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Abstract
Value of statistical life (VSL) is an important measure to support cost-benefit analysis of public policies to improve social welfare. According to existing literature, the marginal willingness to pay (WTP) for reducing fatal risk is affected by heterogeneity in personal characteristics, and thus, the inferred VSL is also different. The impact of income heterogeneity on VSL is of great significance to policy applications and thus has become a hot topic in studies. In this study, we investigated the effect of income heterogeneity on the VSL in Taiwan through quantile regression analysis using the data collected by the "Manpower Utilization Survey." The results of this empirical study show that the hedonic wage function (HWM) constructed using empirical data from Taiwan was in line with the general form of non-linear function rather than the semi-log function that has been often used in previous studies, which should have a great impact on the estimation of the VSL. We also found that the estimated VSL of Taiwanese labor varied with the difference in wages, which needs to be taken into account when discussing public policies using VSL.

JEL code: J17, Q51, C31
Keywords: value of statistical life, income heterogeneity, hedonic wage function, Box-Cox transform, quantile regression model

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1. Research background

In recent years, with the limited national budget, cost-benefit assessment (CBA) has been adopted to examine the efficiency of public construction plans and management policies and is becoming an important reference for making decisions on different plans or policies by public agencies. In general, the construction plans or management policies implemented by public agencies involve external influences that are often ignored by the private sector. Among these influencing factors, the changes in the impact of risks of health or death are often the focus of assessment programs in the public sector (the United States Environmental Protection Agency 2016).

The effect on health or death is often measured with changes in risk indicators, but in the context of assessment of public policies, to enable risk indicators to be effectively integrated into the CBA decision analysis framework, it is necessary to conduct a monetized evaluation. From a methodological point of view, the commonly used fatal risk monetization method is the value of statistical life (VSL). According to the basic concept of VSL, in the minds of people, there is a willingness to pay (WTP) for the reduction of a certain percentage of fatal risk, and VSL refers to the summing up of the WTPs in the unit of risk (Viscusi and Aldy 2003; Viscusi et al. 2014). VSL plays a very important role in the assessment of public decision-making, especially in applications in environmental protection, food safety, etc. Based on past assessment experience, the benefits or costs generated by VSL in the aforementioned public construction or management decisions often account for more than 80% of the total benefit or total cost (Hammitt and Robinson 2011). Therefore, the evaluation and updating of VSL has become an important task in supporting the public sector's management decisions.

To provide a credible and updated VSL estimation for the public sector, continuous empirical evaluation of VSL has been conducted all over the world. In terms of basic methodology, VSL assessment can be performed through two direct evaluation methods. The first is the stated preference approach, in which questionnaire surveys such as the contingent valuation method (CVM) are adopted to measure the WTP for reducing the fatal risk of the public and further to estimate VSL, which has been used extensively (Hammitt and Graham 1999; Corso et al. 2001; Alberini et al. 2004; Hammitt and Haninger 2010; Cameron and DeShazo 2010; Cameron et al. 2010; Chestnut et al. 2012; Cameron and DeShazo 2013; Viscusi et al. 2014). The second is the hedonic wage method (HWM), in which the difference in fatal risk behind wage is used to infer the evaluation of fatal risk by wage-earners in different occupations and further to estimate VSL (Viscusi 2003; Smith et al. 2004; Viscusi 2004; Kneisner and Viscusi 2005; Viscusi and Aldy 2007; Aldy and Viscusi 2008; Viscusi and Hersch 2008; Kniesner et al. 2010; Evans and Schaur 2010; Hersch and Viscusi 2010; Scotton and Talyor 2011; Scotton 2013). In terms of methodology, CVM is more consistent with theory, but because it involves the use of a questionnaire, in addition to the influences of questionnaire design and survey execution, the cost of the actual operation is rather high. HWM estimates VSL using the wage data of the labor market, which are often readily available, thereby resulting in a low operating cost. Thus, HWM is currently one of the mainstream methods in VSL-related investigations.

In addition to the above-mentioned two direct VSL estimation methods using survey data, there are two indirect assessment methods that are based on existing literature: meta-analysis, which conducts cross-studies using a large number of studies (Doucouliagos et al. 2014; United States Environmental Protection Agency 2016; Viscusi and Masterman 2017), and the benefit-

transfer method, which transfers the existing literature results through various adjustment methods.

Regardless of CVM or HWM, operating costs are higher than the indirect methods, and under the premise of limited evaluation resources, it is impossible to estimate VSL in every case. To address this issue, the benefit-transfer method is often adopted to use the existing VSL results as the study site and then use the income heterogeneity present between the study site and the policy site to make adjustments, which is then transferred into the VSL of the policy site. For example, in the United States, the evaluation of the VSL in the coming year is usually transferred and inferred using a value of income elasticity between 0.4 and 0.5, and in the case where the region to be transferred is a low-income country or region, an income elasticity of 1 is generally used as the basis of the transfer and inference (the United States Environmental Protection Agency 2016). The above discussion indicates that the effect of income heterogeneity on VSL is an important research topic in VSL policy assessment.

From the theoretical point of view, because reducing fatal risk is a normal good, the population with a high income should also have a high WTP for reducing fatal risk and vice versa (Viscusi and Aldy 2003; Kniesner et al. 2010; Hammitt and Robinson, 2011). When addressing methodological aspects, in order to grasp the effect of income heterogeneity on VSL, the meta-analysis method is primarily used to examine the effect of income heterogeneity on VSL through cross-studies using a large number of existing VSL-related studies (Viscusi and Aldy 2003; Viscusi and Masterman 2017). Although in terms of empirical methodology, it is easy to use the meta-analysis method, it requires sufficient existing studies as its analytical basis, which is a prerequisite of the meta-analysis. In the absence of adequate literature, it is difficult to investigate the impact of income heterogeneity on VSL through meta-analysis. Moreover, according to Viscusi (2011), the study on the effect of income heterogeneity on VSL using meta-analysis is essentially a type of cross-study on income heterogeneity, which cannot be used when addressing the impact of income heterogeneity on VSL through a single within-study.

On the other hand, Evans and Schaur (2010) and Kniesner et al. (2010) employed a quantile regression model to conduct empirical analysis on the hedonic wage function (HWM), which is characterized by its ability to estimate VSL values corresponding to different wages, which are then used as the basis to examine the impact of income heterogeneity. The results of the above empirical studies supported the conclusion that income heterogeneity exerts a significant impact on VSL. Moreover, the quantile regression approach is able to address the effect of income heterogeneity on VSL through a within-study approach to make up for the inadequacy of meta-analysis.

VSL has been investigated in Taiwan. Prior to 2000, there were several studies, including Wang (1987), Hsueh and Wang (1987), Liu and Zhan (1989), and Liu et al. (1997); however, after 2000, only one empirical study was conducted, by Liu (2011), which involved an estimation of VSL from 2002-2006. The above VSL-related studies conducted in Taiwan mainly adopted HWM to estimate VSL using the data collected in the “Manpower Utilization Survey” conducted by the Directorate-General of Budget, Accounting and Statistics, Executive Yuan. So far, the effect of income heterogeneity on VSL has not been studied in Taiwan. In this regard, to bridge the gap of VSL study in Taiwan, based on HWM and the “Manpower Utilization Survey” data, we employed the quantile regression method to conduct an empirical analysis on the impact of income heterogeneity on VSL in Taiwan.

2. Research methods

2.1 Application of HWM in VSL

HWM establishes the hedonic wage function through the wage-risk tradeoff relationship, in which the assessments of the changes in fatal risks by job seekers are inferred through the wage differences corresponding to the fatal risks faced by employees of different occupations, which are then used as the basis for VSL estimation. In the settings of HWM, it is usually assumed that the wage has a functional relationship between the job and the personal characteristics, i.e., the wage (W_i) of a particular sample i can be expressed as a function that is affected by various variables such as personal characteristics (S_i, e.g., socio-economic background features such as education level, gender, age, work experience, etc.), job characteristics (N_I, e.g., occupation, work location, etc.), fatal risk of the job (FR_i), nonfatal injury risk of the job (NFR_i), etc., as shown in Formula (1).

$$\mathrm{W}_i = f(S_i, N_i, FR_i, NFR_i) \tag{1}$$

By calculating using the empirical data on Formula (1), the coefficient of each characteristic is obtained, which represents the marginal impact of the per-unit change in each characteristic on wage Wi, and that of FR_i represents monetized assessment corresponding to per-unit change in fatal risk probability, which can be further used to infer VSL.

In terms of the specification of empirical function, following the settings in the linear-log hedonic wage function that has been most commonly used in existing literature, VSL can be calculated using Formula (2).

$$\mathrm{VSL}(FR_i) = \left[\left(\frac{\partial \widehat{lnW_i}}{\partial FR_i} = \hat{\delta} * W_i\right) * \text{annual working hours} * \text{unit of risk probability}\right] \tag{2}$$

In which $\hat{\delta}$ is the estimated coefficient of fatal risk probability FR_i; the annual working hours are generally set to 2,000 hours (40 hours/week, 50 weeks/year); and the unit of risk probability depends on the unit of probability adopted in each specific study. For example, the occupational injuries ratio per thousandth under labor insurance in Taiwan mainly uses an index of one thousand persons (1,000%) as the risk measurement unit, and thus here, the unit of risk probability is 1,000.

2.2 **Quantile regression model**

The quantile regression model is a semi-parametric method in which the distribution is presented based on actual data, and the estimation of coefficient corresponding to the specific conditional quantile is obtained but does not require predetermining the form of distribution function, so it is more flexible in applications of empirical estimation. Another advantage of the quantile regression approach is that when the samples themselves are asymmetric, it is less affected by outliers and thus gives rise to a better estimate of the coefficient. As a result, quantile regression has become a popular empirical analysis tool in recent years (Koneker and Hallock 2001; Koneker 2005).

In this study, the concept of traditional HWM was adopted and the hedonic wage function was estimated using the quantile regression approach, and the empirical formula is shown in Formula (4).

$$W_i(FR_i) = \alpha_\theta + S_i'\boldsymbol{\beta}_\theta + N_i'\boldsymbol{\gamma}_\theta + \delta_{1\theta}(FR_i * Age_i) + \delta_{2\theta}(NFR_i * Age_i) + \varepsilon_{\theta i} \quad (4)$$

Wherein *i* represents different samples; θ represents different conditional quantiles; *W* is a variable measuring the hourly wage and assumes a certain functional relationship with *FR;* ***S*** is the vector of variables of personal socio-economic background; ***N*** is the vector of working environment variables; *FR* is the fatal risk corresponding to each of the different occupations; *NFR* is the non-fatal injuries risk corresponding to each of the different occupations; *Age* is the age of the respondent; β, γ, and δ are coefficients to be estimated; and ε is the random error term. Of these, the interaction terms between *Age* and *FR* and *NFR* measure the effect of age differences on VSL estimation results, which have already been shown to be significant factors (Viscusi and Aldy 2003; Smith et al. 2004; Aldy and Viscusi 2007; Aldy and Viscusi 2008; Evans and Schaur 2010; Liu 2011; Viscusi 2011). Through Formula (5), the coefficients to be estimated under different quantile intervals can be obtained.

$$\min_\varphi\left[\sum_{\ln W_i \geq \varphi Z_i} \theta|W_i - \varphi Z_i| + \sum_{\ln W_i < \varphi Z_i}(1-\theta)|W_i - \varphi Z_i|\right] \quad (5)$$

Wherein Z_i *is* the explanatory variable vector containing *S*, *N*, *FR*, and *NFR*.

The characteristics of quantile regression are that under different quantiles, the marginal effect of each characteristic's variable on wage can be estimated. Let the hedonic wage function assume the semi-log function form; then, based on this characteristic of quantile regression, the VSL_θ corresponding to different wage quantile intervals (θ) can be calculated using Formula (6):

$$\mathrm{VSL}_\theta(FR_i) = \left[\left(\frac{\widehat{\partial lnW_i}}{\partial FR_i} = \hat{\delta}_\theta * Age_i * W_i\right) * 2{,}000 * 1{,}000\right] \quad (6)$$

3.3 Choice of empirical function form: Box-Cox transform

In studies involving VSL, the choice of the form of hedonic wage function exerts a certain impact on the estimation of VSL. To avoid issues associated with the subjective choice of the function form, Moore and Viscusi (1988) recommended the use of Box-Cox transform, in which a statistical test is used to determine the form of hedonic wage function. The study found that the semi-log function was more fitting to the empirical data from the US. Due to this characteristic, subsequent studies of VSL using the US empirical data also adopted the setting of semi-log function.

The empirical data from Taiwan may be different from those from the US that have been used by Moore and Viscusi (1988) in various aspects, such as structure and variable characteristics, so directly choosing the semi-log function form based on the empirical study is inappropriate. To avoid the influence of the subjective choice of empirical function form, in this study, we adopted the Box-Cox method to perform the estimation in combination with Formula (7) and determined the optimal empirical function form based on the test result.

$$\frac{\mathrm{W}_i^{\lambda}-1}{\lambda} = \alpha + S_i'\boldsymbol{\beta} + N_i'\boldsymbol{\gamma} + \delta_1(FR_i * Age_i) + \delta_2(NFR_i * Age_i) + \varepsilon_i \quad (7)$$

Wherein λ is the characteristic's coefficient in the Box-Cox transform, and through estimation using Formula (7), the optimal value of λ can be obtained, from which the optimal

hedonic wage function form for the data from Taiwan can be inferred. The forms of the function can vary as λ changes, as shown in Formula (8).

$$\frac{W^{\lambda}-1}{\lambda} = \begin{cases} W-1, \ if\ \lambda = 1 \\ \ln(W), \ if\ \lambda = 0 \\ 1-\frac{1}{W}, \ if\ \lambda = -1 \end{cases} \tag{8}$$

3. Empirical data source and processing

3.1 Manpower utilization survey

In this study, the data from the "Manpower Utilization Survey," which is annually executed by the Directorate-General of Budget, Accounting and Statistics, Executive Yuan, Taiwan, were used in the empirical estimation of hedonic wage function. According to the instruction of the Directorate-General of Budget, Accounting and Statistics, Executive Yuan (2015), the objects of the "Manpower Utilization Survey" are citizens of Taiwan from ordinary households and common business households residing in Taiwan who are aged 15 and above and engage in economic activities; households are surveyed annually through interviews with respondents by designated personnel.

The survey questionnaire contains three major parts. In the first part, items such as the monthly income, regular weekly working hours, employment duration of current job, the number of job changes, the workplace location and title of last job, reasons for leaving last job, the method of obtaining current job, and the plan of changing job or adding more jobs are included to understand manpower utilization and employees' job changes. In the second part, items such as sought-after jobs and the expected benefits of the unemployed, the acceptance of grassroots jobs with irregular working hours and manufacturing or construction sites, employment opportunities during job hunting and the reasons for not being employed, and the source of living expenses during job hunting are included. In the third part, items are designed for the currently unemployed, such as information of last job and reasons for stopping last job, information on job hunting and reasons for stopping job-hunting, employment willingness and expected salary and benefits, etc., and the age information for the respondent's children is also included to understand the influence of children in the household on the labor participation of the respondent.

The information collected in the "Manpower Utilization Survey" contains the personal characteristics and working characteristics variables needed for estimating hedonic wage function and represents the most complete survey data of labor force employment in Taiwan. It is thus suitable for the empirical estimation of hedonic wage function in Taiwan. In this study, the 2014 survey data were chosen for the subsequent empirical analysis.

3.2 Source and processing of fatal risk and non-fatal injuries risk variables

Two risk variables, i.e., fatal risk (*FR*) and non-fatal injuries risk (*NFR*) in different occupations, were measured using the items included in the statistical data in "Occupational injuries ratio per thousandth under labor insurance" from the Ministry of Labor (2016). In addition to the use of the occupational fatality rate corresponding to each of different occupations as the measurement of the fatal risk variable, two additional indicators, i.e., annual occupational injury or sickness ratio per thousandth and disability ratio per thousandth, were used, and the sum of the two was used as the measurement of the non-fatal injuries risk (*NFR*) variable.

3.3 Sample processing

To focus on the research topics of this study, the data with missing information were excluded and further processed as follows:

- Based on the general life cycle of labor, those who are aged below 20 years or over 65 years were excluded;
- Those who receive monthly wages were used as analysis objects;
- Full-time employees were used as analysis objects, and part-time ones were excluded;
- Those who are self-employed, employers, and unpaid homemakers were excluded;
- Those who earn a wage below the minimum wage according to Taiwan's official standard (with a monthly salary of less than $625.4, or an hourly rate of $3.79; the 2014 average exchange rate of NT$ dollar to US dollar: 30.38:1) were excluded; and
- Those who have missing information on monthly salary and working hours were excluded.

After screening and processing according to the above criteria, a total of 3,974 samples were obtained for subsequent empirical analysis.

The empirical variables used in this study can be divided into three broad categories, i.e., risk variables (fatal risk *FR*, nonfatal injury risk *NFR*), personal characteristics variables (S), and working environment variables (N). The definition and descriptive statistics of each variable are shown in Table 1.

4 Empirical analysis results

4.1 Choice of function form: Box-Cox estimation result

As the basis for setting the form of hedonic wage function, the estimation result of the Box-Cox transform shows that the transform coefficient (λ) is -0.7256, which is significant at the 1% level and different from 0, indicating that the hedonic wage function with the empirical data from Taiwan does not show the semi-log relationship but a more ordinary nonlinear relationship. Thus, based on the estimation result of coefficient value (λ) and Formula (9), the hourly wage after nonlinear conversion was redefined and used as the dependent variable to perform subsequent empirical estimation on hedonic wage function.

$$BC\_hour\_wage = \frac{W_i^{\lambda}-1}{\lambda} = \frac{W_i^{-0.7256}-1}{-0.7256} \tag{9}$$

4.2 Estimation result of hedonic wage function

To estimate the VSL at different income intervals, we used the quantile regression model to estimate hedonic wage function under five quantiles, i.e., the 10th percentile (θ=0.1), the 25th percentile (θ=0.25), the 50th percentile (θ=0.5), the 75th percentile (θ=0.75), and the 90th percentile (θ=0.9). Moreover, we also employed the ordinary least squares (OLS) method, which has been frequently used in previous studies, to estimate, and the estimation result was compared with that obtained using quantile regression estimation. In the estimations, virtual variables that have been excluded to be references, i.e., “workplace location is outside Taiwan's five municipalities” *(area_other)*, “having an education level of Ph.D.” *(Edu8)*, “the number of employees of the company of employment is over 500” *(Industry_size7)*, and “the occupational category is mechanical equipment and assembly operators” (*Occu9*), were used as the comparison baselines. The coefficient estimation results of each model are shown in **Table 2**.

The results in **Table 2** show that the estimates of coefficients through the quantile regression model and the conventional OLS estimation were consistent in signs. In terms of the interaction term of occupational fatal risk and age *(FR * Age)*, which is most important for VSL estimation, the estimated coefficients were all statistically significant and varied with differences in income levels, confirming the presence of income heterogeneity. The comparison on the estimation results of OLS and quantile regression show that except for the 25th percentile, the estimated coefficients by quantile regression at the other four percentiles were all higher than those by OLS, indicating that in addition to its inability to reasonably present the fatal risk evaluations under different income levels, the traditional OLS underestimated VSL. Furthermore, the signs of the interaction terms of fatal risk and age by different models were all positive, indicating that the evaluation of fatal risk increased as age increased. This result also indicated that in terms of the empirical data from Taiwan, the higher the age, the higher the VSL that was inferred, which is consistent with the result of Smith et al. (2004).

The signs of the effects of most explanatory variables on wage were consistent with those reported previously. For example, men usually had a higher wage than women, and the difference increased as wage increased. Work experience exerted a positive impact on wage, but the gain began to decline at the 25th percentile. Education level had a significant effect on wage. Age showed a positive impact on wage, but it was not significant until the 50th percentile. In terms of different occupations, generally, those who held management and professional positions earned a higher wage. In terms of the size of company, those who work in companies with more employees had a significantly higher wage, which is consistent with the general observation.

4.3 VSL estimation under different income levels

In this study, the hedonic wage function, constructed using empirical data from Taiwan, was judged as a general non-linear function through a Box-Cox transform test, and the marginal effect of per-unit wage change on income can be derived through Formula (10). On this basis, in combination with the estimation on the coefficient of the interaction term of fatal risk and age in each quantile regression model, the mean VSL value corresponding to each income quantile can be calculated through Formula (11); the result of the calculation is shown in **Table 3**.

$$\partial\left(\frac{\mathrm{W}_i^{\lambda}-1}{\lambda}\right)/\partial FR_i = \hat{\delta}_1 * Age_i \Longrightarrow \partial W_i/\partial FR_i = (\hat{\delta}_1 * Age_i * \mathrm{W}_i^{1-\lambda}) \qquad (10)$$

$$\overline{\mathrm{VSL}_\theta}(FR) = \left[\left(\hat{\delta}_\theta * \overline{\mathrm{Age}} * \overline{W^{1-\lambda}}\right) * 2{,}000 * 1{,}000\right], \lambda = -0.7256. \qquad (11)$$

Results in **Table 3** show that first, the VSL values corresponding to different income levels were significantly different, indicating that income heterogeneity is indeed present in the estimated VSL values of Taiwan. The comparison of VSL values at the 50th percentile (i.e., median) by OLS and quantile regression indicates that the mean VSL value estimated through OLS was $8.54 million, which is lower than that estimated through quantile regression at the 50th percentile ($9.8 million). Using the meta-analysis method, the United States Environmental Protection Agency (2016) estimated the mean VSL value at $10.3 million (in 2013 $). Compared with that of the US, the mean estimated VSL value of Taiwan was lower.

In terms of the VSL values estimated under different income levels, except for the VSL value estimated at the 10th percentile for wage, the VSL values estimated at the other percentiles increased as wage increased, which is consistent with the trend revealed in previous studies.

Comparison between wage at the 75th percentile and that at the 50th percentile, which corresponds to a monthly wage difference of approximately 40%, shows that their estimated VSL values differed by approximately 91%. The estimated VSL value at the 90th percentile increased by approximately 99% compared with that at the 75th percentile, while the monthly wage difference at the two percentiles was approximately 33%. This result indicates that in the high-wage quantile intervals, the gain to VSL from per-unit wage was also high.

Table 3: The estimated value of statistical life by wage

Model	Hourly wage ($/hour)	Monthly wage ($/month)	VSL (million$)	95% C.I. (million$)
QR: 10%	4.46	822.91	9.80	8.52~11.08
QR: 25%	5.14	908.49	6.83	5.76~7.89
QR: 50%	6.17	1086.24	8.85	7.63~10.06
QR: 75%	8.23	1481.24	16.93	15.25~18.61
QR: 90%	11.32	1974.98	33.71	31.34~36.08
OLS	7.25	1254.93	8.54	7.34~9.73

Table 3 shows that the estimated VSL value at the 10th percentile was significantly higher than that at the 25th or 50th percentile, which seems to be inconsistent with the inference that the higher the wage, the higher the VSL. Further investigation revealed that this inconsistency may stem from the impacts of other types of heterogeneity other than income heterogeneity. Previous studies indicated that in addition to income heterogeneity, age heterogeneity is also a factor that exerts a significant impact on VSL (Viscusi and Aldy 2003; Smith et al. 2004; Aldy and Viscusi 2007; Aldy and Viscusi 2008; Evans and Schaur 2010; Liu 2011; Viscusi 2011). To further grasp the effect of age heterogeneity on the estimated VSL value of Taiwan, we used Formula (12) to estimate VLS for each age group at each percentile, and the calculation results are shown in **Table 4**.

$$\mathrm{VSL}_{\theta,Age_j}(FR) = \left[\left(\hat{\delta}_\theta * Age_j * \overline{W^{1-\lambda}}\right) * 2{,}000 * 1{,}000\right], Age_j = 20, 30, 40, 50, 60. \qquad (12)$$

The conclusions on the effect of age heterogeneity on VSL in previous studies are inconsistent. Some found that the higher the age, the lower the VSL, while others drew the opposite conclusion. According to the calculation results shown in **Table 4**, in the empirical data of Taiwan, age had a positive impact on VSL, i.e., the higher the age, the higher the VSL, indicating that even under the same wage interval, the distribution of age groups will affect the interpretation of VSL.

We examined the raw data and found that in 465 samples, the hourly wage was below $4.46 (corresponding to the 10th percentile of income level), and those aged over 30 years accounted for 70% of the total. Because VSL rises with age increase, in the low-wage intervals where high-aged laborers compose a high proportion, the estimated VSL was also higher.

Only a few previous studies have simultaneously addressed the effects of income heterogeneity and age heterogeneity on VSL. Evans & Schaur (2010) also employed quantile regression to simultaneously examine the influences of income heterogeneity and age heterogeneity on VSL in the US and found that under the 50th percentile for wage (equivalent to an hourly wage of $13.07), the VSL of those aged 50 years was $65.59 million. In the case of

Taiwan, the hourly wage of $13.07 represented the 90th percentile for wage in Taiwan, and the estimated VSL of those aged 50 years was $40.71 million, which is much lower than that of the US.

Table 4: The estimated value of statistical life by wage and age (million$)

Model	VSL 20 years old	VSL 30 years old	VSL 40 years old	VSL 50 years old	VSL 60 years old
QR: 10%	4.73	7.10	9.47	11.83	14.20
QR: 25%	3.30	4.95	6.59	8.24	9.89
QR: 50%	4.27	6.41	8.55	10.68	12.82
QR: 75%	8.18	12.26	16.35	20.44	24.53
QR: 90%	16.28	24.42	32.56	40.71	48.85
OLS	4.12	6.19	8.25	10.31	12.37

5. Conclusions

In this study, the effect of income heterogeneity on VSL was examined through the quantile regression method using the 2014 “Manpower Utilization Survey” data, and the results of this empirical study show that first, the more appropriate setting for constructing the hedonic wage function using the empirical data from Taiwan is the general non-linear form rather than the semi-log form that has been commonly used in previous studies. When the semi-log form is used to estimate Taiwan’s VSL, it is prone to generating errors.

Second, the estimated VSL values of Taiwan fluctuated significantly with income differences, which is consistent with the results of previous studies. This finding also indicates that when estimating Taiwan’s VSL, income heterogeneity must be taken into account. Moreover, in this study, the effect of age heterogeneity was also considered simultaneously, and the comparisons on VSL values were made in combination with age heterogeneity under different income levels. Overall, the higher the wage, the higher the age, and the higher the WTP for reducing fatal risk.

In terms of policy implications, because the combination of wage and age was used to estimate VSL in this study, the findings can be applied in more detailed cost-benefit analyses in case studies, thereby improving the quality of public decision-making.

Lastly, because the empirical data of a single year were used in this study, the effect of time dimension on VSL is lacking. An investigation on the cross-year VSL changes using the empirical approach established in this study will be conducted in follow-up studies.

References

- Aldy, J.E., Viscusi, W.K. (2008). Adjusting the value of a statistical life for age and cohort effects. *The Review of Economics and Statistics*, 90(3), 573-581.
- Alberrini, A., Cropper, M., Krupnick, M., Simon, N.B. (2004). Does the value of a statistical life vary with age and health status? evidence from the US and Canada. *Journal of Environmental Economics and Management*, 48(1), 769-792.
- Cameron, T.A., DeShazo, J.R. (2010). Euthanizing the value of a statistic life. *Review of Environmental Economics and Policy*, 4(2), 161-178.
- Cameron, T.A., DeShazo, J.R., Johnson, E.H. (2010). The effect of children on adult demands for health-risk reductions. *Journal of Health Economics*, 29, 364-376.
- Cameron, T.A., DeShazo, J.R., (2013). Demand for health risk reductions: a cross-national comparison between the U.S. and Canada. *Journal of Risk and Uncertainty*, 41, 245-273.
- Chestnut, L.G., Rowe, R.D., Breffle, W.S. (2012). Economic valuation of mortality-risk reduction: stated preference estimates from the United States and Canada. *Contemporary Economic Policy*, 30(3), 399-416.
- Corso, P.S., Hammitt, J.K., Graham, J.D. (2001). Valuing mortality-risk reduction: using visual aids to improve validity of contingent valuation. *Journal of Risk and Uncertainty*, 23(2), 165-184.
- Directorate-General of Budget, Accounting and Statistic, Executive Yuan (2015). *Manpower Utilization Survey, 2014* (AA020037) [data file]. Available from Survey Research Data Archive, Academia Sinica. doi:10.6141/TW-SRDA-AA020037-1.
- Doucouliagos, H., Stanley, T.D., Viscusi, W.K. (2014). Publication selection and the income elasticity of the value of a statistical life. *Journal of Health Economics*, 33, 67-75.
- Evan, M.F., Schaur, G. (2010). A quantile estimation approach to identify income and age variation in the value of a statistical life. *Journal of Environmental Economics and Management*, 59(3), 260-270.
- Hammit, J.K., Robinson, L.A. (2011). The income elasticity of the value per statistic life: transferring estimates between high and low Income populations. *Journal of Benefit-Cost Analysis*, 2(1), 1-27.
- Hammitt, J.K., Haninger, K. (2010). Valuing fatal risks to children and adults: effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty*, 40: 57-83.
- Hammitt, J.K., Graham, J.D. (1999). Willingness to pay for health protection: inadequate sensitivity to probability. *Journal of Risk and Uncertainty*, 8, 33-62.
- Hersch, J.H., Viscusi, W.K. (2010). Immigrant status and the value of statistical life. *The Journal of Human Resource*, 45(3), 749-771.
- Hsueh, L.M., Wang, Su-Wan (1987). *Evaluation of value of statistical life for workers in Taiwan area: theory and practice of wage premium of job-related risk. Economic Papers No.108*, Taipei: Chung-Hua Institution for Economic Research.
- Koenker, R., Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15, 143-156.
- Kniesner, T.J., Viscusi, W.K., Ziliak, J.P. (2010). Policy relevant heterogeneity in the value of statistical life: New evidence from panel data quantile regressions. *Journal of Risk and Uncertainty*, 40(1), 15-31.
- Kniesner, T.J. and W.K. Viscusi, 2005. "Value of a Statistical Life: Relative Position vs. Relative Age," *American Economic Review*, 95(2): 142-146.

- Koenker, R. (2005). *Quantile regression*. Cambridge: Cambridge University Press.
- Liu, Jin-Long (2011). The older the less value?-- an analysis in the effect of age on the value of life. Research Project of National Science Council, NSC 98-2410-H-008-022-MY2, Graduate Institute of Industrial Economics, National Central University.
- Liu, J.T., Hammitt, J.K., Liou, J.L. (1997). Estimated hedonic wage function and value of life in developing country. *Economic Letters*, 57, 353-358.
- Ministry of Labor (2016). *Occupational injuries ratio per thousandth under labor insurance*. https://statfy.mol.gov.tw/.
- Moore, M.J., Viscusi, W.K. (1988). The quantity-adjusted value of life. *Economic Inquiry*, 3, 369-388.
- Scotton, C.R. (2013). New risk rates, inter-industry differential and the magnitude of VSL estimates. *Journal of Benefit-Cost Analysis*, 4(1), 39-80.
- Scotton, C.R., Taylor, L.O. (2011). Valuing risk reductions: incorporating risk heterogeneity into a revealed preference framework. *Resource and Energy Economics*, 33, 381-397.
- Smith, V.K., Evans, M.F., Kim, H., Taylor Jr., D.H. (2004). Do the near-elderly value mortality risks differently? *The Review of Economics and Statistics*, 86(1), 423-429.
- United States Environmental Protection Agency (2016). V*aluing mortality risk reductions for policy: a meta-analytic approach*. https://yosemite.epa.gov/sab/sabproduct.nsf/0/0CA9E925C9A702F285257F380050C842/$File/VSL%20white%20paper_final_020516.pdf.
- Viscusi, W.K., Masterman, C.J. (2017). Income elasticities and global values of a statistical life. *Journal of Benefit-Cost Analysis*, 8(2), 226-250.
- Viscusi, W.K., Huber, J., Bell, J. (2014). Assessing whether there is a cancer premium for the value of a statistical life. *Health Economics*, 23, 384-396.
- Viscusi, W.K. (2011). Policy challenges of the heterogeneity of the value of statistical life. *Foundations and Trends in Microeconomics*, 6(2), 99-172.
- Viscusi, W.K., Hersch, J. (2008). The mortality cost to smokers. *Journal of Health Economics*, 27, 943-958.
- Viscusi, W.K., Aldy, J.E. (2007). Labor market estimates of the senior discount for the value of statistical life. *Journal of Environmental Economics and Management*, 53(3), 377-392.
- Viscusi, W.K. (2003). Racial differences in labor market values of statistical life. *Journal of Risk and Uncertainty*, 27(3), 239-256.
- Viscusi, W.K. (2004). The value of life: estimates with risks by occupation and industry. *Economic Inquiry*, 42(1), 29-48.
- Viscusi, W.K., Aldy, J.E. (2003). The value of a statistical life: a critical review of market estimates throughout the world. *Journal of Risk and Uncertainty*, 27(1), 5-76.
- Wang, W. (1987). *Estimation of value of statistical life*. Master's thesis, Department of Economics, Feng Chia University.

Table1: Empirical variables and Summary statistics

Variable	Definition	Mean	Standard deviation
hour_wage	Hourly wage rate（2014 NT$）	220.3872	103.75
FR	Fatalities per 1,000 workers in the individual's industry	0.0259	0.0407
NFR	Injury per 1,000 workers in the individual's industry	3.1558	2.4898
Area_Taipei	Dummy variable that equals 1 if individual's location of workplace is in Taipei City	0.0722	0.2589
Area_Newtaipei	Dummy variable that equals 1 if individual's location of workplace is in New Taipei City	0.1062	0.3081
Area_Taichung	Dummy variable that equals 1 if individual's location of workplace is in Taichung City	0.1256	0.3314
Area_Tainan	Dummy variable that equals 1 if individual's location of workplace is in Tainan City	0.0833	0.2764
Area_Kaohsiung	Dummy variable that equals 1 if individual's location of workplace is in Kaohsiung City	0.1233	0.3288
Area_other	Dummy variable that equals 1 if individual's location of workplace is outside of the five municipalities in Taiwan	0.4894	0.5000
familysize	Number of family members over 15 years old	3.6228	1.5132
Age	Individual's age in years	39.2285	10.0255
Sex	Dummy variable indicating individual is male	0.5528	0.4973
Exp	Total number of years worked	8.3132	7.2991
Edu1	Dummy variable that equals 1 if individual's education attainment is primary school	0.0216	0.1455
Edu2	Dummy variable that equals 1 if individual's education attainment is junior high school	0.0893	0.2853
Edu3	Dummy variable that equals 1 if individual's education attainment is senior high school	0.2343	0.4236
Edu4	Dummy variable that equals 1 if individual's education attainment is vocational high school	0.0941	0.2920
Edu5	Dummy variable that equals 1 if individual's education attainment is junior college	0.1545	0.3615
Edu6	Dummy variable that equals 1 if individual's education attainment is university	0.3261	0.4689
Edu7	Dummy variable that equals 1 if individual's education attainment is master	0.0730	0.2601
Edu8	Dummy variable that equals 1 if individual's education attainment is Ph.D	0.0065	0.0806
Marital_status	Dummy variable that equals 1 if individual is single without spouse	0.3958	0.4891
Industry_size1	Dummy variable that equals 1 if number of employees of company is 2-9 persons	0.1993	0.3995
Industry_size2	Dummy variable that equals 1 if number of employees of company is 10-29 persons	0.2028	0.4021
Industry_size3	Dummy variable that equals 1 if number of employees of company is 30-49 persons	0.1002	0.3002
Industry_size4	Dummy variable that equals 1 if number of employees of company is 50-99 persons	0.0888	0.2845
Industry_size5	Dummy variable that equals 1 if number of employees of company is 100-199 persons	0.0924	0.2896
Industry_size6	Dummy variable that equals 1 if number of employees of company is 200-499 persons	0.0541	0.2262

Industry_size7	Dummy variable that equals 1 if number of employees of company is above 500 persons	0.1090	0.3116
Public_sector	Dummy variable that equals 1 if individual worked in public sector	0.1535	0.3605
Occu1	Dummy variable that equals 1 if individual's occupation belongs senior officials and chief executives	0.0345	0.1825
Occu2	Dummy variable that equals 1 if individual's occupation belongs technicians and associate professionals	0.2116	0.4085
Occu3	Dummy variable that equals 1 if individual's occupation belongs craft and related trades workers	0.1251	0.3308
Occu4	Dummy variable that equals 1 if individual's occupation belongs clerical support workers	0.1490	0.3561
Occu5	Dummy variable that equals 1 if individual's occupation belongs service workers and sales	0.1095	0.3123
Occu6	Dummy variable that equals 1 if individual's occupation belongs elementary labourers	0.0365	0.1875
Occu7	Dummy variable that equals 1 if individual's occupation belongs professionals	0.1590	0.3658
Occu8	Dummy variable that equals 1 if individual's occupation belongs skilled agricultural, forestry and fishery Workers	0.0025	0.0501
Occu9	Dummy variable that equals 1 if individual's occupation belongs stationary plant and machine operators	0.1724	0.3777
			Number of Observations: 3,974

Table 2: Empirical results from OLS and quantile hedonic wage regressions (dependent variable: BC_hour_wage.)

Variable	Quantile Regression					OLS
	10%	25%	50%	75%	90%	
*FR*Age*	0.0002884***	0.0002009**	0.0002604***	0.0004982***	0.0009922***	0.0002513***
	(0.0001124)	(0.0000889)	(0.0000804)	(0.0000878)	(0.0001094)	(0.0000645)
*NFR*Age*	0.00000105	0.000000928	-0.00000166	-0.00000454**	-.0000123***	-0.00000125
	(0.0000019)	(0.0000015)	(0.00000136)	(0.00000149)	(0.00000185)	(0.00000109)
Area_Taipei	0.0013781***	0.0011091***	0.0019943***	0.0018989***	0.0023835***	0.0017527***
	(0.0005238)	(0.0004142)	(0.0003747)	(0.0004091)	(0.0005099)	(0.0003335)
Area_Newtaipei	0.0008099*	0.0005385	0.0005234*	0.0003548	0.0002017	0.0004699*
	(0.0004431)	(0.0003504)	(0.0003169)	(0.0003461)	(0.0004313)	(0.0002491)
Area_Taichung	0.0005579	-0.000242	-0.000226	-0.0000763	0.0002095	-0.0000787
	(0.0004142)	(0.0003276)	(0.0002963)	(0.0003235)	(0.0004032)	(0.000238)
Area_Tainan	-9.000703	-0.0013288***	-0.0013437***	-0.0012995***	-0.0009199***	-0.001202***
	(9.0004846)	(0.0003833)	(0.0003467)	(0.0003785)	(0.0004718)	(0.0002714)
Area_Kaohsiung	-0.0009599**	-0.0013978***	-0.0011793***	-0.0008468***	-0.0005663	-0.0011269***
	(0.0004156)	(0.0003287)	(0.0002973)	(0.0003246)	(0.0004045)	(0.0002482)
familysize	-0.00000128	-0.0001079	-0.0001599***	-0.0001788***	-0.0001209	-0.0001291***
	(0.0000873)	(0.000069)	(0.0000624)	(0.0000682)	(0.000085)	(0.0000498)
Age	0.0000196	0.000008	0.0000616***	0.0001043***	0.0001245***	0.0000563***
	(0.0000204)	(0.0000161)	(0.0000146)	(0.0000159)	(0.0000199)	(0.0000128)
Sex	0.0024702***	0.0029369***	0.0031623***	0.0034028***	0.003446***	0.0031188***
	(0.0002847)	(0.0002252)	(0.0002037)	(0.0002224)	(0.0002772)	(0.0001662)
Exp	0.000208***	0.0002312***	0.0001881***	0.0001604***	0.0001064***	0.0001885***
	(0.000023)	(0.0000182)	(0.0000164)	(0.000018)	(0.0000224)	(0.0000142)
Edu1	-0.0084669***	-0.0087704***	-0.0082385***	-0.0086995***	-0.0049913***	-0.0083751***
	(0.0018237)	(0.0014424)	(0.0013046)	(0.0014245)	(0.0017753)	(0.0009595)
Edu2	-0.0075871***	-0.0081664***	-0.0075712***	-0.0073866***	-0.004499***	-0.0073786***
	(0.001644)	(0.0013002)	(0.001176)	(0.0012841)	(0.0016004)	(0.0008455)
Edu3	-0.00676***	-0.0076994***	-0.006839***	-0.0069281***	-0.0044606***	-0.0068254***
	(0.0015906)	(0.001258)	(0.0011378)	(0.0012424)	(0.0015485)	(0.0008093)
Edu4	-0.0068993***	-0.0076518***	-0.0065149***	-0.0062865***	-0.0043115***	-0.0065885***
	(0.0016277)	(0.0012873)	(0.0011643)	(0.0012713)	(0.0015845)	(0.0008347)

Edu5	-0.0054355***	-0.0059313***	-0.0053553***	-0.0054605***	-0.0034548***	-0.0054073***
	(0.001588)	(0.0012559)	(0.0011359)	(0.0012403)	(0.0015458)	(0.0008045)
Edu6	-0.0047391***	-0.0051781***	-0.0038849***	-0.0039804***	-0.0020275	-0.0040771***
	(0.00157)	(0.0012417)	(0.0011231)	(0.0012263)	(0.0015284)	(0.000792)
Edu7	-0.0013527	-0.0018709	-0.0017356	-0.0021321**	-0.0012437	-0.0017447**
	(0.0016147)	(0.0012771)	(0.0011551)	(0.0012612)	(0.0015719)	(0.0008064)
Marital_status	-0.0007373**	-0.0009422***	-0.0007062***	-0.0004221*	-0.0007346**	-0.000809***
	(0.0003259)	(0.0002578)	(0.0002331)	(0.0002546)	(0.0003173)	(0.000188)
Industry_size1	-0.0023746***	-0.0022182***	-.0022608***	-0.0023461***	-0.0026641***	-0.0021733***
	(0.0005239)	(0.0004143)	(0.0003747)	(0.0004092)	(0.00051)	(0.0003094)
Industry_size2	-0.002049***	-0.0019274***	-0.0020837***	-0.0017312***	-0.0022873***	-0.0018618***
	(0.0005052)	(0.0003995)	(0.0003614)	(0.0003946)	(0.0004918)	(0.0002961)
Industry_size3	-0.0013959**	-0.0015863***	-0.0018854***	-0.0018369***	-0.0017431***	-0.0015643***
	(0.0005785)	(0.0004576)	(0.0004138)	(0.0004519)	(0.0005632)	(0.0003349)
Industry_size4	-0.0009557	-0.0010787**	-.0013962***	-0.0013849***	-0.0017832***	-0.0011671***
	(0.0005897)	(0.0004664)	(0.0004219)	(0.0004606)	(0.0005741)	(0.0003344)
Industry_size5	-0.0014053**	-0.0007675*	-0.000536	-0.0006075	-0.0006905	-0.0006726**
	(0.0005808)	(0.0004594)	(0.0004155)	(0.0004537)	(0.0005654)	(0.0003357)
Industry_size6	-0.0003976	-0.0006027	-0.0005608	-0.0002648	-0.0001616	-0.0005239
	(0.0006782)	(0.0005364)	(0.0004851)	(0.0005297)	(0.0006602)	(0.0003956)
Public_sector	0.0014538***	0.0026765***	0.0029024***	0.0023867***	0.0014323***	0.0024132***
	(0.0005486)	(0.0004339)	(0.0003924)	(0.0004285)	(0.000534)	(0.0003345)
Occu1	0.010677***	0.0094084***	0.0094971***	0.0100881***	0.0100771***	0.0097225***
	(0.00081)	(0.0006406)	(0.0005794)	(0.0006327)	(0.0007885)	(0.000456)
Occu2	0.0029129***	0.0033637***	0.0034138***	0.0041041***	0.0043597***	0.003535***
	(0.0004726)	(0.0003738)	(0.0003381)	(0.0003691)	(0.0004601)	(0.0002633)
Occu3	0.001042**	0.0008592**	0.0012528***	0.0011157***	0.0012186***	0.0010228***
	(0.0004937)	(0.0003905)	(0.0003532)	(0.0003856)	(0.0004806)	(0.0002643)
Occu4	-0.0005211	-0.0002888	0.0002435	0.0012423***	0.0018234***	0.00041
	(0.0005085)	(0.0004021)	(0.0003637)	(0.0003971)	(0.000495)	(0.0002899)
Occu5	-.0014314***	-0.0011692***	-.0010113***	-0.0001881	0.0010675**	-0.0007602**
	(0.0005355)	(0.0004235)	(0.000383)	(0.0004183)	(0.0005213)	(0.0003254)
Occu6	-0.0021713***	-0.0025366***	-0.0036465***	-0.0030778***	-0.002864***	-0.0030096***

	(0.0007667)	(0.0006063)	(0.0005484)	(0.0005988)	(0.0007463)	(0.0004141)
Occu7	0.0057273***	0.0059855***	0.0060417***	0.0063769***	0.0072263***	0.0062016***
	(0.0005397)	(0.0004269)	(0.0003861)	(0.0004216)	(0.0005254)	(0.0003179)
Occu8	-0.0029242***	-0.0040369**	-0.0019367	-0.0040534**	-0.0062282***	-0.0032063***
	(0.0026016)	(0.0020576)	(0.001861)	(0.0020321)	(0.0025326)	(0.0013535)
Constant	1.3429***	1.3469***	1.3474***	1.3487***	1.3491***	1.3474***
	(0.0018594)	(0.0014706)	(0.0013301)	(0.0014524)	(0.0018101)	(0.0009825)
Pseudo R^2	0.5752	0.3310	0.3701	0.3916	0.3865	--
R^2	--	--	--	--	--	0.5752

Standard errors are in parentheses.
* Indicates significant at the 10% level; ** indicates significant at the 5% level; *** indicates significant at 1% level.

Table 3: The estimated value of statistical life by wage

Model	Hourly wage ($/hour)	Monthly wage ($/month)	VSL (million$)	95% C.I. (million$)
QR: 10%	4.46	822.91	9.80	8.52~11.08
QR: 25%	5.14	908.49	6.83	5.76~7.89
QR: 50%	6.17	1086.24	8.85	7.63~10.06
QR: 75%	8.23	1481.24	16.93	15.25~18.61
QR: 90%	11.32	1974.98	33.71	31.34~36.08
OLS	7.25	1254.93	8.54	7.34~9.73

Table 4: The estimated value of statistical life by wage and age (million$)

Model	VSL 20 years old	VSL 30 years old	VSL 40 years old	VSL 50 years old	VSL 60 years old
QR: 10%	4.73	7.10	9.47	11.83	14.20
QR: 25%	3.30	4.95	6.59	8.24	9.89
QR: 50%	4.27	6.41	8.55	10.68	12.82
QR: 75%	8.18	12.26	16.35	20.44	24.53
QR: 90%	16.28	24.42	32.56	40.71	48.85
OLS	4.12	6.19	8.25	10.31	12.37