Vulnerability to Negative Life Events*: Unemployment and Loss of a Spouse in Japan

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Feb. 2020

Abstract

The purposes of this study are to introduce the idea of a vulnerability score for measuring the potential damage from negative life events as socially embedded hazards, and to show analytical examples of this by using the SSM 2015 data, which is Japanese national survey data. In the analysis, we apply the statistical method of causal inference for estimating the degree of vulnerability to negative life events from cross-sectional social survey data and define the vulnerability score as this measurement of vulnerability. We analyze the SSM survey data to assess people's vulnerability in terms of household income and subjective well-being in response to negative life events, such as unemployment and loss of a spouse, and reveal differences based on gender, age, and educational attainment.

As for unemployment, we find from the analyses that both men and women who are around 40 years old and has less education face the most severe risk of damaging household income, while younger men are at severe risk of damaging their subjective well-being through the event. As for loss of a spouse, we found that women are more vulnerable than men in terms of objective well-being, while men are more vulnerable than women in terms of subjective well-being.

Keywords: vulnerability, risk, negative life event

*The study was supported by JSPS KAKENHI Grant Number JP25000001, 19K02123. The author thanks the Social Stratification and Social Mobility (SSM) Research Committee of 2015 for permission to use the SSM 1955-2015 data.

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1 Introduction

In recent years, the notion of vulnerability to natural hazards has become attractive to researchers in disaster studies as well as practitioners of disaster prevention (Hewitt, 1997; Cutter et al., 2003; Turner et al., 2003; Wisner et al., 2004, 2012).

Generally speaking, vulnerability to natural hazards means there are potential damages that a group or an individual might incur from the hazards. The notion of vulnerability stresses the social aspects of disasters. A hazard itself is a natural phenomenon. When a hazard is combined with vulnerability, it develops into a major disaster. Additionally, the vulnerability of individuals and their community is associated with their resilience to disasters. The degree of vulnerability varies according to social status and the social conditions in which a community or an individual is placed (Cutter et al., 2003).

Wisner et al. (2004, 11) defines the notion of vulnerability as “the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard (an extreme natural event or process).” Moreover, for describing the relationship among the concepts of risk, hazard, and vulnerability, they propose a simple pseudo-equation, such as,

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability}.$$

The risk of a disaster is supposed to be “a compound function of the natural hazard and the number of people, characterized by their varying degrees of vulnerability to that specific hazard, who occupy the space and time of exposure to the hazard event” (Wisner et al., 2004, 49).

There have been a series of studies proposing measurements of vulnerability to natural hazards in relation to risk and hazards at a national or community level (Cutter et al., 2003; Birkmann, 2013).

Along with this stream of disaster research, the concept and measurement of vulnerability have also been attracting attention in poverty research. In poverty research, the concept of vulnerability is typically defined as “the exposure to uninsured risk leading to a socially unacceptable level of well-being” (Hoogeveen et al., 2004), and several methods of measuring vulnerability to poverty have been proposed and applied in empirical data analysis (Ligon and Schechter, 2003; Hoddinott and Quisumbing, 2003; Calvo and Dercon, 2005; Klasen and Povel, 2013; Fujii, 2016).

With reference to the concepts and measurements of vulnerability in disaster research as well as poverty research, in this paper we focus on individuals’ vulnerability to the negative life events that happen occasionally and can negatively affect the individual. Additionally, referring to the method of causal inference, we propose a way of measuring an individual’s vulnerability to a certain negative life event that considers both the possibility of encountering the negative event and the potential damage caused by it.

In this article, we exclusively focus on two types of negative life events, unemployment as a typical negative event related to one’s professional life and economic status, and loss of a spouse through divorce or bereavement as a typical negative event related to one’s family life and social network. Such events can suddenly befall anyone, and from the victims’ view, they tend to be seen as being caused by uncontrollable factors. In that sense, these events may be regarded as socially embedded hazards.

For this purpose, this study will introduce the idea of a “vulnerability score,” which is expected to measure the potential damage caused by negative life events considered socially embedded hazards and to provide analytical examples by using Japanese national survey data. In our analysis, we will apply the statistical method of causal inference to estimate degrees of vulnerability to negative life events from cross-sectional social survey data, define the vulnerability score as a measurement of vulnerability to a negative life event, and demonstrate differences based on age, educational attainment, and gender.

In section 2, we introduce the definition of the vulnerability score. In section 3, we denote data, variables of interest, and the actual methodological procedure. In section 4 and 5, we share the results of the analysis of SSM 2015 data, and draw conclusions in section 6.

2 Vulnerability score

How can we measure an individual’s degree of vulnerability to negative life events? The simplest and most reasonable way to answer this question is through an experiment.

For this experiment, gather people with a particular profile, randomly assign them to either the group who experiences the event or the group who does not, and observe how much “actual” suffering occurs for those who experience the event. In this way, you will certainly know the causal effect.

However, such an experiment is methodologically and ethically unrealistic. Therefore, we consider an alternative method that generates the negative event virtually and randomly on individuals and tests the degree of damage caused in a certain well-being dimension, based on the obtained survey data.

Concretely, a virtual damage test for a certain negative event is conducted for the group that has not experienced that event at the time of the survey. In the test, the damaging event is randomly virtually generated for the group members with the same probability as the actual occurrence rate of the event. The average difference between members' scores in a certain well-being index before and after the test is measured.

Let us formulate the method accurately.

Let $Z = 1, 0$ be a dummy random variable indicating the occurrence of the negative event that is expected to affect an individual's well-being, and let Y be a continuous random variable that is supposed to be a dimension of an individual's well-being.

Y is potentially divided into two random variables: Y_1 , which is the potential outcome when the event occurs, and Y_0 , which is the potential outcome when the event does not occur. However, the actual observation from the survey data is the realized value of the random variable $Y = Z \cdot Y_1 + (1 - Z)Y_0$. In other words, the realized value of Y_1 when $Z = 0$ and that of Y_0 when $Z = 1$ cannot be observed. This is called "the fundamental problem of causal inference" (Holland, 1986).

Furthermore, let $\mathbf{X}$ be covariates, a bundle of social and demographic factors that might affect the degree of the effect of the negative event on well-being.

$Pr(Z = 1|\mathbf{X})$ indicates the probability that the event Z occurs in the group that shares a specific profile $\mathbf{X}$, and $Pr(Z = 0|\mathbf{X}) = 1 - Pr(Z = 1|\mathbf{X})$ indicates the probability that Z does not occur in the group $\mathbf{X}$.

$E(Y_i|Z = i, \mathbf{X})$ indicates the expected value of Y_i , which is the potential outcome when the event occurs ($i = 1$) or does not occur ($i = 0$), conditioned by $Z = i$ and $\mathbf{X}$.

The expected value of Y in the virtual damage test, denoted by $E_t(Y)$, is given by the law of iterated expectations, that is,

$$\begin{aligned} E_t(Y) &= Pr(Z = 0|\mathbf{X})E(Y|Z = 0, \mathbf{X}) + Pr(Z = 1|\mathbf{X})E(Y|Z = 1, \mathbf{X}) \\ &= Pr(Z = 0|\mathbf{X})E(Y_0|Z = 0, \mathbf{X}) + Pr(Z = 1|\mathbf{X})E(Y_1|Z = 1, \mathbf{X}). \end{aligned}$$

The conversion from the first line to the second line can be obtained by substituting the condition $Z = i$ in the definition of Y .

Meanwhile, the expected value of Y with no test, denoted by $E_0(Y)$, is

$$E_0(Y) = E(Y|Z = 0, \mathbf{X}) = E(Y_0|Z = 0, \mathbf{X}).$$

Then, the vulnerability score of the outcome Y of the event Z conditioned by the profile $\mathbf{X}$, denoted by $v(Y, Z, \mathbf{X})$, is defined as the difference between the expected value of Y in the test and that with no test, that is,

$$\begin{aligned} v(Y, Z, \mathbf{X}) &= E_t(Y) - E_0(Y) \\ &= Pr(Z = 0|\mathbf{X})E(Y_0|Z = 0, \mathbf{X}) + Pr(Z = 1|\mathbf{X})E(Y_1|Z = 1, \mathbf{X}) \\ &\quad - E(Y_0|Z = 0, \mathbf{X}) \\ &= Pr(Z = 1|\mathbf{X})[E(Y_1|Z = 1, \mathbf{X}) - E(Y_0|Z = 0, \mathbf{X})]. \end{aligned}$$

If the event is assigned randomly in the virtual test conditioned by $\mathbf{X}$, the assignment does not affect the realization of the potential outcome¹. In other words, Y_1, Y_0 , and Z are all independent of each other under the condition of $\mathbf{X}$. This is called “strongly ignorable treatment assignment condition” (Rosenbaum and Rubin, 1983)².

From this assumption, we obtain

$$\begin{aligned} E(Y_1|Z = 1, \mathbf{X}) &= E(Y_1|\mathbf{X}), \\ E(Y_0|Z = 0, \mathbf{X}) &= E(Y_0|\mathbf{X}). \end{aligned}$$

¹More precisely, it is also assumed that the assignment is random even when the test is not conducted.

²More generally, “strongly ignorable treatment assignment condition” is the condition that the joint probability of (Y_1, Y_0) and Z are independent of each other under the condition of $\mathbf{X}$. This is also denoted as $(Y_1, Y_0) \perp\!\!\!\perp Z|\mathbf{X}$. To be precise, let $f(y_1, y_0|z, \mathbf{x})$ be the joint probability density function of (Y_1, Y_0) , conditioned by covariates $\mathbf{X}$ and the assignment Z . Then, the strongly ignorable treatment assignment condition is defined as

$$f(y_1, y_0|z, \mathbf{x}) = f(y_1, y_0|\mathbf{x}).$$

Transforming the equation, we get

$$f(y_1, y_0, z|\mathbf{x}) = f(y_1, y_0|\mathbf{x})f(z|\mathbf{x}).$$

Marginalizing both sides of the equation by y_j subject to $j = 1 - i$, we also get

$$f(y_i, z|\mathbf{x}) = f(y_i|\mathbf{x})f(z|\mathbf{x}), \quad i = 1, 0.$$

In the end, the vulnerability score can be rewritten as

$$\begin{aligned} v(Y, Z, \mathbf{X}) &= Pr(Z = 1|\mathbf{X})[E(Y_1|\mathbf{X}) - E(Y_0|\mathbf{X})] \\ &= Pr(Z = 1|\mathbf{X})E(Y_1 - Y_0|\mathbf{X}). \end{aligned}$$

In other words, under this assumption, the vulnerability score v is defined as the conditional average treatment effect (CATE), which is weighted by the probability of $Z = 1$ and conditioned by the covariates $\mathbf{X}$. Summarizing this in a simpler form, we get

$$v = p \times \text{CATE}, \quad (1)$$

where p denotes the event occurrence probability in a certain group, and CATE is the conditional average treatment effect in a certain group. If p corresponds to the probability of a hazard and CATE corresponds to the degree of potential damage, it can be assumed that v measures some sort of “risk” of the negative event.

3 Method

We have thus far introduced and formalized the notion of the vulnerability score. In this section and the following sections, to illustrate the analysis of the vulnerability score, we will present the analytic procedure for estimating the score and results drawn from Japanese survey data from 2015.

3.1 Data

We use data from the 2015 Social Stratification and Mobility survey (SSM survey, in short) for our analysis. The SSM survey is a Japanese nation-wide cross-sectional random-sampling survey on social stratification and mobility, and it contains rich information on individual’s demographic, social, and economic status, as well as their self-evaluations and attitudes toward social stratification. Shirahase (2018) gives a short summary of the 2015 survey.

The target population of the survey is Japanese nationals from 20-79 years old who lived in Japan at the end of 2014. The target sample size is 15605, and the valid sample size is 7817 (50.1% respondent rate).

3.2 Variables

When measuring a specific vulnerability score, it is necessary to determine what causes damage (event dummy variable Z), what kind of damage it is (outcome variable Y), and who receives the damage (covariates $\mathbf{X}$).

First, in terms of the event dummy variable Z , we picked up “unemployment,” which is operationally defined as responding “no job but looking for a job” to the question of current job status, for working persons as a typical negative event related to one’s professional life. In addition, we picked up “loss of a spouse,” which is operationally defined as having experienced “divorce” or “bereavement” within the past 20 years, for married persons as a typical negative event related to one’s family life.

Second, in terms of the outcome variable Y , we picked “household income”³ as an objective evaluation of well-being, and picked “subjective well-being,” measured by the 11-scale Cantril ladder, as a subjective evaluation of well-being.

Third, regarding covariates $\mathbf{X}$, we take up the three basic demographic and status variables that are least likely to be changed once acquired: “gender,” “age,” and “educational attainment.” As for age, we focus on people aged from 25 to 64, the majority of whom are not students or retirees and are of so-called “active ages.” As for educational attainment, we use the variable of years of education⁴. These variables are considered to be the basis of status division in modern Japan (Kikkawa, 2018), and as the most basic analysis, this study analyzes the distribution of vulnerability along these variables.

3.3 Procedure for the analysis

The analysis of the vulnerability score presented here was conducted through a two-step procedure. The first step is to estimate the two quantities, p and CATE, both of which are components of the vulnerability score. The second step is to assess the standard error of the vulnerability score by utilizing bootstrap techniques.

³If information about household income was missing, it was supplemented as follows. If both individual income and spouse income were available, the total of both incomes was considered the household income. If only of these was available, the available income was considered the household income.

⁴Years of education is converted as follows: junior high school is 9 years, high school is 12 years, junior college / technical college is 14 years, university is 16 years, graduate school is 18 years.

To estimate the vulnerability score, we demonstrate one procedure based on the idea of model-based inference, where p and CATE are expressed as an adequate regression model, and the vulnerability score can be obtained by utilizing estimated parameters of models.

As with the estimation for p , we simply employ the logistic regression model for dichotomous variables with parameters $\boldsymbol{\gamma}$ to be estimated, that is,

$$Pr(Z = 1|\mathbf{X}) = \frac{\exp(\mathbf{X}\boldsymbol{\gamma})}{1 + \exp(\mathbf{X}\boldsymbol{\gamma})},$$

and obtain the estimators of parameters, denoted as $\hat{\boldsymbol{\gamma}}$, through the method of maximum likelihood estimation.

For CATE, we refer to the framework of the marginal structure model (Robins et al., 2000). In the marginal structure model, the expected value of each potential outcome conditional on $\mathbf{X}$ is expressed in the form of a regression model, such as,

$$\begin{aligned} E(Y_0|\mathbf{X}) &= \mathbf{X}\boldsymbol{\beta}_0, \\ E(Y_1|\mathbf{X}) &= \mathbf{X}\boldsymbol{\beta}_1. \end{aligned}$$

With these equations, we can rewrite CATE for a profile of $\mathbf{X}$ as the subtraction of $\boldsymbol{\beta}_0$ from $\boldsymbol{\beta}_1$ as follows:

$$E(Y_1 - Y_0|\mathbf{X}) = \mathbf{X}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_0).$$

Therefore, as far as relying on the marginal structure model for the quantification of CATE, it requires an adequate method to estimate $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_0$ based on the observable variables. For this aim, we employ weighted least squares with inverse probability weight (IPW).

Now, letting $\mathbf{U}$ be the set of covariates that are assumed to sufficiently predict Z , and that include $\mathbf{X}$ as a subset. In addition, it is assumed that the propensity score $e(\mathbf{U})$, which is a predictive probability for $Z = 1$ based on $\mathbf{U}$, satisfies the strongly ignorable treatment assignment condition, denoted as $Y_1, Y_0 \perp\!\!\!\perp Z | e(\mathbf{U})$. If these conditions hold, we can safely obtain estimates $\hat{\boldsymbol{\beta}}_1, \hat{\boldsymbol{\beta}}_0$ from the results of the least squared of the multiple regression model for observed outcome Y , such as,

$$E(Y|\mathbf{X}) = \mathbf{X}\boldsymbol{\beta}$$

with weighting $1/e(\mathbf{U}), 1/(1 - e(\mathbf{U}))$ for the sample $Z = 1$, and $Z = 0$, respectively.

Since $\mathbf{U}$ is assumed to sufficiently predict Z , the concrete variables used in $\mathbf{U}$ vary depending on the negative event being analyzed. However, whichever event is to be analyzed, it is important to balance the covariates between $Z = 1$ and $Z = 0$ in order to gain a valid result. In pursuit of this balancing, we adopt the covariate balancing propensity score (CBPS) (Imai and Ratkovic, 2014), which is an estimated propensity score with consideration for balancing the distribution of covariates.

In relation to the validity of the result, common support is another important standard in achieving a plausible result (Morgan and Winship, 2014). Common support is about whether the range of the probability to be assigned to $Z = 1$ of the treated group overlaps that of the control group (and vice versa). In this analysis, we attain common support through eliminating the sample with value of CBPS that goes beyond the region shared by both control and treatment groups.

Through the procedures stated above with consideration for the balancing of covariates and common support, we obtain the estimator, $\hat{\gamma}, \hat{\beta}_1, \hat{\beta}_0$, and are able to utilize them for calculating the vulnerability score. Therefore, the vulnerability score of the particular profile $\mathbf{X} = \mathbf{x}$ is expected to be well estimated by

$$\begin{aligned} v(Y, Z, \mathbf{X} = \mathbf{x}) &= Pr(Z = 1|\mathbf{x})E(Y_1 - Y_0|\mathbf{x}) \\ &= \frac{\exp(\mathbf{x}\hat{\gamma})}{1 + \exp(\mathbf{x}\hat{\gamma})}\mathbf{x}(\hat{\beta}_1 - \hat{\beta}_0). \end{aligned}$$

In the process of estimating the vulnerability score, we apply the bootstrap method for acquiring information on the sampling distribution and standard error of the estimated score, as well as that of the estimated parameters $\hat{\gamma}, \hat{\beta}$.

4 Analysis of unemployment

4.1 Balancing of covariates

We first show the result of the vulnerability score and its components where unemployment is the focal negative event, and empirically clarify who — concretely characterized by gender, age, and educational background — is more vulnerable to unemployment among workers. It should note that the

term “unemployed” is restricted to the state in which the respondent does not have a job but is searching for one.

We use gender, age, squared age, and total years of education as the covariates $\mathbf{X}$. Regarding $\mathbf{U}$ that is assumed to sufficiently predict the occurrence of unemployment, the variables below are adopted in addition to $\mathbf{X}$.

- city size where the respondent lives
- spouse’s job (including the categories of no spouse, DK/NA)
- number of children
- type of housing
- father’s job when the respondent was 15 years old (including the categories of no father, DK/NA)
- owning a house when the respondent was 15 years old

Since the purpose of this analysis is to determine the effects of unemployment, the respondents who do not have a job and are not searching for one are eliminated from the analysis. Additionally, considering one’s age at entering the labor market which varies depending on education background and the *de facto* mandatory retirement for elders in Japan, the analysis is limited to respondents aged from 25 to 64 years old.

As noted in the above section on the procedure for the analysis, the respondents who are not in the region of common support are excluded. In detail, the CBPS for $Z = 1$ is estimated to range from 0.004 to 0.251 and that for $Z = 0$ ranges from 0.000 to 0.285; therefore, respondents with a CBPS outside the range of 0.004 to 0.251 are eliminated.

After eliminating the respondents who do not have jobs and are not searching for one and those who are outside the common support, the dataset contains 3982 respondents. We use all of them for the estimation of $\hat{\gamma}$, and due to the missing value, we use 3931 and 3775 respondents for the estimation of $\hat{\beta}_1, \hat{\beta}_0$ on SWB and household income respectively.

To check the balancing of covariates by CBPS, Figure 1 displays the absolute standardized mean difference (Austin, 2009) of each covariate in $\mathbf{U}$ before and after adjustment CBPSs⁵. Absolute standardized mean differences are major descriptive statistics for the diagnostics of balancing between the treated ($Z = 1$) and the control ($Z = 0$) in terms of the mean of covariates.

⁵We use the “cobalt” package in R for drawing plots (Greifer, 2019). Once estimated CBPS are used to eliminate the samples outside the common support, we re-estimated CBPS without the eliminated sample for further analysis.

[Figure 1 about here.]

It is shown that, in most variables, the absolute standardized difference after adjustment is lower than that before adjustment and is lower than 0.1, which is a conventional criterion for judging balance.

There are some exceptions. A few covariates, that is “female” and “no job” as one of categories of the partner job variable, exceed 0.1; however, the adjustment by CBPS significantly reduces their absolute standardized mean⁶. Additionally, some variables, such as “divorced/widowed” as one of categories of the partner job variable, became more imbalanced after adjustment with CBPS. However, their differences are not problematically large and their absolute standardized differences after adjustment are still below 0.1.

Therefore, we can conclude that the covariates are adequately balanced by the adjustment with CBPS and safely proceed to estimating the parameters necessary for obtaining vulnerability scores from the data.

4.2 Estimation for parameters

We conducted a bootstrap estimation for parameters replicated 1000 times. Table 1 and Table 2 summarize the result of $\hat{\gamma}$, and $\hat{\beta} = \hat{\beta}_1 - \hat{\beta}_0$ for household income and subjective well-being (SWB) when unemployment is the negative event.

[Table 1 about here.]

[Table 2 about here.]

4.3 Occurrence rate

By using the bootstrap sample of parameters $\hat{\gamma}$, we can illustrate the trajectory of occurrence rate $p = Pr(Z = 1|\mathbf{X})$ in the event of unemployment depending on gender, age, and years of education. Figure 2 shows that the trajectory consists of the bootstrap mean of the occurrence rate for each profile determined by gender, age, and years of education.

⁶In addition, for the analytical framework, we employed the marginal structure model that is considered a doubly robust method for causal inference. Hence, even when some imbalance remained in covariates among $\mathbf{U}$, we would be able to supplementary adjust the remaining imbalance included in $\mathbf{X}$ within a weighted regression framework (Morgan and Winship, 2014).

We can see from Figure 2 that women (as opposed to men), younger people, and less educated people are more likely to experience an unemployment event. This result, especially in relation to women, partly reflects the pattern of female participation in the Japanese labor force, called an “M-shaped curve” pattern (Cabinet Office, 2017), in which the female labor force participation rate declines at around 30 years of age due to childbirth and childcare.

[Figure 2 about here.]

4.4 Vulnerability score in terms of household income

Figure 3 shows the trajectory of the estimated CATE, expressed as $E(Y_1 - Y_0|\mathbf{X})$, in terms of household income by the bootstrap samples $\hat{\beta}$.

[Figure 3 about here.]

Figure 3 reveals that men, people in their mid-40’s, and more educated people suffered much more damage with respect to their household income from becoming unemployed. This is not surprising, since the extent of potential damage on household income is assumed to be proportional to their individual income and the extent of their individual contribution to the household. In other words, the person who earns more will find their household income more damaged when experiencing unemployment events. In Japan, male workers, on average, earn more than female workers due to employment types and the gender gap within regular full-time workers (Yamaguchi, 2011). Educational attainment has been persistently associated with income level (Sato and Arita, 2016). Additionally, while it is well known that wages increase according to the years of experience, the trend of plateauing wages after age 40 has been recently reported in Japan (Hamaaki et al., 2010). Our findings obtained from Figure 3 seem to mirror these characteristics.

By combining occurrence rate with CATE, we get the trajectory of the vulnerability score as it appears in Figure 4.

[Figure 4 about here.]

From Figure 4, we find that the similarities between the genders, in which people who are around 40 years old and has less education face the most

severe risk that is defined by vulnerability score for household income. Additionally, among this age group, we can see that the level of risk seems not to differ greatly by gender.

This similarity among those in their 40s seems interesting because, as confirmed in Figure 2 and Figure 3, there is certainly a gender difference in terms of the occurrence rate of unemployment and the damage brought about by unemployment. In general, men are less likely to experience unemployment but are more damaged by unemployment if it happens. On the contrary, women are more likely to experience unemployment but are less damaged by it. While this gender difference exists, when assessing the risk consisting of both the possibility and the level of damage, both men and women aged around 40 face the same level of risk.

Figure 4 also provides an interesting insight into how risk levels change throughout life. Generally, the possibility of becoming unemployed decreases with age, and the degree of damage increases up to one's 40's and decreases afterwards, as shown in Figure 2 and Figure 3. Hence, the level of risk early in life stays low because of less damage, but in entering middle age, the level of risk becomes more severe according to an increase in damage, while the possibility of becoming unemployed starts to decrease. In later life, the risk again returns to a lower level because the potential damage is mitigated.

It is important to understand that these findings on risk assessed by vulnerability score are not the same as looking at either occurrence rate or CATE, and thus they demonstrate the usefulness of the vulnerability score in how it provides a new perspective on risk to life events.

4.5 Vulnerability score in terms of subjective well-being

Next, we examine subjective well-being as the dimension of potential damage. Figure 5 shows the trajectory of conditional ATE on subjective well-being.

[Figure 5 about here.]

Figure 5 shows that the subjective well-being of men and younger people seems to be more damaged by encountering an unemployment event. For men, this finding is consistent with the argument that the non-pecuniary effect of unemployment partly stems from the deprivation of personal status and identity gained from work (Jahoda, 1981). The degree of the negative impact of being unemployed becomes harsher if being employed is strictly

normative in one’s society (Clark, 2003; Stutzer and Lalive, 2004), and the traditional gender role where the man is expected to be the family’s “breadwinner” is considered a specific form of such norms (Knabe et al., 2016). The level of approval for gender roles relating to employment is relatively high in Japan (Fortin, 2005). Thus, we can infer that men are more severely affected by unemployment because they seriously perceive being employed as normal and being unemployed as abnormal, which consequently results in a lowering of their subjective well-being.

As for younger people, the “scare” effect of unemployment can be applied for interpretation. Not only being unemployed at present, but also the experience of being unemployed is detrimental to their subjective well-being because the unemployed experience makes them scared for their future jobs (Knabe and Rätzel, 2011). Japanese youth tends to feel more anxious about their future than other generations (Hommerich, 2017). Hence, we can interpret that younger people might suffer from the unemployment event because they have more anxiety toward the future and are likely to severely recognize the possibility of future unemployment, which is aroused by their unemployed experience.

Figure 6 shows the trajectory of the vulnerability score for unemployment on subjective well-being.

[Figure 6 about here.]

We find from Figure 6 that, for both men and women, the level of risk is much higher at a younger age and tends to be mitigated with age. Furthermore, less educated people are exposed to higher levels of risk to unemployment in terms of subjective well-being.

Similar to the case of household income as shown in Figure 4, Figure 6 indicates the interesting findings that are not derived solely from occurrence rate or CATE. Specifically, we can infer that the reason why young men face a higher risk is that the damage they experience from unemployment is more severe for younger people (Figure 5), and additionally, their possibility of being unemployed is higher than that of other generations (Figure 2). To phrase it differently, the subjective well-being of young men is at a higher risk of being damaged by an unemployment event because they are more likely to become unemployed and to be more severely impacted by unemployment. This is also true for women, and it is even harsher for people with less education.

Thus, from the perspective of risk defined as a vulnerability score, we illustrate that younger people are at severe risk of damaging their subjective well-being through unemployment. These findings are not obtained solely from a higher possibility (occurrence rate) or the degree of damage (CATE), but from both. This again shows the utility of the vulnerability score.

5 Analysis of loss of a spouse

5.1 Balancing of covariates

Next, we show the result of the vulnerability score and its components where a loss of a spouse is the negative event, and we empirically clarify who — concretely characterized by gender, age, and educational background — is more vulnerable to losing their spouse.

As stated, we use gender, age, squared age, and years of education as the covariates $\mathbf{X}$. In addition to $\mathbf{X}$, we adopt the following covariates for $\mathbf{U}$ that are necessary for calculating CBPS.

- first job (including the categories of never worked, DK/NA)
- age of marriage
- number of children
- spouse’s job at the beginning of the marriage (including the categories of no job, DK/NA)
- father’s job when the respondent was 15 years old (including the categories of no father, DK/NA)
- owning a house when the respondent was 15 years old

Since the purpose of this analysis is to investigate the effect of losing a spouse, the respondents who have never married are naturally eliminated from analysis. We also restrict the respondents’ age in the sample to be analyzed from 25 to 64 years old for the sake of matching the analytical conditions to the analysis of unemployment.

Furthermore, the respondents who are not in the region of common support are excluded. Specifically, the CBPSs for $Z = 1$ are estimated to range from 0.025 to 0.543, and those for $Z = 0$ range from 0.003 to 0.508; therefore, the respondents with a CBPS outside the range of 0.025 to 0.508 are eliminated.

After eliminating the respondents who have never married and are outside the region of common support, the dataset contains 3691 respondents. Of them, we use all of them for estimation of $\hat{\gamma}$, and due to the missing value, we use 3641 and 3507 respondents for the estimations of $\hat{\beta}_1, \hat{\beta}_0$ on SWB and household income, respectively.

Figure 7 shows that in almost all variables the absolute standardized differences after adjustment are lower than before adjustment, except for a few variables, such as age, squared age, and “DK/NA” at first job. All absolute standardized differences after adjustment are below 0.1, which is a conventional threshold for judging balance. From this result, we safely conclude that the covariates are balanced and proceed to estimate the parameters necessary for obtaining a vulnerability score from the data.

[Figure 7 about here.]

5.2 Estimation for parameter

We conducted a bootstrap estimation for parameters with 1000 replications. Table 3 and Table 4 summarize the results of $\hat{\gamma}$ and $\hat{\beta} = \hat{\beta}_1 - \hat{\beta}_0$ for household income and subjective well-being (SWB) when losing a spouse is the negative event.

[Table 3 about here.]

[Table 4 about here.]

5.3 Occurrence rate

By using the bootstrap sample of parameters $\hat{\gamma}$, we can illustrate the trajectory of occurrence rate $p = Pr(Z = 1|\mathbf{X})$ of the loss of a spouse event depending on gender, age, and years of education. Figure 8 shows that the trajectory consists of the bootstrap mean of the occurrence rate of loss of a spouse in each profile determined by gender, age, and years of education.

Figure 8 reveals that less educated men and women aged mid-40s to 50 are more likely to experience the loss of a spouse. Women have a higher probability of losing their spouse than men if their age and educational level are similar.

[Figure 8 about here.]

5.4 Vulnerability score in terms of household income

Figure 9 shows the trajectory of estimated CATE in terms of household income by bootstrap samples of $\hat{\beta}$.

We see from Figure 9 that more educated women around 50 suffer more from the loss of a spouse in terms of household income. These findings are reasonable based on the fact that more highly educated middle-aged male workers earn a much higher income on average. Therefore, the negative effect on the household caused by loss of a spouse as an earner is more severe for the women who are more likely to marry them.

[Figure 9 about here.]

Figure 10 is the trajectory of the vulnerability score of household income to the loss of a spouse. From Figure 10, we find that less educated women around 50 years of age are the group most at risk to losing a spouse in terms of household income. This is due to the synergistic effect of multiple reasons, including that middle-aged women with less education are the most likely to lose a spouse (Figure 8), they greatly depend on their spouses in terms of income, and they suffer more damage from the loss of a spouse (Figure 9).

[Figure 10 about here.]

5.5 Vulnerability score in terms of subjective well-being

We now turn to confirm the vulnerability to loss of a spouse in terms of subjective well-being. Figure 11 shows the CATE of subjective well-being. We can see from this figure that men suffer greater psychological damage from losing a spouse than women, and among them, less educated and younger men suffer much more damage from this loss.

[Figure 11 about here.]

Combined, the potential damage and the occurrence rate of the loss event yield the vulnerability score of subjective well-being to the loss of a spouse as shown in Figure 12. From this result, we find that less educated men in their mid-30s are the most at risk to losing a spouse in terms of their subjective well-being.

[Figure 12 about here.]

Generally speaking about the potential risk of losing a spouse, women are more vulnerable than men in terms of objective well-being, while men are more vulnerable than women in terms of subjective well-being, suggesting the kinds of aspects each gender tends to rely on in their spouse in current Japan.

6 Conclusion

So far, we introduced the vulnerability score and its estimation and demonstrated its analysis by using Japanese survey data. From the analysis of unemployment and loss of a spouse, we obtained several interesting findings that are not obvious and were first revealed by the score.

As for unemployment, we found that both men and women who are around 40 years old and has less education face the most severe risk of damaging household income, while younger men are at severe risk of damaging their subjective well-being through the event. As for loss of a spouse, we found that women are more vulnerable than men in terms of objective well-being, while men are more vulnerable than women in terms of subjective well-being.

In future research, the vulnerability score is expected to measure multiple vulnerabilities to different combinations of negative life events and dimensions of measuring well-being, and to be used in the study of the patterns and changes in people's vulnerabilities to ordinal life events through time-series and international comparisons.

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Figure 1: Absolute standardized mean differences (unemployment)

Figure 2: Trajectory of occurrence rate (unemployment event)

Figure 3: Trajectory of CATE of household income (unemployment event)

Figure 4: Trajectory of vulnerability score of household income (unemployment event)

Figure 5: Trajectory of CATE of SWB (unemployment event)

Figure 6: Trajectory of vulnerability score of SWB (unemployment event)

Figure 7: Absolute Standardized Mean Differences (loss of a spouse)

Figure 8: Trajectory of occurrence rate (loss of a spouse event)

Figure 9: Trajectory of CATE of household income (loss of a spouse event)

Figure 10: Trajectory of vulnerability score of household income (loss of a spouse event)

Figure 11: Trajectory of CATE of SWB (loss of a spouse event)

Figure 12: Trajectory of vulnerability score of SWB (loss of a spouse event)

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	Mean	S.E.	95% C.I.	
Intercept	-0.071	1.379	-2.827	2.492
Female	0.779	0.173	0.445	1.114
Age	-0.098	0.061	-0.212	0.020
Squared age	0.001	0.001	0.000	0.002
Years of education	-0.080	0.039	-0.162	-0.007

Table 1: Estimation result of $\hat{\gamma}$ for unemployment

Household income	Mean	S.E.	95% C.I.	
Intercept	1157.609	804.219	-593.171	2532.761
Female	218.289	109.898	-53.468	384.979
Age	-68.506	30.884	-114.170	-7.731
Squared age	0.784	0.349	0.164	1.310
Years of education	-6.757	29.316	-56.520	51.103
SWB	Mean	S.E.	95% C.I.	
Intercept	-0.224	4.393	-8.651	8.291
Female	0.967	0.603	-0.301	1.976
Age	-0.079	0.168	-0.407	0.265
Squared of age	0.001	0.002	-0.003	0.005
Years of education	-0.007	0.136	-0.267	0.263

Table 2: Estimation result of $\hat{\beta}$ for unemployment

	Mean	S.E.	95% C.I.	
Intercept	-2.672	1.439	-5.522	0.113
Female	0.327	0.132	0.054	0.588
Age	0.092	0.059	-0.023	0.214
Squared age	-0.001	0.001	-0.002	0.000
Years of education	-0.161	0.036	-0.232	-0.092

Table 3: Estimation result of $\hat{\gamma}$ for loss of a spouse

Household income	Mean	S.E.	95% C.I.	
Intercept	826.779	588.943	-1056.915	1447.691
Female	-83.300	65.147	-170.254	120.070
Age	-28.646	21.119	-54.227	37.442
Squared age	0.279	0.212	-0.377	0.545
Years of education	-25.192	19.214	-47.489	37.209
SWB	Mean	S.E.	95% C.I.	
Intercept	-5.207	4.406	-11.480	7.266
Female	0.699	0.526	-0.947	1.330
Age	0.125	0.144	-0.218	0.380
Squared of age	-0.001	0.001	-0.004	0.002
Years of education	0.050	0.075	-0.110	0.191

Table 4: Estimation result of $\hat{\beta}$ for loss of a spouse