How to Identify and Estimate the Demand for Job Safety?

Zhang, Nan and Mendelsohn, Robert and Shaw, Daigee

Department of Economics and Management, Univeristy of Trento, School of the Environment, Yale University, Institute of Economics, Academia Sinica

2023

How to Identify and Estimate the Demand for Job Safety?

Nan Zhang[1]; Robert Mendelsohn[2]; Daigee Shaw[3]

Abstract:

The hedonic wage equation is the relationship between wages and job and personal attributes (such as safety and working experiences) when the labor market is in equilibrium. The estimated equations have often been used to measure marginal values of risk reduction (safety) (or the value of a statistical life) in the literature. To measure the nonmarginal value of risk reduction, we need to estimate the demand for safety equation. However, no paper has estimated the demand function for safety because identifying the demand function requires data from multiple labor markets, which is difficult to find within a country. Thus, most papers estimate the hedonic wage equation of a single labor market in a country. By taking advantage of a panel dataset regarding the labor market in Taiwan, we divide the labor market into three sequentially separated markets to solve the identification problem. We first estimate the hedonic wage equation for each labor market in the first stage. Then, we estimate the demand for safety in the second stage using the IV approach to address the endogeneity problem in the demand equation. The main contributions of this study are twofold: First, we point out that job risk is not endogenous in estimating the hedonic wage equation, which is different from most hedonic wage studies where job risk has always been taken to be endogenous following Viscusi (1978). Second, this is the first study that has successfully estimated the demand for job risk reduction in the hedonic literature. We find significant income and substitution effects: workers with higher potential income or exposed to higher risks exhibit a higher marginal willingness to pay (MWTP). We also find heterogeneity in MWTP: older workers have higher MWTP, while there are no significant differences between genders. We then conduct welfare analyses regarding nonmarginal changes in risks.

Keywords: hedonic wage model; identification; endogeneity; demand for safety; the value of a nonmarginal change in risk reduction

JEL: J17, J28, Q51

[1] Nan zhang, Corresponding author. Department of Economics and Management, University of Trento, Via Vigilio Inama, 5, 38122 Trento TN, Italy. ORCID: 0000-0002-5399-5780. nan.zhang@unitn.it

[2] Robert Mendelsohn, School of the Environment, Yale University, 195 Prospect Street, New Haven, CT, US. ORCID: 0000-0002-3650-6201. robert.mendelsohn@yale.edu

[3] Daigee Shaw, Institute of Economics, Academia Sinica, 128, Section 2, Academia Road, Nangang, Taipei, Taiwan. ORCID: 0000-0002-5781-0296. dshaw@.sinica.edu.tw, shawdg@gmail.com

How to Identify and Estimate the Demand for Job Safety?

1. Introduction

The hedonic wage model was first used to study the job market by Thaler and Rosen (1976). These authors were specifically interested in the tradeoff between wage and job attributes. Labor market economists call the hedonic wage model a model of compensating wage differentials (CWD).

An important feature of the hedonic wage model is that wage is a function of both job characteristics and workers' characteristics. Job characteristics such as job fatality risk, union, full-time, fringe benefits, and vacation all affect wages. Features of a worker such as their education, experience, and intelligence can also affect wages through their productivity.

In the literature, the most widely studied job attribute is the job fatality risk (Brown,1980; Kniesner et al. 2012; Viscusi, 1978) with other attributes such as gender, experience, education, unions, and workplace amenities controlled (Roback, 1982; Zhang et al., 2021). The job fatality risk is important to the labor market and to policy issues related to job safety. The job fatality risk is also very important to environmental and other public policy decisions that involve risks to human health (Viscusi and Aldy, 2003; Muller and Mendelsohn, 2009). The estimated hedonic wage equations can be used to derive the marginal implicit price (MIP) for different levels of job fatality risk, which is viewed as the marginal value of risk reduction. The MIP of job fatality risk, or the willingness to pay for a micro risk reduction ($WTP\mu r$), is often used to estimate the value of a statistical life (VSL) (Cameron, 2010). Note that the hedonic wage equations do not reveal what level of risk people choose.

Some studies in the hedonic wage literature argue that risk is endogenous in the hedonic wage regression. Viscusi (1978) argues that the OLS regression of wages on risk is biased by selection bias because wealthier people select jobs with less risk since safety is a normal good. Some others claim that omitted variables (such as motivation, intelligence, and cool-headedness) can cause the risk to be endogenous in the hedonic wage equation (Brown, 1980; Duncan and Holmlund, 1983; Garen, 1988, Alberini, 2019). In order to correct for the believed risk endogeneity, these papers and many papers in the literature consequently use IV to estimate the hedonic wage regression (Garen, 1988; Siebert and Wei, 1994; Sandy and Elliott, 1996; Shanmugam, 2001).

This literature is inconsistent with the general literature on the hedonic price model. On the one hand, the hedonic price equation is simply the locus of prices observed for that good and there is no fundamental endogeneity problem involved (Mendelsohn, 1984). The regression of wages on risk only reveals the marginal implicit price that the market charges for different levels of risk, but it does not reveal how people choose their preferred risk levels. Only the second-stage estimation of the demand for attributes has the endogeneity problem. The endogeneity problem arises because of the non-linearity of the hedonic price function, which results in a non-constant MIP, implying that the MIP of an attribute varies with its quantity demanded. On the other hand, for those omitted personal characteristics to bias the hedonic wage estimation, they have to affect both the choice of job risks and the wage at the same time. Though the unobservable worker's motivation or intelligence is positively correlated with one's productivity and wage, they are not necessarily correlated with job risks. Similarly, workers who are more 'cool-headed' may have a lower risk on the job, but it doesn't lead to a higher wage. Such unobservable characteristics may affect what jobs people choose but do not bias the hedonic wage equation.

To estimate the demand for risk reduction (safety), two problems should be solved. The first one is the identification problem. In hedonic price studies for housing markets, it is widely recognized that data from multiple housing markets is a must to identify the demand for housing attributes (Brown and Rosen, 1982; Diamond and Smith, 1985; Mendelsohn, 1984, 1985; Palmquist, 1984; Bartik, 1987a, b; and Epple et al., 1987; Bishop and Timmins, 2018 & 2019)[4]. However, only a few hedonic price studies (Brown and Mendelsohn, 1984; Palmquist, 1984; Parsons, 1986; Englin and Mendelsohn, 1991; Wei,1999; Zabel and Kiel, 2000; Bishop and Timmins, 2018 & 2019; Shaw et al., 2021) have estimated the demand for attributes by using multiple housing markets because data from multiple markets are hard to get. Similarly, it is even harder to get data from multiple labor markets for estimating the demand function for risk reduction since there usually is only one labor market in a country due to the fact that workers usually have freedom to move within a country to find gainful employment.

The second problem in estimating the demand for safety is the endogeneity problem. In the general hedonic models, the hedonic price/wage equation is nonlinear, causing the MIP of an attribute to be a function of its quantities. This correlation between the price and quantity of an attributes causes the endogeneity problem in estimating the demand for safety, which can be addressed by the IV approach. For example, Brown and Mendelsohn (1984) use income, experience, and dummies as instrumental variables, Palmquist (1984) uses income and socioeconomic variables as instrumental variables, Bartik (1987a) uses income, treatment group dummies, a time trend, a dummy variable for the city, and interaction terms between the city variable and demand shifters, Zabel and Kiel (2000) use regional dummies and time indicator variables as instruments, and Shaw et al. (2021) uses dummy variables for regions, zip

[4] Some studies rely on non-parametric estimation and assumptions on function form to help achieve identification with single market data (Ekeland et al., 2002; Ekeland et al., 2004; Heckman et al., 2010) and repeated cross-sectional data (Bishop and Timmins, 2018 and 2019).

codes, and years as instruments.

In this study, we first point out the drawbacks of the hedonic wage literature regarding the identification problem and the endogeneity problem. Then we estimate the demand for safety using a panel data on Taiwan labor market. As far as we know, this is the first study that estimates the demand for safety through the hedonic wage model.

The section arrangement is as follows: In Section 2, we introduce a hedonic wage model and show the relationship between the hedonic wage equation and the demand equation for risk reduction. We also discuss the identification problem and the endogeneity problem associated with estimating the demand function for risk reduction. In Section 3, we utilize a panel data of the Taiwan labor market to identify and estimate the demand for safety equation. Section 4 presents two applications of this demand equation in welfare analysis. Section 5 concludes.

2. Model

2.1 Hedonic wage model

A job is a heterogeneous market good with an observed price or wage, W. Each job has job characteristics such as risk, R, and other job attributes, X, such as union, full-time, fringe benefits, vacation, indoor air quality, and temperature. Unlike the housing market where the characteristics of the buyer or seller are not relevant, the wage of a job also reflects a worker's productivity. So, characteristics of the worker, Y, that affect productivity, such as education and work experience, all belong in the hedonic wage equation:

$$W = W(R, X, Y) \tag{1}$$

The MIP of each characteristic such as risk, R, can be calculated by taking the derivative of (1) with respect to each characteristic. The MIP of risk, P_R is

$$P_R = \partial W / \partial R \tag{2}$$

The nonlinearity of the hedonic wage equation implies that the MIP of each attribute is not constant but a nonlinear function of quantities of this attribute. We expect $P_R > 0$, since according to the hedonic wage theory, workers engaged in higher job risks should be paid higher wages. This nonlinear MIP schedule is depicted as P_R in Figure 1.

The demand function for each attribute is distinct from this MIP schedule. For example, the demand for job safety (risk reduction) for a risk-averse worker would be upward-sloping and steeper than the MIP schedule and would intercept the MIP schedule from below (see Figure 1). Factors such as higher wealth would cause the demand function for risk reduction to shift upwards from D_2 to D_1 in Figure 1. Thus, wealthier workers would tend to choose jobs with lower risk (see Figure 1).

Workers with different tastes over job risks have different safety demand functions. For example, less risk-averse workers would choose riskier jobs than risk-averse workers. Note that the workers do not change the MIP schedule in the market, they simply choose where to be along that schedule. At every point on the MIP schedule, the MIP accurately reflects the marginal value of risk to the workers who choose that job. However, movement along the MIP schedule does not reflect the underlying demand for risk because movements along the MIP schedule inherently involve movements across people with different demand functions for risk.

The MIP schedule, which depicts the marginal value of risk, does not reflect the value of nonmarginal changes in risk. From Figure 1, it is clear that the MIP schedule consistently overestimates the value to an individual of any nonmarginal risk reduction and underestimates the value of any nonmarginal increase in risk.

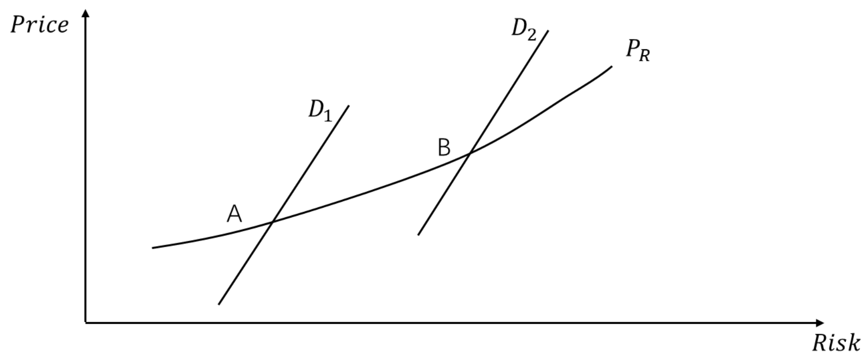

Figure 1. MIP function and the safety demand function

There is no theoretical reason why the MIP schedule should have any specific shape other than it cannot be steeper than the underlying demand functions of workers.

2.2 Identifying the risk demand equation

In a single job market, it is straightforward to estimate the hedonic wage schedule by regressing wages on risk using OLS. Each worker is a (marginal implicit) price taker and cannot influence the MIP schedule. The MIP schedule correctly measures the marginal willingness to pay (MWTP) for safety of a worker at the chosen amount of risks. Only the demand for safety function can answer how worker's MWTPs are affected by income and individual demographic factors that affect tastes.

However, with a single market, researchers cannot identify and estimate the demand function for safety. With only a single price schedule, the safety demand functions D_1 or D_2 could have any shape that goes through the single observed point on the MIP schedule. Identifying the underlying demand function for safety requires information about how a worker would make different choices given different prices of risk. As shown in Figure 2, one needs at least two MIP schedules, P_R^1 and P_R^2, of two markets to identify the underlying demand functions.

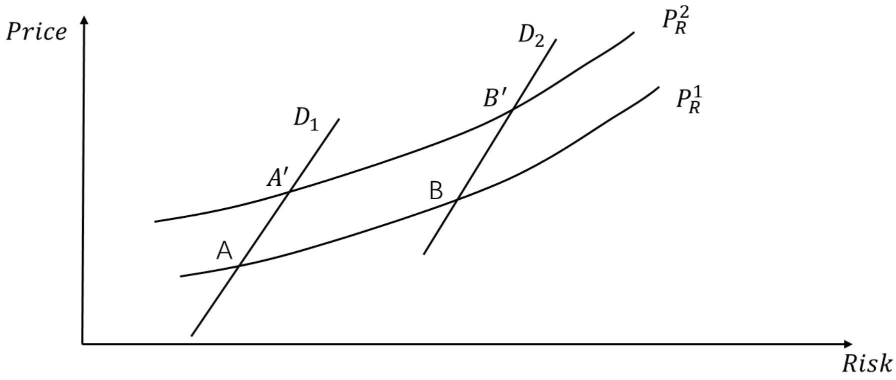

Figure 2: Identification in multiple markets

The underlying demand functions, called structural equations in Mendelsohn (1984, 1985, 1987) or the marginal bidding function in Bartik (1987a, 1987b), can be recovered with a two-step approach as first discussed by Rosen (1974) using housing market data. In the first step, we estimate the hedonic wage equation in each job market and then calculate the MIP schedule, $\widehat{P}_R$, given the amount of risk chosen by each worker. In the second stage, we estimate an inverse demand function for risk.

The non-constant MIP schedule implies the MIP depends on the level of risk chosen and the level of risk chosen depends on the price. In the case of the inverse demand function, self-selection and unobserved characteristics will cause there to be a correlation between the observed risk and the error term (Brown, 1980; Duncan and Holmlund, 1983; Garen, 1988, Black et al., 2003; and Hintermann et al. 2010). A similar issue applies to the price of risk in the estimation of the demand function.

2.3. Estimating the Second Stage with an IV Approach

In order to estimate the second stage demand function, the estimation process has to address the endogeneity of the price of risk (in the demand function) or the risk chosen (in the inverse demand function) caused by the nonlinear hedonic wage equation. An IV approach can address either problem.

Garen (1988) develops a weighted 2SLS approach to solve the risk endogeneity problem. Non-labor income and factors influencing one's degree of risk aversion are used as instrumental variables, including the marital status, the number of dependents, house value, the spouse's schooling, and a dummy variable indicating whether or not the spouse works, and whether the respondent is disabled and if so, for how long. Several other studies have adopted this 2SLS approach with cross-sectional data (Siebert and Wei 1994; Sandy and Elliott, 1996; Shanmugam, 2001).

The only problem with this literature is that these studies have applied this 2SLS approach to estimating the hedonic wage schedule. Since risk is not endogenous in the hedonic wage regression, applying 2SLS to the hedonic wage regression only biases the results. 2SLS introduced the influence of demand shift variables which are not wanted in the hedonic wage regression. The 2SLS approach is only needed in the second stage estimation of the (inverse) demand functions.

As far as we know, there are only two studies that estimate the demand function for safety with job market data. First, Wei (1999) solved the identification problem by treating that south and north England as two separate markets. However, he mistakenly thought there was a risk endogeneity problem in the hedonic wage equation rather than the safety demand equation, and consequently applies the IV approach to the estimation of the hedonic wage equation but not the safety demand equation. Second, Hammitt et al. (2022) have successfully addressed both the identification problem and the endogeneity problem in the second-stage estimation. However, they still applied a 2SLS approach in estimating the hedonic wage equations, as they claimed there is an endogeneity problem in estimating the hedonic wage equation.

However, hedonic wage studies have not taken good advantage of panel data in identifying the (inverse) demand for safety. Since the structures of a labor market change over time, researchers could plausibly use these intertemporal variations to estimate the demand for job characteristics, including risk. These intertemporal changes could be related to specific people changing jobs, or, it could also come from changes in risk at existing jobs. Workers would then bargain for changes in wages to reflect these new risks. Thus, the MIP of risk might change without anyone changing jobs. These changes over time would allow researchers to estimate the underlying demand functions for risk or other job characteristics. In the next section, we use the intertemporal variations in the labor market of Taiwan to identify and estimate the demand for safety.

3. Estimating the Demand Function for Safety with Panel Data from the Taiwan Labor Market.

3.1 Data

The main data set used in this study is the Panel Survey of Family Dynamics (PSFD). The PSFD survey is a face-to-face survey and has been conducted in Taiwan and three eastern provinces (cities) in mainland China. The Taiwan part, initiated in 1999, is conducted with randomly sampled individuals born in 1953-1964 by the Research Center for Humanities and Social Science, Academia Sinica. It is an unbalanced panel with refreshment samples of adult respondents first interviewed in the years 2000, 2003, 2009, and 2016, respectively. The follow-up surveys were conducted annually before 2012, and every other year after 2012. The survey collects information on the respondent’s demographic traits, work status, job information, marital status, demographic traits of parents, housing and living arrangements, income, and so on.

The job risk data are obtained from the Bureau of Labor Insurance, Ministry of

Labor. The data span is 1999-2018. All jobs are classified into 11 industries according to the Statistical Classification of Industry System of the Republic of China (Rev.6, 1996). We use the moving average of the job fatality rates for the past three years to proxy the current year's job risk to reduce the influence of a stochastic shock.

The regional climate may also play a role in the dwelling choices and job choices of workers. Thus, we further control the 25-year average temperatures in January and July, which is the temperature of the coldest and warmest month, respectively. The data span is 1981-2005.

By taking advantage of the panel structure of the PSFD data from 1999 to 2018, we divided the long span into three periods and thus three sequentially separated labor markets. We choose the year 2004 as our first market because it was the first year that cover the age from 25 to 68. The second market is the year 2009 when new samples (young workers aged between 25 and 32) are added to the sample. The third market is the year 2016 when another wave of new workers (also aged between 25 and 32) is included in the sample.

The variable definition and source are shown in Table 1, and the summary statistics for the three markets are shown in Table 2.

Table 1 Variable Definition and Source

Categories	Variable	Definition	Source
Worker attributes	wage	yearly wage in 2014 values (TWD)	PSFD 1999-2018
	female	dummy, 1 if female, 0 otherwise	
	eduyear	education years	
	wexp	work experience years since first full-time job	
	age	age	
	healthleve l	health, 1-5, 1 very, 5 very good	
Job attributes	scale1	1 if the number of employees lies between 10-49, 0 otherwise	
	scale2	if the number of employees lies between 50-499, 0 otherwise	
	scale3	1 if the number of employees is more than 500, 0 otherwise	
	risk	industrial fatality rates (1/1,000,000)	
Site attributes	north	1 if job location is in northern Taiwan, 0 otherwise	
	central	1 if job location is in central Taiwan, 0 otherwise	
	east	1 if job location is in eastern Taiwan, 0 otherwise	
	TJAN	township-level average January temperature (Celsius) from 1981 to 2005	Research Center for Environmental Changes, Academia Sinica
	TJUL	township-level average July temperature (Celsius) from 1981 to 2005	
Family attributes	feduyear	father's education years	PSFD 1999-2018
	marriage	1 if married or have a cohabited partner, 0 otherwise	

Table 2 Descriptive Statistics for the Year 2004, 2009, and 2016

Variable	Year 2004 (Obs. 1054)		Year 2009 (Obs. 1223)		Year 2016 (Obs.2700)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
wage (2014 TWD)	534206.8	395589.3	416999.9	184726.9	511708.7	311819
risk (1/1,000,000)	60.02	52.34	29.23	26.13	23.03	25.67
female	0.44	0.50	0.48	0.50	0.44	0.50
eduyear	11.97	3.25	13.87	2.19	14.15	2.50
wexp	19.28	11.38	8.38	5.60	12.01	9.73
age	38.99	10.31	29.20	4.19	33.63	8.27
healthlevel	3.73	0.85	3.96	0.80	3.6	0.77
scale1	0.31	0.46	0.27	0.44	0.23	0.42
scale2	0.26	0.44	0.28	0.45	0.23	0.42
scale3	0.19	0.39	0.23	0.42	0.26	0.44
north	0.55	0.50	0.46	0.50	0.52	0.50
central	0.19	0.39	0.26	0.44	0.23	0.42
east	0.03	0.18	0.02	0.14	0.02	0.13
TJAN	16.11	1.23	16.25	1.21	16.18	1.17
TJUL	28.97	0.64	28.96	0.58	29.04	0.59
feduyear	6.67	4.54	8.32	2.74	9.46	3.69
marriage	0.39	0.49	0.28	0.45	0.44	0.50

As we can see, the wage structure is changing over time. Our survey data confirms the fact that the real wage in Taiwan has been stagnant since 2003. The mean wage in 2004 is about the same as in 2016, and year 2009 has a slightly lower wage. However, as the wages are stagnant, the job risks across industries are decreasing, indicating that the risk premium is changing over time. Another thing worth noticing is the worker demographics. Both the worker age and education years are different across the three markets. The average age is 39, 30, and 35, in 2004, 2009, and 2016, respectively, because the new workers aged between 25 to 32 are injected into the sample in 2009 and 2016. The average education years in these three years are 12, 13.9, and 14.2, respectively, showing an increasing trend as young workers are getting more education. The stagnant wages, declining job risks, and changes in worker attributes all show that the wage structure has changed over time. We also conduct the Chow tests to check the differences in the wage structures (Appendix 1). The results of the Chow tests confirm that the wage structures of these markets are different.

3.2. First-stage Estimation

In the first stage, we estimate the hedonic wage equation for each market with OLS. The hedonic wage equation is non-linear because repacking the attributes is costly and sometimes impossible. Econometrically, the hedonic wage equation is therefore estimated using a log-linear form:

$$lnW_{ij} = \delta_{0j} + \delta_{1j}R_{ij} + \theta_j X_{ij} + \pi_j Y_{ij} + \varepsilon_j \tag{3}$$

where W_{ij} is worker i's yearly wage in market j, R_{ij} is worker i's job risk in market j, X_{ij} is a vector of other job attributes worker i is exposed to in market j, and Y_{ij} is a vector of individual attributes of worker i in market j. $\delta_{0j}, \delta_{1j}, \theta_j, \pi_j$ are market-specific parameters to be estimated, $\varepsilon_j \sim N(0,\ \sigma^2)$.

The results of first-stage regressions are shown in Table 3.

Table 3 Hedonic Wage Regressions for the Three Markets

Dep. var. lnwage	(1) Year 2004	(2) Year 2009	(3) Year 2016
risk	0.000762***	0.000718*	0.000516*
	(0.0003)	(0.0004)	(0.0003)
female	-0.333***	-0.179***	-0.213***
	(0.0276)	(0.0201)	(0.0158)
eduyear	0.0881***	0.0754***	0.0774***
	(0.0057)	(0.0060)	(0.0042)
lnwexp	0.202***	0.101***	0.153***
	(0.0181)	(0.0156)	(0.0105)

healthlevel	0.0542^{***}	0.0550^{***}	0.00836
	(0.0169)	(0.0122)	(0.0098)
scale1	0.172^{***}	0.124^{***}	0.00439
	(0.0372)	(0.0314)	(0.0218)
scale2	0.290^{***}	0.171^{***}	0.0780^{***}
	(0.0380)	(0.0316)	(0.0218)
scale3	0.405^{***}	0.232^{***}	0.188^{***}
	(0.0466)	(0.0319)	(0.0216)
TJAN	-0.0422^{***}	-0.0407^{***}	-0.0460^{***}
	(0.0110)	(0.0091)	(0.0064)
TJUL	0.0748^{***}	0.108^{***}	0.0826^{***}
	(0.0213)	(0.0180)	(0.0149)
_cons	9.629^{***}	8.880^{***}	9.933^{***}
	(0.6070)	(0.5120)	(0.4050)
N	1054	1223	2700
R^2	0.456	0.300	0.286

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As can be seen in Table 3, there is a positive and significant risk premium for each of the three markets. Workers ask for a wage increase of 0.076%, 0.0718%, and 0.0516% as job risks increase by one unit (1/1,000,000) in 2004, 2009, and 2016, respectively, with other factors being equal.

The coefficients of other factors are also as expected. For example, females earn about 18%-33% less than males when other factors are equal. Education and work experience enhance one's human capital and has a significant and positive effect on one's wage. Workers with one more year of work experience earn about 10%-20% higher. Workers in larger firms earn more than workers in smaller firms.

Also, it can be seen from Table 3 that, in all three years, climate attributes play an important role in affecting wages. In places with warmer winters (higher January temperature) and cooler summers (lower July temperature), workers are paid less, while in places with colder winters (lower January temperature) and hotter summers (higher July temperature), workers are paid more, indicating that warmer winter and cooler summer are amenities, while colder winter and warmer summer are disamenities.

Using an estimated hedonic wage equation, we can predict the values of *ln*(*wage*):

$$\widehat{ln\,(W)} = \widehat{\delta_0} + \hat{\delta}_1 R + \hat{\theta} X + \hat{\pi} Y \tag{4}$$

Then, wages can be recovered through a transformation as follows[5]:

$$\widehat{W} = e^{\widehat{\delta_0}+\widehat{\delta_1}R+\hat{\theta}X+\hat{\pi}Y+0.5\hat{\sigma}^2} \tag{5}$$

where $\hat{\sigma}^2$ is the unbiased estimator of σ^2. Thus, the MIP of risk ($\widehat{P_R}$) can be calculated from the predicted wage, $\widehat{W}$ as follows:

$$\widehat{P_R} = \frac{\partial\widehat{W}}{\partial R} = \widehat{\delta_1}e^{\widehat{\delta_0}+\widehat{\delta_1}R+\hat{\theta}X+\hat{\pi}Y+0.5\hat{\sigma}^2} \tag{6}$$

The predicted price of risk is called the marginal implicit price (MIP) of risk. As the MIP schedule of risk is the equilibrium price of risk, it equals both the consumers' (workers') MWTP for risk reduction and the employers' marginal cost of providing safety, as shown in Section 2. Since the unit of risk is 1/1,000,000 in this study, thus, the MIP of risk also equals the willingness to pay for a micro risk reduction, $WTP_{\mu r}$, as suggested by Cameron (2010).

In a given labor market, for each consumer, the MIP of risk is a function of the quantity of risk born by a worker Thus, the price of risk moves simultaneously with the quantity of risk demanded, which is different from the market good where for each consumer, the price of a good is a constant for any quantity demanded and consumed.

3.3. Second-stage Estimation

In the second-stage estimation, we pool the observations and predicted risk prices from the three markets and estimate the inverse demand for risk reduction (safety). The dependent variable is the price of risk predicted from the first stage, and risk is the core independent variable.

As mentioned earlier, because of the non-linearity of the hedonic wage function, the price of risk is not a constant but a function of the quantities of risk, which means that the price and quantity of risk move simultaneously, causing the endogeneity problem in estimating the (inverse) demand function for risk reduction. We adopt the IV approach to address the endogeneity of risk in the inverse demand function. The instrumental variables include dummy variables of location (north, central, and east), year dummies that refer to different markets, and marital status (marriage). The instrumental variables are chosen in a typical way as studies estimating the demand for attributes do, such as Shaw et al. (2021).

Other demand shift variables such as gender, age, health, and (potential) income are also controlled. According to the law of demand, the demanded quantity of a good increases (decreases) as its price decreases (increases), which is also the substitution effect. In our case, as the price of risk (or safety) increases, the demand for safety decreases, thus, risk increases, denoting a positive slope for the (inverse) demand for

---

[5] Since $\varepsilon_1 \sim N(0,\ \sigma^2)$, $lnW \sim N(\mu,\ \sigma^2)$, thus, $W = e^{lnW} \sim Log\text{-}N(m, v)$, where $m = e^{\mu+0.5\sigma^2}$, $v = (e^{\sigma^2} - 1)$. In our case, $\mu = E\left(\widehat{\delta_0} + \widehat{\delta_1}R + \hat{\theta}X + \hat{\pi}Y + \varepsilon_1\right) = \widehat{\delta_0} + \widehat{\delta_1}R + \hat{\theta}X + \hat{\pi}Y$, thus $\widehat{W} = E(W) = e^{\mu+0.5\sigma^2} = e^{\widehat{\delta_0}+\widehat{\delta_1}R+\hat{\theta}X+\hat{\pi}Y+0.5\sigma^2}$. Since σ^2 is unknow, we use the unbiased estimator of σ^2, $\hat{\sigma}^2$, instead.

risk reduction, as shown in Figure 1. Since safety is a normal good (Viscusi, 1978), the income effect predicts that higher (potential) income causes larger demand for risk reduction (or higher willingness to pay for risk reduction), thus we expect workers with higher income (or potential income) or wealth to present a higher willingness to pay for risk reduction.

From the survey, we don't have data on workers' non-labor income or wealth, however, some factors like one's education and her parents' education can be used to proxy one's income or potential income. In general, better-educated people earn more. In studies on the return of education, the education of the parents is often used to proxy one's IQ (Blackburn and Neumark (1993), Murray and Herrnstein (1994)). A higher parents' education denotes a higher child's IQ, and thus a higher capability to earn money. Thus, we use the subject's education and father's education as proxies for non-labor income or wealth (because the mother's education is highly correlated to the father's education, thus we include here only the father's education years, to avoid multicollinearity). We expect to find that both education of workers and his/her father's education have a positive effect on the willingness to pay for risk reduction.

The results of the second-stage estimation are shown in Table 4. Models 3-5 are the results of the IV approach using a linear, log-linear, and log-log function form, respectively, which are our baseline models. We also show the OLS estimation results without dealing with the endogeneity problem (Model 1 and Model 2) for comparison.

In Models 1 and 3, the dependent variable is *pricehat* calculated from the first stage estimation. The estimated price of risk measures the marginal willingness to pay for risk reduction (MWTP), since the unit of risk is 1/1,000,000, it also equals to $WTP_{\mu r}$. In Models 2, 4, and 5, the dependent variable is the natural log of *pricehat*. In Models 1 and 2, though the risk variables (*risk* or *lnrisk)* in the OLS estimations (Model 1 and Model 2) have the desired positive coefficients, their magnitudes are very different from the results with the 2SLS estimations. Besides, the coefficients of *feduyear* are negative in Models 1 and 2, which do not make sense. The unreasonable results of the OLS estimations make it clear that the IV approach is needed to deal with the endogeneity problem in the second-stage estimation. We conduct the post-estimation tests for Models 3-5, and the results show that the IVs we choose are effective. The first stage regression results of the IV are shown in Appendix 2.

Table 4 OLS and 2SLS Estimation of the Inverse Demand Equation for Risk Reduction

	Model 1 OLS1(level-level)	Model 2 OLS2(log-log)	Model 3 IV1(level-level)	Model 4 IV2(log-level)	Model 5 IV3(log-log)
risk	0.839***		5.873***	0.0171***	
	(0.0468)		(0.3250)	(0.0009)	
lnrisk		0.116***			0.629***
		(0.0042)			(0.0201)
female	-58.81***	-0.187***	1.221	-0.0244	-0.00539
	(2.2770)	(0.0067)	(6.0390)	(0.0177)	(0.0158)
age	5.000***	0.0137***	3.314***	0.00845***	0.0118***
	(0.2530)	(0.0006)	(0.4530)	(0.0013)	(0.0010)
eduyear	22.82***	0.0751***	35.30***	0.109***	0.112***
	(0.7840)	(0.0016)	(1.6720)	(0.0045)	(0.0033)
feduyear	-2.109***	-0.00734***	2.957***	0.00607**	0.00958***
	(0.4530)	(0.0011)	(1.0230)	(0.0029)	(0.0023)
healthlevel	18.21***	0.0542***	13.43***	0.0453***	0.0219**
	(1.5350)	(0.0042)	(3.4650)	(0.0100)	(0.0089)
_cons	-242.3***	3.701***	-571.9***	3.064***	1.559***
	(18.6000)	(0.0415)	(39.1500)	(0.1070)	(0.1080)
N	4834	4834	4834	4834	4834
R^2	0.425	0.497			

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As shown in Models 3-5, the coefficients of risk/lnrisk are all significant and positive. In Model 3, the coefficient of risk is 5.873, meaning that a unit increase in risk will cause the marginal willingness to pay for safety (MWTP) to increase by 5.873 TWD in magnitude. In Model 4, we use the log-level functional form, which measures the semi-elasticity of risk on the willingness to pay for safety. As we can see in Model 4, the coefficient of risk is 0.0171, meaning a marginal increase in risk will increase MWTP by 1.17%. The log-level functional form indicates that the elasticity of risk to price is not constant but varies with the quantity of risk. In Model 5, the functional form is log-log, which assumes a constant elasticity of risk on the MWTP. The risk elasticity of MWTP, i.e., the coefficient of lnrisk, is 0.629, which means that one percent of the increase in risk would cause MWTP to increase by 0.629 percent. Thus, the price elasticity of risk is 1.6[6], which also means that the elasticity of safety to its price is -1.6. The absolute value of this elasticity is larger than 1, meaning the demand for risk reduction (safety) is elastic. Compared with Model 4, we prefer Model 5, the constant elasticity model, as economists are interested in elasticity. Besides, it will enable comparisons with other studies focusing on the demand for other environmental goods.

Since we don't have direct observations on one's non-labor income or wealth, the coefficients of one's education and his/her father's education provide evidence for income effect: both higher education and higher father's education increase income or potential income, thus higher MWTP. The findings in Models 3-5 confirm this income effect.

Besides the significant substitution effect and income effect, the coefficients of age and health in Models 3-5 are all significant. Age has a positive effect on willingness to pay for safety, meaning older people are willing to pay more for safety. Health also has a positive effect on the MWTP. However, there is no significant gender differences in the marginal willingness to pay for safety. The findings with age have important implications. Many VSL studies has assumed that VSLs decrease with ages (see Viscusi and Aldy (2003) for a review) or inverted-U shaped relationship between VSL and age (Aldy and Viscusi, 2007, 2008; Kniesner et al., 2006). Many institutions have adopted a senior discount adjusted VSL for old people in their policy analysis, such as EPA, which has caused substantial controversy. Our findings suggest that the opposite is true: older people actually have higher MWTP for mortality risk reduction.

As we have discussed in Section 2, the slope of the inverse demand for risk should be steeper than the slope of the price schedule for each market. The (natural logarithm of) price schedule of risk in the separated markets and the inverse demand curve for risk reduction are presented in Figure 3. The quantity of risk is on the x-axis. The natural logarithm of the marginal willingness to pay for one unit of risk reduction, *lnpricehat*, is on the y-axis, reflecting the percent changes in the MWTP associated with different quantities of risk. As shown in Figure 3, the market 2004 lies at the top, as the (natural logarithm of) price of risk

[6] The price elasticity of risk=1/0.629≈1.6.

in 2004 is the largest among the three markets, the year 2009 comes next, and the year 2016 lies at the bottom. Besides, the price schedules of the three markets are flatter than the reverse demand for risk, which is the estimation results of Model 4 through the 2SLS approach.

Figure 3 shows clearly that, when risk is larger than the intersection of the inverse demand curve and the price schedule (around 60 for the year 2004), the price of the risk underestimates the marginal willingness to pay for risk reduction, while for risk lower than the intersection, the price of the risk overestimates the marginal willingness to pay for risk reduction.

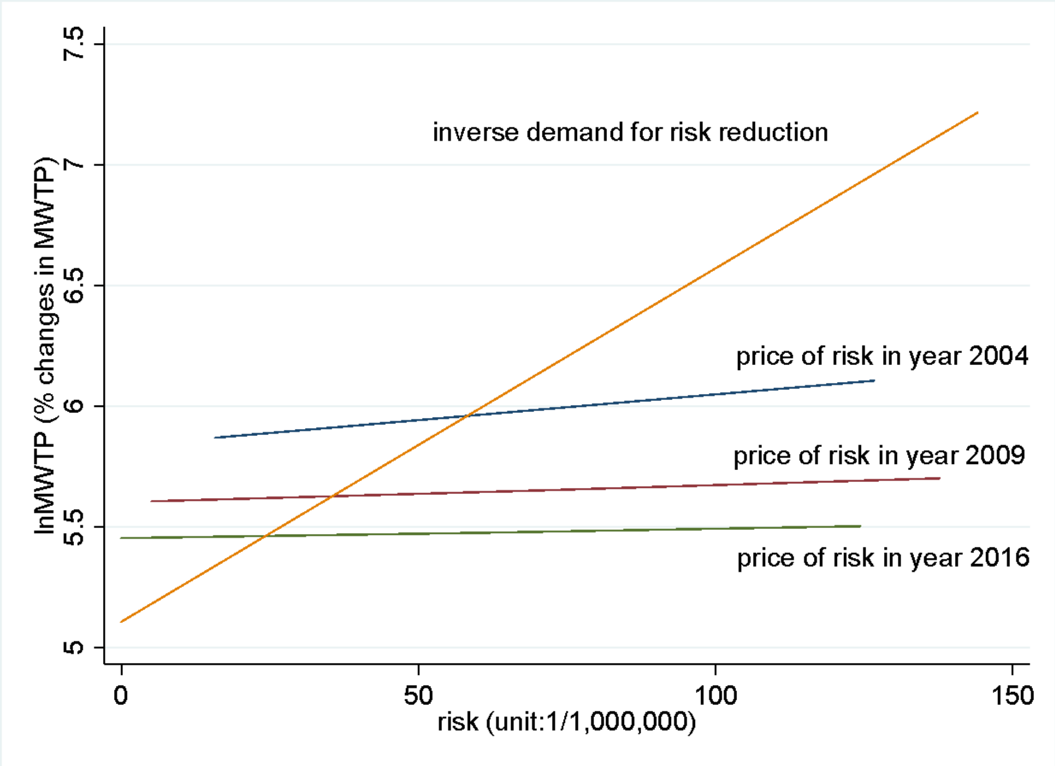

Figure 3 Estimated Price Schedules for Three Markets and the Reverse Demand Function for Risk Reduction

3.4 Robustness Check

We use a different market setting to check the robustness of our results. We use the adjacent three years as a single market rather than using a single year as a market as in the baseline models, to reduce the unwanted fluctuations in the predicted prices of risk. Specifically, we pool the observation from 2002 to 2004 and use them as our first market, and pooled observations from 2009 to 2011 are used as our second market, and observations in 2016 and 2018 are used as our third market.

We re-estimate the hedonic wage regression (first stage estimation) using the pooled observations for each of the three markets. The results of the first stage estimation of pooled observations are in Appendix 3. The coefficients of control variables estimated with pooled regressions have similar coefficients as in Table 3. We re-estimate the inverse demand function for risk reduction (second stage estimation) using the 2SLS approach. The results of the second stage estimation with pooled observations are shown in Table 5.

Table 5 The 2SLS Estimation of the Reverse Demand Function for Risk Reduction with Pooled Observations

	Model 6 (Level-Level)	Model 7 (Log-Level)	Model 8 (Log-Log)
risk	6.673***	0.0157***	
	(0.3710)	(0.0008)	
lnrisk			0.567***
			(0.0181)
female	-6.577	-0.0473***	-0.0330**
	(6.8510)	(0.0162)	(0.0142)
age	4.173***	0.00902***	0.0121***
	(0.5130)	(0.0012)	(0.0009)
eduyear	43.25***	0.109***	0.111***
	(1.9180)	(0.0041)	(0.0030)
feduyear	3.626***	0.00620**	0.00913***
	(1.1700)	(0.0027)	(0.0021)
healthlevel	15.84***	0.0437***	0.0228***
	(3.9450)	(0.0091)	(0.0081)
_cons	-678.2***	3.328***	1.986***
	(44.6900)	(0.0979)	(0.0971)
N	4834	4834	4834

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As we can see from Table 5, the results with pooled observations are almost the same as the results in the baseline Models 3-5. The coefficient of risk in Model 6 is 6.67, slightly larger than that of Model 3 (5.87); similarly, the estimated semi-elasticity of risk to its price is 0.0157, comparable to Model 4 (0.0171). The estimated elasticity of risk to its price is 0.567, slightly smaller than that of Model 5 (0.629). The coefficients of other demand shifters do not change much either. The results shown above with pooled observations suggest that the results of our baseline models are robust.

4. Applications

In this section, we illustrate how the inverse demand function for safety can be used to evaluate the nonmarginal reduction in risks with two case studies. As we know, the MIP of risk estimated from the hedonic wage equation can only be used to measure the value of marginal changes in risks. In order to measure the value of a nonmarginal change in risk, the (inverse) demand function for risk reduction is a must.

Just like the demand equation for a market good, the changes in consumer surplus (CS) associated with a nonmarginal change in risk can be measured by the changes in the area below the Marshallian demand curve, as shown in Figure 4. When risk reduces from r_0 to r_1, the value of this nonmarginal change in risk is the shaded area (ABr_1r_0), which equals the increases in consumer surplus (ΔCS). Mathematically,

$$V = \Delta CS = -\int_{r_0}^{r_1} D(r)\,dr \tag{9}$$

where $D(r)$ is the inverse demand function for risk reduction, which can be linear (as in Model 3) or non-linear (as in Model 4 and Model 5). Here we use the results of Model 5, a constant elasticity model.

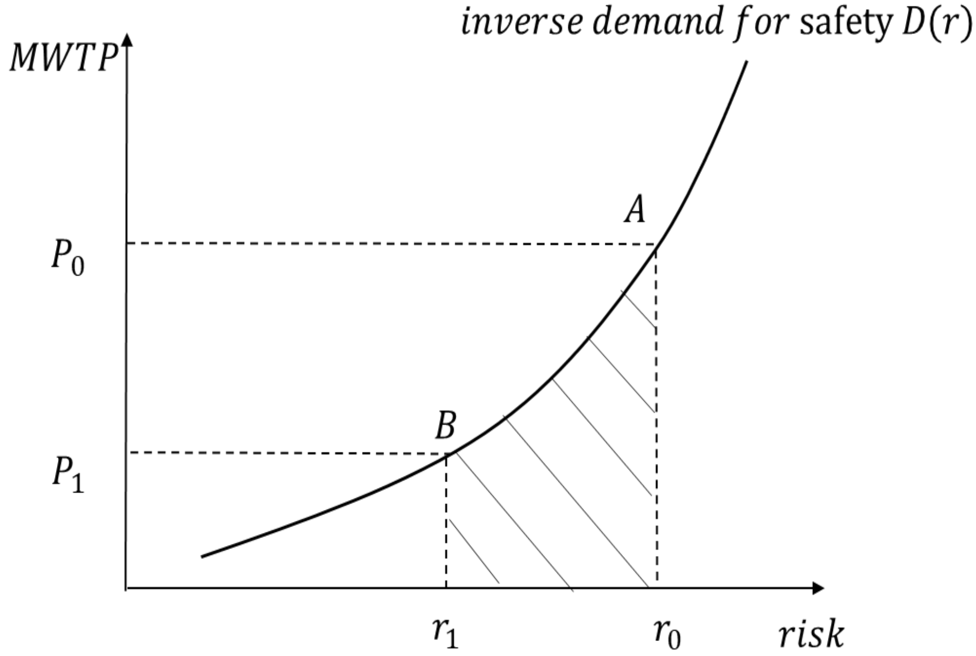

Figure 4 Value of a Nonmarginal Risk Reduction

Since on the right side of the starting point (r_0, for instance), marginal willingness to pay for risk reduction (MWTP) is larger than the price of risk (MIP), and on the left side of the starting point, MWTP is smaller than MIP.

Two case studies evaluating the nonmarginal risk reduction with the estimated inverse demand function are presented here. Firstly, we measure the value of job safety improvement in Taiwan from 1999 to 2018. Secondly, we measure the value of the death rates reduction associated with air quality improvement (specifically, PM_{10}) in Taiwan from 2010 to 2020. These two cases are two examples showing how the demand function for risk reduction can be used to conduct welfare analyses regarding the nonmarginal changes in risks.

4.1 Nonmarginal Value of Risk Reduction from 1999 to 2018

The average industrial fatality rate in Taiwan has been decreasing over time. To be specific, the total fatality rate (unit: 1/1,000,000) has dropped from 85 in 1999 to 24 in 2018, which is a substantial nonmarginal change in risks.

Using the results of Model 5, the inverse demand function for risk reduction can be written as:

$$\ln(MWTP) = 1.559 + 0.629 * \log(risk) - 0.005 * female + 0.012 * age$$
$$+0.112 * eduyear + 0.010 * feduyear + 0.022 * healthlevel \quad (10)$$

with all demand shifters remaining at their mean values, the inverse demand function for risk reduction can be reduced to the following form:

$$D(r) = MWTP = e^{0.629*loglog\,(risk)\,+2.174} \quad (11)$$

Thus, replacing $P(r)$ in equation (7) with equation (9), we have:

$$V = \Delta CS = -\int_{r_0}^{r_1} e^{0.629*lnln\,(risk)\,+2.174}\, dr = 6547 \quad (12)$$

Then, replacing r_0 with 85, r_1 with 24, we get the value of the nonmarginal risk reduction, which is 6,547 TWD per person, about 218 US dollars (at the exchange rate of 30 TWD to 1 US dollar).

4.2 Benefits Associated with Improvement in Air Quality

There is a large body of studies examining the impact of air pollution on human health. WHO updated the air pollution guideline in 2021 with newfound evidence regarding the health effects of air pollution (Chen and Hoek, 2020). In the new guideline, the combined hazard ratios (HRs) for all natural-cause mortality is 1.04 (95% CI:1.03, 1.06) per 10 $\mu g/m^3$ increase in PM_{10}. The recommended annual mean air quality guideline (AQG) level for PM_{10} is 15 $\mu g/m^3$. For concentrations higher than the interim target 1 (70$\mu g/m^3$), the concentration-response function may no longer be linear. Here we only focus on the health effects of long-term exposure of PM_{10}. The guideline and interim targets for PM_{10} is shown in Table 6. Currently, Taiwan has adopted Interim Target 2 as its air quality standard of PM_{10}, and mainland China has adopted Interim Target 1.

Table 6 Recommended Annual Mean AQG Level and Interim Targets for PM_{10}

Recommendation	$PM_{10}(\mu g/m^3)$
Interim target 1	70
Interim target 2	50
Interim target 3	30
Interim target 4	20
AQG level	15

Source: WHO air pollution guideline 2021 (https://www.who.int/publications/i/item/9789240034228)

The long-term PM_{10} concentrations in Taiwan have been falling over the past 10 years, as shown in Column 2, Table 7. The annual PM_{10} concentration has dropped from 57.2 ($\mu g/m^3$) in 2010, to 30.2 ($\mu g/m^3$) in 2020, which is a nonmarginal change[7].

To calculate the benefits associated with the reduction in death risk due to air pollution, the first step is to get the mortality in a population exposed to PM_{10} at the AQG level, R_{AQG}. The R_{AQG} can be different in different years. And to get R_{AQG}, we need the annual PM_{10} concentrations and the natural-causes death rates[8] from 2010 to 2020.

[7] Data on PM10is from the Air Quality Annual Report of Taiwan (2020). https://www.epa.gov.tw/Page/672FA2BDDEAA22C7/71fedbd8-9829-49e0-b02b-0addb5bd470a.

[8] The natural cause death rate is from the Ministry of Health and Welfare, https://www.mohw.gov.tw/np-128-2.html.

We use 2010 as an example to show how the R_{AQG} is calculated. Given the average annual PM_{10} concentrations (57.2 $\mu g/m^3$) and the natural-causes death rate in 2010 (5797.13 per million people), we have:

$$\left(\frac{(57.2-15)}{10} * 0.04 + 1\right) * R_{AQG2010} = 5797.13 \tag{13}$$

thus,

$$R_{AQG2010} = \frac{5797.13}{\frac{(57.2-15)}{10}*0.04+1} = 4959.9 \tag{14}$$

then we can get R_{AQG} for each year in a similar way, as shown in column 4, Table 7. To reduce the unwanted variations in R_{AQG} from a specific year, we use the average R_{AQG} from 2010 to 2020, $\underline{R_{AQG}}$ (which is 5797.25), to calculate the death rates associated with air pollution.

Now, with the hazard ratios suggested by WHO, the death rates associated with PM_{10} exposure in 2010 can be calculated as follows:

$$death\ rate\ (per\ million) = \frac{(57.2-15)}{10} * 0.04 * \underline{R_{AQG}} = 978.58 \tag{15}$$

Similarly, we can calculate the death rates associated with PM_{10} exposure in each year, as shown in Column 5, Table 7. The death rate associated with long-term exposure to PM_{10} has dropped from 978.58 in 2010 to 352.47 in 2020, which is a nonmarginal change in risks.

Table 7 The Welfare Analysis of Deaths Rates Changes Associated with Changes in PM_{10} Concentration (Unit: TWD/person)

Year	Annual mean PM_{10} ($\mu g/m^3$)	Natural-causes death rates (1/1,000,000)	R_{AQG} (1/1,000,000)	Death rates associated with PM_{10} (1/1,000,000)	ΔCS (TWD/person)
2010	57.2	5797.13	4959.90	978.58	-
2011	54.9	6113.65	5272.20	925.24	35054
2012	51.2	6153.06	5374.79	839.44	53754
2013	53.9	6176.57	5344.90	902.05	-38902
2014	52.9	6504.37	5648.12	878.86	14614
2015	47.7	6515.22	5761.60	758.28	72053
2016	43.5	6865.43	6162.86	660.89	53195
2017	44.7	6835.81	6109.95	688.71	-14725
2018	42.9	6876.48	6186.11	646.97	21949
2019	36	6989.31	6447.71	486.97	75845
2020	30.2	6896.90	6501.61	352.47	52758
Total					325594

Source: Data on PM10is from the Air Quality Annual Report of Taiwan (2020); Natural-causes death rates are from the Ministry of Health and Welfare; R_{AQG}, Death rates associated with PM_{10}, and ΔCS are calculated by this study.

Assuming that the demand function for risk reduction we estimate with labor market data also applies to the risks associated with air pollution, the value of the nonmarginal risk reduction associated with the improvement in air quality can be calculated in a similar way, as shown in column 6, Table 7.

To sum up, the decrease in PM_{10} from 2010 ($57.2\ \mu g/m^3$) to 2020 ($30.2\ \mu g/m^3$) has caused the death rates associated with long-term PM_{10} concentration to drop from 978.58 to 352.47 (per million people). The total value of the nonmarginal reduction in risk associated with the improvement in air quality is about 0.33 million (TWD/person), which is about 10,853 US dollars per person. Other negative effects of air pollution (such as the cleaning cost, and the effect on mobility) are not considered here.

5. Conclusion

This study has two major contributions to the hedonic wage literature. Firstly, we show that applying the IV approach to estimating the hedonic wage equation is unnecessary because there is no risk endogeneity problem in estimating the hedonic wage equation. The risk endogeneity problem is important in the estimation of the second-stage regression of the (inverse) demand function for risk reduction (safety). For now, most hedonic wage studies focus only on one labor market, in which the demand equation for risk reduction cannot be identified. Only two studies (Wei, 1999; Hammitt et al. 2022) estimated the (inverse) demand for safety. However, they both thought there is an endogeneity problem in estimating the hedonic wage equation and applied the 2SLS approach to the first stage estimation to address the endogeneity of risk.

Secondly, our study is the first study that estimates the demand function for risk reduction with labor market data which concerns both the identification problem and the endogeneity problem in the second-stage hedonic estimation. The findings of this study enable the welfare analysis regarding changes in mortality risks and shed light on the heterogeneity of the value of a statistical life (VSL).

Taking advantage of the Panel Survey of Family Dynamics (PSFD) from 1999 to 2018 in Taiwan, we divide the Taiwan labor market into three sequentially segregated submarkets to address the identification problem in estimating the demand function for safety. Moreover, we also address the endogeneity problem in estimating the demand equation by adopting the IV approach. We find significant income effect and substitution in demand for safety: people with higher potential income have higher MWTP for risk reduction; at the same time, people facing higher risk have higher MWTP for risk reduction. This study also finds that older people pay more for risk reduction than younger workers. However, there is no significant gender difference regarding MWTP. The findings of this study can be used to measure the value of the nonmarginal changes in risks, which has important policy implications regarding evaluating nonmarginal changes in risk.

Reference

Alberini, A., 2019. Revealed versus Stated Preferences: What Have We Learned About Valuation and Behavior? *Review of Environmental Economics and Policy*, *13*(2), pp.283-298.

Aldy, J. E., & Viscusi, W. K. (2007). Age differences in the value of statistical life: revealed preference evidence. *Review of Environmental Economics and Policy*.

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.

Bajic, V., 1985. Housing-market segmentation and demand for housing attributes: some empirical findings. *Real Estate Economics*, *13*(1), pp.58-75.

Bartik, T.J., 1987 a. The estimation of demand parameters in hedonic price models. *Journal of Political Economy*, *95*(1), pp.81-88.

Bartik, T.J., 1987 b. Estimating hedonic demand parameters with single market data: the problems caused by unobserved tastes. *The Review of Economics and statistics*, pp.178-180.

Bender, B., Gronberg, T.J., and Hwang, H.S., 1980. Choice of functional form and the demand for air quality. *The Review of Economics and Statistics*, pp.638-643.

Bishop, K. C., & Timmins, C. (2018). Using panel data to easily estimate hedonic demand functions. *Journal of the Association of Environmental and Resource Economists*, *5*(3), 517-543.

Bishop, K.C., and Timmins, C., 2019. Estimating the marginal willingness to pay function without instrumental variables. *Journal of Urban Economics*, *109*, pp.66-83.

Black, D.A., Galdo, J., and Liu, L., 2003. How Robust are Hedonic Wage Estimates of the Price of Risk? *Prepared for the US Environmental Protection Agency*.

Blackburn, M.L. and Neumark, D., 1993. Omitted-ability bias and the increase in the return to schooling. *Journal of labor economics*, *11*(3), pp.521-544.

Brown, C. (1980). Equalizing differences in the labor market. *The Quarterly Journal of Economics*, *94*(1), 113-134.

Brown, J.N., and Rosen, H.S., 1982. *On the estimation of structural hedonic price models* (No. t0018). National Bureau of Economic Research.

Brown Jr, G., and Mendelsohn, R., 1984. The hedonic travel cost method. *The Review of Economics and Statistics*, pp.427-433.

Cameron, T.A., 2020. Euthanizing the value of a statistical life. *Review of Environmental Economics and Policy*.

Chattopadhyay, S., 1999. Estimating the demand for air quality: new evidence based on the Chicago housing market. *Land Economics*, pp.22-38.

Chay, K.Y. and Greenstone, M., 2005. Does air quality matter? Evidence from the housing market. *Journal of Political Economy*, *113*(2), pp.376-424.

Chen, J. and Hoek, G., 2020. Long-term exposure to PM and all-cause and cause-specific mortality: a systematic review and meta-analysis. *Environment international*, *143*, p.105974.

Costa, D.L., and Kahn, M.E., 2004. Changes in the Value of Life, 1940–1980. *Journal of Risk and Uncertainty*, *29*(2), pp.159-180.

Diamond Jr, D.B. and Smith, B.A., 1985. Simultaneity in the market for housing characteristics. *Journal of Urban Economics*, *17*(3), pp.280-292.

Duncan, G. J., and Holmlund, B. (1983). Was Adam Smith right after all? Another test of the theory of compensating wage differentials. *Journal of Labor Economics*, *1*(4), 366-379.

Ekeland, I., Heckman, J. J., & Nesheim, L. (2004). Identification and estimation of hedonic models. *Journal of Political Economy*, *112*(S1), S60-S109.

Englin, J. and R. Mendelsohn. 1991. "A hedonic travel cost analysis for valuation of multiple components of site quality: The recreation value of forest management", *J. of Environmental Economics and Management* **21:** 275-290.

Epple, D. (1987). Hedonic prices and implicit markets: estimating demand and supply functions for differentiated products. *Journal of Political Economy*, *95*(1), pp.59-80.

Garen, J. (1988). Compensating wage differentials and the endogeneity of job riskiness. *The Review of Economics and Statistics*, 9-16.

Greenstone, M., and Gallagher, J., 2008. Does hazardous waste matter? Evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, *123*(3), pp.951-1003.

Hammitt, J. K., Liu, J. T., & Liu, J. L. (2023). Is survival a luxury good? Income elasticity of the value per statistical life. *Journal of Risk and Uncertainty*, 1-22.

Heckman, J. J., Matzkin, R. L., & Nesheim, L. (2010). Nonparametric identification and estimation of nonadditive hedonic models. *Econometrica*, *78*(5), 1569-1591.

Hintermann, B., Alberini, A., and Markandya, A. (2010). Estimating the value of safety with labor market data: Are the results trustworthy? *Applied Economics*, *42*(9), 1085-1100.

Huang, J.C., Shaw, D., Chien, Y.L., and Zhao, M.Q., 2016. Valuing environmental resources through demand for related commodities. *American Journal of Agricultural Economics*, *98*(1), pp.231-253.

Kniesner, T. J., Viscusi, W. K., & Ziliak, J. P. (2006). Life-cycle consumption and the age-adjusted value of life. *Contributions in Economic Analysis & Policy*, *5*(1).

Kniesner, T. J., Viscusi, W. K., Woock, C., and Ziliak, J. P. (2012). The value of a statistical life: Evidence from panel data. *Review of Economics and Statistics*, *94*(1), 74-87.

Lancaster, K.J., 1966. A new approach to consumer theory. *Journal of Political Economy*, *74*(2), pp.132-157.

Mendelsohn, R., 1984. Estimating the structural equations of implicit markets and household production functions. *The Review of Economics and Statistics*, 66, 673-677.

Mendelsohn, R., 1985. Identifying structural equations with single market data. *The Review of Economics and Statistics*, 67, 525-529.

Mendelsohn, R. 1987. "A review of identification of hedonic supply and demand functions", *Growth and Change* **18:** 82-92.

Muller, N. and R. Mendelsohn. 2009. “Efficient Pollution Regulation: Getting the Prices Right” *American Economic Review* **99**: 1714-1739.

Murray, C. and Herrnstein, R.J., 1994. Race, genes, and IQ–An apologia. *The New Republic*, *211*(18), pp.27-37.

Palmquist, R.B., 1984. Estimating the Demand for the Characteristics of Housing. *The Review of Economics and Statistics*, 66, 394-404.

Parsons, G.R., 1986. An almost ideal demand system for housing attributes. *Southern Economic Journal*, pp.347-363.

Pope, J.C., 2008. Buyer information and the hedonic: the impact of a seller disclosure on the implicit price for airport noise. *Journal of Urban Economics*, *63*(2), pp.498-516.

Quigley, J.M., 1982. Nonlinear budget constraints and consumer demand: An application to public programs for residential housing. *Journal of Urban Economics*, *12*(2), pp.177-201.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, *90*(6), 1257-1278.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34-55.

Sandy, R., and Elliott, R., 1996. Unions and Risk: Their Impact on the Level of Compensation for Fatal Risk. *Economica, 63*(250), pp.291-309.

Shanmugam, K.R., 2001. Self Selection Bias in the Estimates of Compensating Differentials for Job Risks in India. *Journal of Risk and Uncertainty*, *22*(3), pp.263-275.

Shaw, D., Huang, J.C., Lin, C.Y., Hsu, T.Y. and Tsai, M., 2021. Estimating Demand for Good Climate and Air Quality in Taiwan. *Climate Change Economics*.

Siebert, W.S., and Wei, X., 1994. Compensating wage differentials for workplace accidents: evidence for union and nonunion workers in the UK. *Journal of Risk and Uncertainty*, *9*(1), pp.61-76.

Thaler, R., and Rosen, S., 1976. The value of saving a life: evidence from the labor market. In *Household production and consumption*, pp. 265-302. NBER.

Viscusi, W. K., 1978. Wealth effects and earnings premiums for job hazards. *The Review of Economics and Statistics*, pp.408-416.

Viscusi, W.K., and 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), pp.5-76.

Wei, X., 1999. Estimating British workers' demand for safety. *Applied Economics*, *31*(10), pp.1265-1271.

Zabel, J.E., and Kiel, K.A., 2000. Estimating the demand for air quality in four US cities. *Land Economics*, pp.174-194.

Zhang, N., Shaw, D. and Lin, C.Y., 2022. Implicit Prices Of Job Risk, Climate, And

Air Pollution: Evidence From Taiwan. *Climate Change Economics*, 13(04), p.2250007.

Appendix 1: Chow test

We conduct the Chow test to see if there are structure changes in wage structures in our three markets: year 2004, 2009, and 2016. We perform the Chow test which allows for heteroskedasticity by three pairs: 2004 & 2009, 2009 & 2016, and 2004 & 2016, to test whether each of the pair shares the same wage structures.

The Chow statistics follow the F-distribution with the degree of freedom $k+1$. The null hypothesis of the Chow test is: H_0: there is no structural break.

$$F\ (k+1, n) = \frac{SSR_P - (SSR_1 + SSR_2)}{SSR_1 + SSR_2} * \frac{n - 2(k+1)}{k+1} \tag{A1}$$

where SSR_P is the sum of squared residuals of the pooled regression of the two markets, SSR_1 and SSR_2 are the sum of squared residuals of the regression in each of the two markets. n is the total number of observations in two markets, and k is the number of control variables in the regressions.

The resulting Chow statistics for the pair 2004 and 2009 is $F(11, 2255) = 13.2$, and the corresponding p-value is zero, thus rejecting the null hypothesis, the market 2004 and market 2009 have different wage structures. Similarly with the other two pairs. The Chow statistics for market 2009 and 2016 is $F(11, 3901) = 8.56$, and the Chow statistics for market 2004 and 2016 is $F(11, 3732) = 7.96$, both have a p-value equal to zero. Thus, the null hypothesis is rejected for both pairs. The labor markets in 2004, 2009, and 2016 have different wage structures.

Appendix 2: First stage of IV regression

Table A1 The first stage of the IV regressions

	Model 3	Model 4	Model 5
female	-12.1382***	-12.1382***	-0.3648***
	(0.8933)	(0.8933)	(0.0229)
age	0.1330	0.1330	0.0008
	(0.0843)	(0.0843)	(0.0018)
eduyear	-1.5169***	-1.5169***	-0.0456***
	(0.2492)	(0.2492)	(0.0050)
feduyear	-0.5917***	-0.5917***	-0.0181***
	(0.1684)	(0.1684)	(0.0036)
healthlevel	-0.3161	-0.3161	0.0161
	(0.5919)	(0.5919)	(0.0142)
marry	-0.0914	-0.0914	0.0063
	(1.0012)	(1.0012)	(0.0269)
year_2009	-25.3004***	-25.3004***	-0.5685***
	(1.7817)	(1.7817)	(0.0321)
year_2016	-31.4982***	-31.4982***	-0.9068***
	(1.6764)	(1.6764)	(0.0292)
north	-2.3070*	-2.3070*	-0.0478*
	(1.2842)	(1.2842)	(0.0283)
center	-1.8676	-1.8676	-0.0027
	(1.3973)	(1.3973)	(0.0319)
east	6.7540	6.7540	-0.1360
	(5.2050)	(5.2050)	(0.0985)
_cons	85.1389***	85.1389***	4.6162***
	(5.7787)	(5.7787)	(0.1191)
N	4834	4834	4834
F	61.82	61.82	172.40
R^2	0.220	0.220	0.275

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix 3: The First Stage Estimation for Three Markets with Pooled Observations

Table A2 The First Stage Estimation for Three Markets with Pooled Observations

	(1)	(2)	(3)
	y02_04	y09_11	y16_18
risk	0.000827***	0.000801***	0.000606***
	(0.0002)	(0.0003)	(0.0002)
female	-0.313***	-0.194***	-0.217***
	(0.0208)	(0.0129)	(0.0117)
eduyear	0.0909***	0.0725***	0.0786***
	(0.0042)	(0.0039)	(0.0031)
lnwexp	0.158***	0.0826***	0.164***
	(0.0155)	(0.0112)	(0.0083)
healthlevel	0.0606***	0.0353***	0.0199***
	(0.0120)	(0.0082)	(0.0071)
scale1	0.148***	0.122***	0.0170
	(0.0288)	(0.0214)	(0.0162)
scale2	0.242***	0.151***	0.0806***
	(0.0292)	(0.0213)	(0.0160)
scale3	0.369***	0.231***	0.202***
	(0.0330)	(0.0224)	(0.0162)
TJAN	-0.0580***	-0.0416***	-0.0489***
	(0.0086)	(0.0058)	(0.0048)
TJUL	0.0883***	0.101***	0.0855***
	(0.0160)	(0.0116)	(0.0106)
_cons	9.664***	9.249***	9.817***
	(0.4470)	(0.3240)	(0.2880)
N	1902	3323	4869
R^2	0.436	0.279	0.297

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$