, from the viewpoint of parameter identifiability, it is recommended to exclude at least one variable in $\mathbf{w}_i$ from $\mathbf{x}_i$. This study used variables other than covariate-based EMS transport time in the selection and outcome equations. However, among the variables related to the EMS transport time, the time interval between ambulance call and arrival at the patient's side (ETT1) was used only in the outcome equation, and the time interval from ambulance call to hospital arrival (ETT2) was used only in the selection equation to maintain the stability and reliability of the parameter estimates.

4.2 Estimation results

Table 2 shows the results of estimating the bivariate probit model with sample selection using the Utstein-style data. Standard errors are computed using a robust variance matrix estimator (e.g., White, 1982). First, the correlation coefficient ρ between the error terms is estimated significantly at the 1% level, indicating that estimating the selection and outcome equations separately would lead to a sample selection bias problem, as expected. It is easily seen from the Wald statistic that the null hypothesis that all coefficients are zero ($\mathrm{H}_0\colon \boldsymbol{\beta} = \mathbf{0}$) is rejected at the 1% significance level.

Regarding EMS transport time, the coefficient estimate of lnETT1 in the outcome equation is neg

Table 2 Estimation results for the probit model with sample selection

Variable	Selection equation		Outcome equation	
	Coefficient	SE	Coefficient	SE
lnETT 1	—	—	-0.160 ***	0.043
lnETT 2	-0.222 ***	0.023	—	—
Witness	0.410 ***	0.018	0.389 ***	0.048
Sex	-0.003	0.016	-0.055 *	0.033
Young	0.601 ***	0.045	0.273 ***	0.103
Old	-0.289 ***	0.017	-0.317 ***	0.040
ELST	0.053	0.051	-0.162	0.113
Doctor	0.315 ***	0.039	0.037	0.084
ACLS	-0.047	0.030	-0.054	0.063
CC	0.113 ***	0.016	0.103 ***	0.034
RB	0.024	0.026	0.056	0.051
AED	0.439 ***	0.043	0.557 ***	0.076
VF/VT	-0.226 ***	0.036	-0.505 ***	0.069
PEA	-0.845 ***	0.023	-1.164 ***	0.049
Asystole	-1.525 ***	0.026	-1.893 ***	0.085
DFEP	0.176 ***	0.031	0.070	0.068
CO	0.348 ***	0.019	0.488 ***	0.041
CVD	0.062	0.040	-0.255 ***	0.091
RD	0.376 ***	0.029	-0.200 *	0.105
MT	-0.704 ***	0.085	-0.684 ***	0.245
EXC	0.274 ***	0.023	-0.169 **	0.082
Other	0.144 ***	0.025	0.038	0.057
Correlation (ρ)	0.593 (0.000)			
Log-likelihood	-21228.4			
Wald	2007.6 (0.000)			

Note 1: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Note 2: Figures in parentheses indicate P-values.

ative and significant at the 1% level, which supports the hypothesis that early initiation of medical treatment facilitates the rehabilitation of patients. In addition, the coefficient estimate of lnETT2 is negative and significant at the 1% level in the selection equation, which supports the hypothesis that early hospital admission promotes patient survival. Therefore, reducing the time between an ambulance call and arrival at the patient’s side may improve survival and rehabilitation.

Regarding the control variables other than the time variables, first, the coefficient estimate of Witness is significantly positive at the 1% level, indicating that when a bystander witnesses the patient's cardiac arrest, the likelihood of survival and rehabilitation is high. Furthermore, the result that the coefficient estimate of Sex is negative and significant at the 10% level only in the outcome equation suggests that men are more likely to return to society. For the age variables, the coefficient estimates for Young and Old are significant at the 1% level. However, the coefficient for Young is negative, indicating that the likelihood of survival and rehabilitation is higher when younger than 18 years old. In contrast, the coefficient for Old is positive, indicating that the likelihood of survival and rehabilitation is higher when the age is less than 81 years, which is consistent with intuition. Concerning the ambulance system, the coefficient estimates for ELST and ACLS were insignificant, and the coefficient estimate for Doctor was significantly positive at the 1% level only in the selection equation. This suggests that the chance of survival increases when a doctor is on board an ambulance. For bystander first aid, both CC and AED were significant and positive at the 1% level, but RB was not significant. Therefore, chest compressions and AED use by bystanders can effectively improve survival and rehabilitation. As expected, the estimated coefficient of DFEP was significantly positive only for the selection equation, indicating that defibrillation by EMS personnel influences survival and mortality. Regarding the initial cardiac rhythm, the coefficient estimates for VF/VT, PEA, and systole were all negative and significant at the 1% level. Thus, the initial cardiac rhythm of ventricular fibrillation, pulseless ventricular tachycardia, pulseless electrical activity, and asystole are associated with a low probability of survival and return to society. The presumed causes of cardiac arrest yielded different results for different equations. In the selection equation, the coefficient estimates for all variables except CVD, which represents cerebrovascular disease, are significant at the 1% level, while those for CO, RD, EXD, and Other are positive, and those for MT are negative. Thus, the likelihood of survival was high for presumed cardiac origin, respiratory diseases, external causes, and other non-cardiogenic causes but low for malignant tumors. In the outcome equation, the estimated coefficients were significant, except for Other, representing other cardiogenic causes (at the 5% level for EXD and the 10% level for RD), but CO was positive. At the same time, CVD, MT, EXD, and RD were negative, suggesting that the likelihood of returning to society was high for presumed cardiac origin but low for cerebrovascular diseases, respiratory diseases, malignant tumors, and exogenous causes.

Furthermore, for comparison, Table 3 reports the results of estimating the selection equations for the full sample ($N = 121392$) and the outcome equation for the survival sample ($N = 6210$) only, assuming separate univariate probit models, without considering the sample selection mechanism. However, this approach may have selection bias, as mentioned above. Although the coefficient estimates and significance of the selection equation are almost the same as in Table 2, the coefficient of lnETT1 is slightly overestimated in the outcome equation, and the coefficients of Young, CC, and MT are no longer significant. In particular, even the sign of the Young coefficient is reversed, indicating that bias is incurred by ignoring sample selection. In addition, Table A2 in the Appendix shows the same estimation results using ETT1 and ETT2 without the log transformation of the time variables. However, the coefficient estimate of ETT1, an essential variable in our model, is no longer survival

Table 3 Estimation results for each probit model without considering sample selection

Variable	Selection equation		Outcome equation	
	Coefficient	SE	Coefficient	SE
lnETT 1	—	—	-0.135 ***	0.050
lnETT 2	-0.224 ***	0.022	—	—
Witness	0.410 ***	0.018	0.229 ***	0.043
Sex	-0.003	0.016	-0.063 *	0.038
Young	0.596 ***	0.045	-0.003	0.088
Old	-0.289 ***	0.017	-0.214 ***	0.043
ELST	0.054	0.051	-0.216 *	0.127
Doctor	0.315 ***	0.039	-0.109	0.082
ACLS	-0.046	0.030	-0.029	0.071
CC	0.112 ***	0.016	0.054	0.037
RB	0.023	0.026	0.054	0.058
AED	0.437 ***	0.043	0.421 ***	0.085
VF/VT	-0.227 ***	0.036	-0.487 ***	0.075
PEA	-0.845 ***	0.023	-0.912 ***	0.050
Asystole	-1.525 ***	0.026	-1.368 ***	0.062
DFEP	0.176 ***	0.031	-0.010	0.073
CO	0.348 ***	0.019	0.383 ***	0.045
CVD	0.062	0.040	-0.342 ***	0.094
RD	0.376 ***	0.029	-0.452 ***	0.074
MT	-0.703 ***	0.085	-0.393	0.286
EXC	0.274 ***	0.023	-0.358 ***	0.059
Other	0.144 ***	0.025	-0.038	0.062
Correlation (ρ)	—		—	
Log-likelihood	-17656.6		-3576.1	
Wald	10818.3 (0.000)		1249.2 (0.000)	

Note 1: *** and * indicate significance at the 1% and 10% levels, respectively.

Note 2: Figures in parentheses indicate P-values.

significantly different from zero in the negative direction. This comparison reveals that capturing the and mortality processes in a sample selection mechanism, which would avoid bias in the estimation, plays a substantial role.

Next, to investigate the appropriateness of applying a log transformation to the time variables ETT1 and ETT2 in terms of model selection, the sample selection bivariate probit model was estimated using ETT1 and ETT2 instead of lnETT1 and lnETT2, and the results are provided in Table A1 in the Appendix. Compared to the results in Table 2, the coefficient estimates for ETT1 and ETT2 are smaller in absolute value in both equations. However, the coefficient estimates for the other variables that can be considered control variables do not change significantly, and their significance does not differ substantially, except for a few variables. However, ETT1 in the outcome equation dropped to the 10% significance level, possibly due to the severely distorted distributions of the abovementioned time variables. Since this study aims to obtain predicted probabilities, considering that these two specifications are non-nested, we examine the logarithmic transformation from a model selection using two information criteria: AIC (Akaike, 1973) and BIC (Schwarz, 1978). Each information criterion, which can be easily calculated from the log-likelihood in Table 2 using lnETT1 and lnETT2 as time variables, is $AIC = 42546.7$ and $BIC = 42983$, and those for Table A1, which uses ETT1 and ETT2 without log transformation, is $AIC = 42636.0$ and $BIC = 43072.8$. Therefore, we can see that the model with log transformation on the time variable is preferable and supported from the viewpoint of model selection based on the information criterion. It follows from the above that the benefits measurement in the next section employs the estimation results in Table 2; that is, the predicted probabilities obtained by modeling with logarithmic time variables.

5. Measurement of benefits

Using the estimation results in the previous section, we attempted to measure the benefits of a hypothetical public project. Specifically, we focus on the time interval from ambulance call to arrival at the patient's side and measure the benefit of a public project that reduces that time by one minute. As previously mentioned, if the time interval between an ambulance call and arrival at the patient's side is shortened, medical treatment can be initiated quickly, and the probability of survival and rehabilitation can be improved. Examples of public projects that shorten this time interval include the introduction of emergency medical helicopters and the construction of roads. If a helicopter can access a patient needing medical help, the transport time can be reduced significantly compared to land transport by ambulance. The construction of highways and other public facilities also leads to quicker access to patients.

It was shown from the estimation results that a reduction in the time from ambulance call to arrival at the patient's side improves survival and rehabilitation. However, to measure the benefits, we need to estimate how much the probability of survival and probability of rehabilitation increase with a reduction in the time from ambulance call to arrival at the patient's side. To this end, we consider a case in which this time interval is reduced by Δt min for all samples, resulting in a reduction of Δt min from ambulance call to hospital arrival. Thus, for all i, we subtracted Δt from ETT1 and ETT2, and the new vectors of covariates are expressed as $\mathbf{x}_i^*(\Delta t)$ and $\mathbf{w}_i^*(\Delta t)$. Then, for all i, $\mathbf{x}_i$ is replaced with $\mathbf{x}_i^*(\Delta t)$, and $\mathbf{w}_i$ with $\mathbf{w}_i^*(\Delta t)$, and using the estimates from the previous section $\widehat{\boldsymbol{\theta}} = (\widehat{\boldsymbol{\beta}}', \widehat{\boldsymbol{\gamma}}', \hat{\rho})'$ we can obtain the following predicted probabilities that individual i are saved:

$$\pi_{11i}(\widehat{\boldsymbol{\theta}}, \Delta t) = \Phi_2(\mathbf{x}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\beta}}, \mathbf{w}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\gamma}}; \hat{\rho}), \tag{31}$$

$$\pi_{01i}(\widehat{\boldsymbol{\theta}}, \Delta t) = \Phi_2(-\mathbf{x}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\beta}}, \mathbf{w}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\gamma}}; -\hat{\rho}). \tag{32}$$

From Eqs. (31) and (32), for the case where both ETT1 and ETT2 were reduced by Δt min for all samples, the predicted probabilities of survival and rehabilitation can be defined as follows:

$$\hat{s}_j(\Delta t) = \frac{1}{N}\sum_{i=1}^{N}\{\pi_{11i}(\widehat{\boldsymbol{\theta}}, \Delta t) + \pi_{01i}(\widehat{\boldsymbol{\theta}}, \Delta t)\} = \frac{1}{N}\sum_{i=1}^{N}\Phi(\mathbf{w}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\gamma}}), \tag{33}$$

$$\hat{r}_{j1}(\Delta t) = \frac{1}{N}\sum_{i=1}^{N}\frac{\pi_{11i}(\widehat{\boldsymbol{\theta}}, \Delta t)}{\pi_{11i}(\widehat{\boldsymbol{\theta}}, \Delta t) + \pi_{01i}(\widehat{\boldsymbol{\theta}}, \Delta t)} = \frac{1}{N}\sum_{i=1}^{N}\frac{\pi_{11i}(\widehat{\boldsymbol{\theta}}, \Delta t)}{\Phi(\mathbf{w}_i^{*'}(\Delta t)\,\widehat{\boldsymbol{\gamma}})}. \tag{34}$$

Assuming a public project that reduces the time interval from ambulance call to arrival at the patient's side by one minute, the survival and rehabilitation probabilities before and after the implementation of this project, as well as the increase in each of these probabilities, are predicted as follows:

$$\hat{s}_j^0 = \hat{s}_j(0) = 0.0512335, \qquad \hat{s}_j^1 = \hat{s}_j(1) = 0.0518110, \qquad \Delta\hat{s}_j = 0.0005775, \tag{35}$$

$$\hat{r}_{j1}^0 = \hat{r}_{j1}(0) = 0.2734664, \qquad \hat{r}_{j1}^1 = \hat{r}_{j1}(1) = 0.2788709, \qquad \Delta\hat{r}_{j1} = 0.0054045. \tag{36}$$

In 2012, the total population of Japan was about 126 million, that is, $\overline{N} = 126 \cdot 10^6$, and 121,392 cardiopulmonary arrest patients were transported by ambulance per year, which allows us to easily obtain the estimated hazard probability as the empirical probability given by $\hat{p}_j^0 = 0.00096$. Thus, if this hypothetical project is implemented, the increment of survival and rehabilitation per year are calculated as

$$\Delta\widehat{N}_j^s = \overline{N}\hat{p}_j^0\Delta\hat{s}_j \approx 70, \tag{37}$$

$$\Delta\widehat{N}_j^r = \overline{N}\hat{p}_j^0\hat{s}_j^0\Delta\hat{r}_{j1} \approx 33. \tag{38}$$

Multiplying these values by unit benefits yields the total benefit B_j as in Eq. (20).

Next, we set the unit benefits of Eqs. (16)–(18) using the benefit transfer approach. Although there are few studies on VSL estimates in Japan, Tsuge et al. (2005) and Itaoka et al. (2007) adopt the stated preference approach, and Miyazato (2011) and Munro (2018) adopt the revealed preference approach. Table 4 shows these studies' VSL and VSI estimates, our unit benefits calculated from them, and Eqs. (35) and (36), and the total benefit of our hypothetical project. Since Koyama and Takeuchi (2004) derived the estimated ratio of VSI for severe disability to VSL as 0.224, the VSI estimates in Table 4 were calculated. As presented above, the benefits of a project can be easily measured using the framework proposed in this study. We can see from Table 4 that the higher the VSL estimates, the higher the total annual benefits, and that the stated preference approach appears to yield larger VSL

Table 4 Unit and total benefits based on benefit transfer from previous studies

	Tsuge et al. (2005)	Itaoka et al. (2007)	Miyazato (2011)	Munro (2018)
Approach	SP	SP	RP	RP
Data year	2002	1999	1999-2001	2009-2017
(VSL (million JPY))	(350)	(103-344)	(818-2236)	(440-646)
(VSI (million JPY))	(78)	(23-77)	(183-501)	(99-145)
$\widehat{\omega}_j^p$ (million JPY)	335	99-329	783-2140	421-618
$\widehat{\omega}_j^s$ (million JPY)	293	86-288	685-1872	368-541
$\widehat{\omega}_j^r$ (million JPY)	78	23-77	183-501	99-145
Total benefit (billion JPY/year)	23	7-23	54-148	29-43

Note: Figures in parentheses are taken or calculated from the results of previous studies.

estimates than the revealed preference approach. The median annual total benefit is around 15-35 billion yen, except for Miyazato (2011), in which VSL estimates take the highest value. Here, we focus on the Tohoku region, which is assumed to be a large mountainous area lacking a dense transportation network, making emergency transport more time-consuming. Since the population of the Tohoku region is known to be approximately 7% of Japan's total population, the annual total benefit is estimated to be 1.0 to 2.4 billion yen for the entire Tohoku region or 160 to 400 million yen per prefecture in the Tohoku region. It is suggested that the net benefit per prefecture would be generated if the cost was less than this amount. Thus, the effect of reducing emergency transport time would be significant. Such a cost-benefit analysis provides useful information for policy evaluation and budget processes in the central government and local governments that enhance public safety.

6. Conclusion

This study proposes a theoretical framework for measuring the benefits of a project that changes the probability of injury/illness along with the probability of death. To this end, we extended a standard model and defined the project's benefits by introducing the probability of a hazardous event that may cause death or injury/illness as well as the conditional probability of survival or recovery under the occurrence of such an event. As these benefits are associated with VSL and VSI, benefit transfer can be applied to their evaluation. In addition, assuming the availability of individual data, mainly on the existence of death or injury/illness of individuals who have experienced a disaster or accident, we provided a statistical approach for estimating the changes in the conditional probabilities of survival and recovery brought about by the project. Specifically, a binary response model with sample selection was adapted to describe the two-step process in which some individuals who faced an event that caused death and injury/illness survived, and some of the survivors recovered. Furthermore, we applied our method to instances of cardiopulmonary arrest and EMS transport as specific events that could cause death and injury/illness using Japanese Utstein-style data. Focusing on the case where the time interval between ambulance call and arrival at the patient's side was shortened by one minute, the estimated changes in the probabilities of survival and recovery were derived, whereby we attempted to measure the benefits of this reduction. The remaining issues in this study are as follows:

Although the class of standard models with only mortality risk has been extended to cases where the individual lives for multiple periods, as in Garber and Phelps (1997) and Hammitt and Liu (2004), unfortunately, it seems that no such extension has been made for models with both mortality and morbidity risk, including ours. For example, if a project changes the hazard probability, as well as the conditional probability of survival and recovery, the probabilities of death and injury/illness will also change over time. Therefore, the unit benefits associated with the VSL and VSI should be derived to account for such dynamic effects. Furthermore, introducing altruism into our model is an important potential concern because Jones-Lee (1991) showed that if altruism is exclusively safety-focused, VSL should be supplemented not only by what people would be willing to pay to improve their own safety but also by what they would be willing to pay to improve the safety of others. Moreover, Jones-Lee (1992) proposed a VSL multiplier that is determined by the magnitude of safety-focused altruism for others relative to wealth-focused altruism for others, and Long (2022) recently attempted to estimate it. Since these properties are expected to hold for VSI, the derivation of unit benefits through altruism will be a fruitful direction for our model.

The theoretical model presented in this paper allows for multiple injuries and illnesses; however, in the empirical analysis representing an example of benefit measurement using Utstein-style data, only severe disability, including coma, was treated as an injury/illness. Since the Utstein-style data collected data on good performance, moderate disability, severe disability, and coma as the prognosis status after one month, it would be possible to add moderate disability to the analysis. However, it is necessary to replace the outcome equation with an ordinal response model and obtain an estimated VSI for moderate disability. Furthermore, it may be useful to measure the benefits of each presumptive cause of cardiopulmonary arrest in the Utstein-style data using the fact that this study can cover multiple events that lead to death and injury/illness. Similarly, since the Utstein-style data include information on the prefecture of the patient, it is necessary to examine differences in policies and public capital related to emergency medical care by the local government.

Finally, regarding the statistical analysis aspect, as argued by Wilde (2013) and Swan and Baumstark (2022), for example, albeit in different contexts, endogeneity may exist in the EMS transport time variable, which is also regarded as a key variable in the modeling for the estimation using the

Utstein-style data in this study. However, under the binary response model with sample selection discussed in this paper, an estimation approach that allows for the simultaneous inclusion of endogenous variables in both the outcome and selection equations would not have been established at present. Development in this direction is a challenging problem for future research.

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Appendix

Table A1 Estimation results for the probit model with sample selection

Variable	Selection equation		Outcome equation	
	Coefficient	SE	Coefficient	SE
ETT 1	—	—	-0.008 *	0.004
ETT 2	-0.003 ***	0.001	—	—
Witness	0.404 ***	0.018	0.377 ***	0.058
Sex	-0.001	0.016	-0.056	0.034
Young	0.613 ***	0.045	0.252 **	0.122
Old	-0.287 ***	0.017	-0.310 ***	0.046
ELST	0.053	0.051	-0.164	0.117
Doctor	0.302 ***	0.039	0.024	0.092
ACLS	-0.053 *	0.030	-0.051	0.064
CC	0.117 ***	0.016	0.096 ***	0.036
RB	0.023	0.026	0.055	0.052
AED	0.437 ***	0.043	0.548 ***	0.081
VF/VT	-0.210 ***	0.036	-0.502 ***	0.070
PEA	-0.837 ***	0.023	-1.154 ***	0.062
Asystole	-1.521 ***	0.026	-1.871 ***	0.085
DFEP	0.166 ***	0.031	0.062	0.072
CO	0.351 ***	0.019	0.484 ***	0.045
CVD	0.065	0.040	-0.267 ***	0.098
RD	0.378 ***	0.029	-0.224 *	0.128
MT	-0.704 ***	0.085	-0.676 ***	0.257
EXC	0.274 ***	0.023	-0.185 *	0.100
Other	0.144 ***	0.025	0.031	0.061
Correlation (ρ)	0.548 (0.007)			
Log-likelihood	-21273.0			
Wald	1604.0 (0.000)			

Note 1: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
Note 2: Figures in parentheses indicate P-values.

Table A2 Estimation results for each probit model without considering sample selection

Variable	Selection equation		Outcome equation	
	Coefficient	SE	Coefficient	SE
ETT 1	—	—	-0.006	0.005
ETT 2	-0.003 ***	0.001	—	—
Witness	0.404 ***	0.018	0.227 ***	0.043
Sex	-0.001	0.016	-0.064 *	0.038
Young	0.608 ***	0.045	-0.002	0.088
Old	-0.287 ***	0.017	-0.212 ***	0.043
ELST	0.053	0.051	-0.212 *	0.127
Doctor	0.301 ***	0.039	-0.111	0.082
ACLS	-0.052 *	0.030	-0.027	0.071
CC	0.116 ***	0.016	0.050	0.037
RB	0.023	0.026	0.054	0.058
AED	0.435 ***	0.043	0.418 ***	0.085
VF/VT	-0.211 ***	0.036	-0.480 ***	0.075
PEA	-0.837 ***	0.023	-0.908 ***	0.050
Asystole	-1.521 ***	0.026	-1.367 ***	0.062
DFEP	0.166 ***	0.031	-0.010	0.073
CO	0.351 ***	0.019	0.381 ***	0.045
CVD	0.066 *	0.040	-0.342 ***	0.094
RD	0.378 ***	0.029	-0.452 ***	0.074
MT	-0.703 ***	0.085	-0.403	0.285
EXC	0.274 ***	0.023	-0.356 ***	0.059
Other	0.144 ***	0.025	-0.038	0.062
Correlation (ρ)	—		—	
Log-likelihood	-17696.0		-3579.0	
Wald	10802.4 (0.000)		1243.7 (0.000)	

Note 1: *** and * indicate significance at the 1% and 10% levels, respectively.

Note 2: Figures in parentheses indicate P-values.