Does the Value per Statistical Life Vary with Age or Baseline Health? Evidence from a compensating wage study in France

Daniel Herrera-Araujo*, Lise Rochaix†

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Abstract

This paper provides an empirical assessment of the effects of age and baseline health on the Value per Statistical life (VSL) by reporting the results of a compensating wage differential for occupational fatality risk in France. To our knowledge, this is the first paper that uses a population-based cohort combining respondents' full medical history elicited using face-to-face interviews with physicians and respondents' actual work history extracted from administrative records. Focusing on blue-collar men, aged between 20 to 59 years old, we find an average VSL estimate of 8 million euros. Our results support the hypothesis that VSL varies with age and baseline health: indeed VSL decreases with age and increases with baseline health.

JEL Codes: C23, I11, L40.

Keywords: Value per Statistical Life, Wage compensating differentials, Age, Baseline Health, France.

*Corresponding author (e-mail: daniel.herrera@dauphine.psl.eu), Université Paris-Dauphine, LEDA (CGEMP)

†Paris School of Economics, Hospinnomics - Université de Paris 1 Panthéon-Sorbonne

1 Introduction

All humans face a wide array of risks to health and life induced by environmental and other factors, but they differ in their valuations of wealth, health and life. It seems natural to expect that individuals' valuations for reducing risks to health and life depend on personal characteristics. That is, for a similar life or health risk reduction, the gains may not be valued in the same way by young (healthy) individuals compared to older (sicker) ones. Thus, the willingness to pay (WTP) for a small mortality risk reduction, namely the Value per statistical life (VSL), may depend on the context in which it is valued. By combining a dataset on French industry related mortality risks, along with a population-based panel containing individuals' medical and work history, we provide the first revealed preference study (RP) investigating the relationship between VSL, age and baseline health.

As VSL is a key statistic used to measure the benefits of mortality risk reduction generated by public policies, it is important to both researchers and policy-makers across many fields of application. Yet, adopting a context-dependent VSL estimate for benefits' valuation might be highly controversial. In the US, the US Environmental Protection Agency's (EPA) decision to use an age-adjusted VSL was highly criticized by members of the general public[1], and the agency quickly withdrew its proposal. Similarly, in their guidance for impact assessment, the European Commission and the Treasury in England prescribed using context-specific VSL estimates, with higher estimates for a particular health condition (cancer), because of the dreaded nature of the disease (European Commission 2001; H.M. Treasury 2003); a decision that has not generated the same public attention as in the US-EPA's case.

Insights from theory, however, suggest that VSL does vary with age and baseline health. Yet, there is no agreement as to how VSL varies with respect to each dimension. The signs and magnitudes of the effects of age and baseline health on VSL are ambiguous. Some models predict that VSL should decline steadily with age (Jones-Lee, 1989), others, that the age-VSL relationship could either be increasing, decreasing, or even independent of age (Johansson, 2002; Aldy and Viscusi, 2004; and Ehrlich and Yin, 2005). Theoretical models linking VSL with health also predict ambiguous results (Hammitt, 2002; Bleichrodt et al., 2006; Rheinberger et al. 2016). In this paper, we define a simple theoretical framework that combines quality-of-life (defined here as a single index function which combines individuals' longevity with their health) and wealth dimensions. In line with previous theoretical models, we find ambiguous results. The absence of clear theoretical predictions therefore makes the relationship between VSL, age and baseline health an empirical question.

From an empirical perspective, most of the literature focusing on the link between age, health and VSL is based on stated preferences (SP). An asset of these methods is the abil-

[1]The EPA, under the Clear Skies initiative, proposed to use a VSL estimate for those aged 65 and older that was 37% lower than for those aged 18-64 (Viscusi & Aldy, 2007)

ity to combine health-related information with individuals' trade-off between wealth and mortality risks. SP methods consist in presenting individuals with hypothetical choices. They include contingent-valuation methods, and discrete-choice experiments (Bateman et al. 2002). Alberini et. al (2004), provide an empirical assessment of the effects of age and baseline health on WTP for mortality risk reductions by reporting the results of two contingent valuation surveys. They find weak support for the hypothesis that WTP declines with age, heart disease, lung disease, and cancer. Cameron and Deshazo (2013) estimate a structural model with survey data, allowing them to infer how WTP estimates for reductions in the risks of sick-years and lost life-years depend upon the individual's age, income, marginal utility of other consumption, and discount rate.

Using an RP method, Viscusi and Aldy (2003) use an age-dependent fatal risk measure to estimate age-specific hedonic wage regressions. They find that VSL exhibits an inverted-U-shaped relationship with age. To our knowledge, there are two revealed preference studies valuing health related-risks in a VSL context. Gayer et al. (2002) addresses the valuation of cancer risks on housing prices. They examine the effect of cancer risks from chemical exposures from hazardous waste sites. Gentry and Viscusi (2016) propose a methodological framework to distinguish the fatality and morbidity components of VSL. They show that VSL can be separated into two additive components, the morbidity associated with fatal injuries and the fatality per-se, providing the first revealed preference estimates distinguishing both effects.

This article extends the existing literature by examining the effects of baseline health and age on VSL. We use individual level data on demographic characteristics from Constances, a large population-based cohort in France. It is a nationally representative sample of adults, which includes information such as age, sex, medical history and professional career. Constances matches detailed individuals' characteristics with their professional history. Annual information is collected on gross wages, number of quarters worked in a year, occupation, as well as firm and industry identifiers. For our analysis, we follow the VSL-literature and focus on blue-collar men, aged between 20 to 59 years old. Using industry identifiers, we link the Constances cohort with data on work-related mortality risks from the French National Health Insurance Fund. This publicly available data gathers information on accidents from all French workers covered by the National Technical Committee (NTC).[2] It contains information on the total number of workers, the number of hours worked, and the number of deaths on an annual basis per industry.

To identify the effects of age and baseline health on VSL, two complementary approaches are used: one analysis uses cross-sectional variation, while the other uses panel variation. The first has a comparative advantage over the second, in that Constances' breadth of variables allows us to control for a large range of potential confounding factors that, if not controlled for, might lead to biased effects. This large array of controls, however, is not available through time and cannot be used in a panel setting. On the other

[2]The dataset covers all French industries and around 29 millions workers.

hand, panel data allows for more observations, while still controlling for unobserved time-invariant individual characteristics. The identification strategy exploits individual-level health shocks, defined as the age of onset of either heart disease or cancer, along with job changes, to identify the effect that baseline health may have on VSL.

Our results suggest that the average VSL estimate is close to 8 million euros. which is similar to previous RP-based estimates. We find that individuals with heart disease require more compensation than healthy individuals for a similar mortality risk exposure. However, we do not find evidence that individuals with cancer require a larger compensation. In fact, as individuals suffering from cancer require long-term treatment, the incentives for a job change are weaker. Given that the identifying variation in our analysis comes from job changes to industries with different levels of mortality risk, we do not observe a larger risk premium for cancer patients. Moreover, our results suggest that VSL varies with age. VSL estimates range from 18, 6, 8 and 7 million euros for individuals below 30, between 30 to 39, between 40 and 49, and more than 50, respectively. Our study, however, suffers from the same limitations as other hedonic wage studies. In particular, it does not capture preferences of those individuals who remain outside the study sample.

The structure of this paper is as follows. In the next section we develop a theoretical model on the relationship between VSL and age/health status. In section 3, we describe the datasets we use for the empirical analyses. In section 4 and 5, we describe the empirical implementation and the results, respectively. A final section summarizes and concludes.

2 The model

Consider an individual that derives utility $u(w, q)$ from wealth w and quality-of-life q. Let quality-of-life be a single index function, which combines individual's longevity with their health. This implies that any improvement in health or longevity improves quality-of-life. In the following, we denote first (second) derivatives of the utility function with respect to wealth by the subscript 1 (11) and those with respect to quality-of-life by the subscript 2 (22). Further, we assume non-satiation with respect to income: $u_1(w, h) > 0$; non-satiation with respect to quality-of-life: $u_2(w, q) > 0$; weak financial risk aversion: $u_{11}(w, q) \leq 0$, which that states that less risk over wealth is preferable to more risk; and correlation affinity: $u_{12}(w, q) \geq 0$. This last assumption implies that the marginal utility of wealth does not decrease with better quality-of-life. Viscusi and Evans (1990), Sloan et al. (1998), and more recently Finkelstein et al. (2013) provide empirical support for this last assumption.

Consider now an individual who is facing a work-related risk resulting in one of two states of the world: in the next working period she will either live or die. Let π denote the probability of dying; hence the survival probability is $1 - \pi$. Conditional on survival, quality-of-life is q. If the individual does not survive, quality-of-life is equivalent to that of being dead, and is denoted as $\underline{q}$.

The individual's expected utility is given by:

$$EU(w,q) = (1-\pi)u\left(w,q\right) + \pi u\left(w,\underline{q}\right),$$

where $u\left(w,q\right)$ and $u\left(w,\underline{q}\right)$ are the utilities associated with wealth w conditional on the state of the world, either with baseline health or equivalent-to-death health, respectively.

Assume the individual is offered an opportunity to decrease the mortality probability, π, by the amount θ_π. In return for the decreased risk of premature death, the individual is willing to decrease her current wealth by $C\left(w,h,\pi,\theta_\pi\right)$. By definition, this equals the amount that leaves the individual with the same expected utility as in the initial (pre-intervention) situation. Formally, the compensating variation is defined as:

$$\begin{aligned}(1-\pi^*)u\left(w - C\left(w,q,\pi,\theta_\pi\right),q\right) \\ +\pi^* u\left(w - C\left(w,q,\pi,\theta_\pi\right),\underline{q}\right) = EU(w,q),\end{aligned} \tag{1}$$

with $\pi^* \equiv \pi - \theta_\pi$. To simplify notation in the analysis presented below, let:

$$\begin{aligned}C\left(w,q,\pi,\theta_\pi\right) &\equiv C_\pi, \\ w - C_\pi &\equiv w^*, \\ (1-\pi^*)u_1\left(w^*,q\right) + \pi^* u_1\left(w^*,\underline{q}\right) &\equiv EU_1(w^*,q), \\ (1-\pi)u_1\left(w,q\right) + \pi u_1\left(w,\underline{q}\right) &\equiv EU_1(w,q), \\ (1-\pi)u_{12}\left(w,q\right) + \pi u_{12}\left(w,\underline{q}\right) &\equiv EU_{12}(w,q),\end{aligned}$$

2.1 Deriving values for fatal risk reductions

We obtain the corresponding marginal willingness to pay (MWTP) for a reduction in mortality risk by differentiating Equation (1) with respect to θ_π:

$$MWTP_{\theta_\pi} \equiv \frac{\partial C_\pi}{\partial \theta_\pi} = \frac{u(w^*,q) - u(w^*,\underline{q})}{EU_1(w^*,q)} > 0, \tag{2}$$

where the numerator equals the gain in utility from reduced risk of dying and the denominator represents the expected marginal utility of consumption. When the mortality-risk reduction approaches zero (i.e., $\theta_\pi = 0$), we find that,

$$MWTP_{\theta_\pi}\Big|_{\theta_\pi=0} \equiv \frac{\partial C_\pi}{\partial \theta_\pi}\Big|_{\theta_\pi=0} = \frac{u(w,q) - u(w,\underline{q})}{EU_1(w,q)} = VSL(q), \tag{3}$$

where $VSL(q)$ stands for the Value per Statistical Life at the quality-of-life q. As both the expected gains in utility and the expected marginal costs are positive, a marginal reduction in mortality risk is valuable.

A better quality-of-life state may increase or decrease VSL. This is because a better quality-of-life state improves both the numerator and the denominator of equation (3). On the one hand, surviving with better quality-of-life is more desirable. On the other hand, better quality-of-life increases the marginal utility of consumption, thus the opportunity cost of reducing mortality risks. The relationship between quality-of-life and VSL is obtained by differentiating Equation (3) with respect to quality-of-life, q, as follows:

$$\frac{\partial VSL(q)}{\partial q} = \frac{u_2(w,q)}{EU_1(w,q)} - VSL(q)\frac{EU_{12}(w,q)}{EU_1(w,q)}. \tag{4}$$

The first term on the right hand side (RHS) corresponds to the marginal gain from improving the individual's quality-of-life state. As individuals care about quality-of-life, this first term is positive. The second term on the RHS captures the effect of an improved quality-of-life state on the opportunity cost of spending resources on mortality risk reductions. Due to the correlation affinity between quality-of-life and wealth, this second term is also positive. Thus, the effect of quality-of-life on VSL is undetermined; hence, how VSL varies with age and health is an empirical question.

3 Data

The following section describes in turn the two datasets used in the estimation: the individual level dataset containing socio-economic and demographic information, including income and professional history; and an industry wide dataset that characterizes the occupational risks.

3.1 Individual level: Constances and CNAV data

We obtain individual level data on demographic characteristics from Constances, a large population-based cohort created to contribute to epidemiological research in France. It is a nationally representative sample of adults and includes information such as age, sex, health status, medical and professional history. Information is collected through questionnaires sent to respondents' homes. Respondents, however, are also asked to come to a medical center to have an exhaustive medical check. Most of the health-related questions, including their medical history, are elicited by physicians at these centers.

Constances matches individuals' detailed personal characteristics with their professional history extracted from the National Retirement Insurance Fund administered by the French National Insurance Fund for the Elderly[3], hereafter CNAV. This dataset contains annual information on gross wages, number of quarters worked in a year, as well

[3]In French it is called "Caisse Nationale Assurance Vieillesse" or CNAV. The system allows to collect social and occupational data from different funds that manage various insurance schemes and other social transfers

as occupation, firms and industry identifiers of where respondents were employed during their whole careers. For our analysis, we focus on blue-collar men aged between 20 and 59 years old. The final dataset contains the working histories for a panel of over 7202 blue-collar male workers between 2002 and 2016.

Table 1: Summary statistics on Constances' selected variables

	Mean	Std. Dev.	Min	Max	Type
Average age	40.96	10.31	20.00	59.00	P
less than 30 years old	0.17	0.38	0.00	1.00	P
between 30 and 39 years old	0.26	0.44	0.00	1.00	P
between 40 and 49 years old	0.32	0.47	0.00	1.00	P
more than 50 years old	0.25	0.43	0.00	1.00	P
Average gross hourly wage	13.50	5.52	0.28	28.50	P
Less than 8 years of education	0.04	0.19	0.00	1.00	C
Between 9 and 15 years of education	0.87	0.34	0.00	1.00	C
More than 16 years of education	0.09	0.29	0.00	1.00	C
Has a partner?	0.72	0.45	0.00	1.00	C
Considers himself to be happy	0.76	0.43	0.00	1.00	C
Considers himself as a smoker	0.31	0.46	0.00	1.00	C
Audit drinking score	5.83	4.87	0.00	38.00	C

Notes: The sample is limited to male blue-collar men aged between 20 and 59 years. The average hourly gross wage is computed by dividing the annual gross wage by 1607, the legal maximum number of hours that an individual can work in a year. Respondents were asked to self-assess their smoking status: if they considered themselves to be smokers, the variable takes a value of 1 and 0 otherwise. AUDIT score ranges from 0 to 38. A score between 0 to 7 is considered as low-risk of dependence, 8 - 15 as hazardous levels of dependence, 16 - 20 as high risk of dependence, and 20+ as almost certainly dependent.

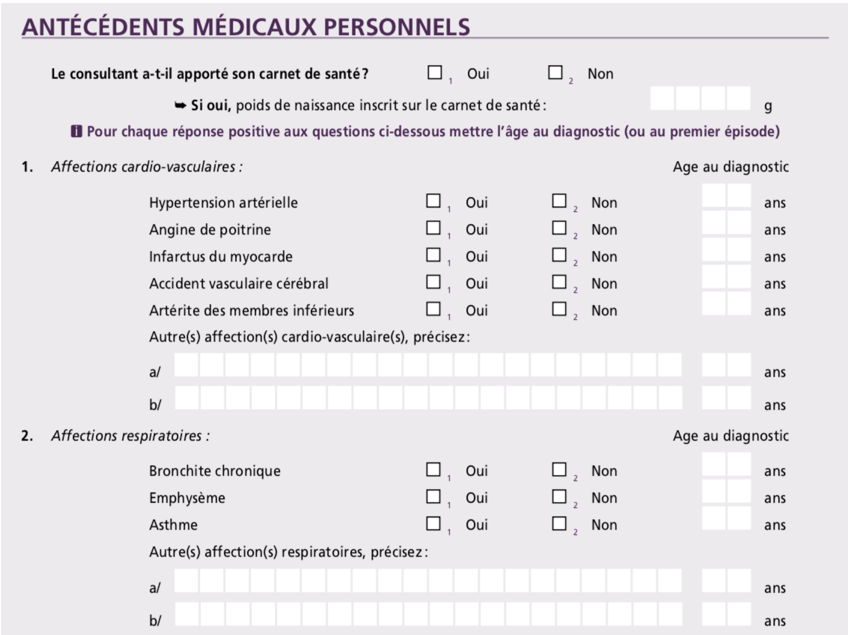
Table 1 presents the summary statistics of the sample of respondents included in the analysis. As reported in Table 1 our sample is composed of respondents aged between 20 and 59, with an average age of 41 years. Around 20% of respondents are below 30, 26% of respondents are in their 30's, 32% are in their 40's, and the rest above 50. The hourly gross wage earned is of 13.50 euros per hour.[4] The proportion of respondents declaring between 9 to 15 years of education is of 87%, 4% declared having less than 9 years, and 9% declared having more than 15 years. Most respondents report having a partner, and consider themselves to be happy most of the time.

In terms of life style, we selected two questions dealing with smoking and alcohol behaviors. A third of respondents (= 32%) considered themselves as a smoker. Alcohol status was derived using an Alcohol Use Disorders Identification Test (AUDIT). The AUDIT is

[4] In France, the average percentage difference between gross and net is 23%. Estimates need to be adjusted by this difference to be re-expressed in net terms. The average wage for blue-collar workers in France equals 13.3 € in 2014. Constances' data proves to be closely related to national averages.

a 10-item screening tool developed by the World Health Organization (WHO) to assess alcohol consumption, drinking behaviors, and alcohol-related problems. A score between 0 to 7 is considered as low-risk of dependence, 8 - 15 as hazardous levels of dependence, 16 - 20 as high risk of dependence, and 20+ as almost certainly dependent. As the AUDIT score average for our sample of respondents is 6 (on a scale from 0 to 38), the average respondent in our sample is considered as low-risk.[5]

Although we observe respondents' professional history, including wages, we only have demographic characteristics for the year respondents were surveyed. That is, if we are to use the panel dimension of Constance, we are limited to the use of the demographic variables available that can be exploited with the panel dimension of our professional history data. This is the case for respondents' medical history. For clarity's sake, we categorize demographic variables into two main categories: cross-section and panel variables. Variables in Table 1 of type "C" are considered for cross-sectional use only, while variables of type "P" can be followed throughout time and are considered valid for panel use. Variables of type "P" can be used in the cross-section analysis as well.



ANTÉCÉDENTS MÉDICAUX PERSONNELS

Le consultant a-t-il apporté son carnet de santé? ☐ 1 Oui ☐ 2 Non

➥ **Si oui,** poids de naissance inscrit sur le carnet de santé: g

Pour chaque réponse positive aux questions ci-dessous mettre l'âge au diagnostic (ou au premier épisode)

1. *Affections cardio-vasculaires :*

			Age au diagnostic
Hypertension artérielle	☐ 1 Oui	☐ 2 Non	ans
Angine de poitrine	☐ 1 Oui	☐ 2 Non	ans
Infarctus du myocarde	☐ 1 Oui	☐ 2 Non	ans
Accident vasculaire cérébral	☐ 1 Oui	☐ 2 Non	ans
Artérite des membres inférieurs	☐ 1 Oui	☐ 2 Non	ans

Autre(s) affection(s) cardio-vasculaire(s), précisez:

a/ ans

b/ ans

2. *Affections respiratoires :*

			Age au diagnostic
Bronchite chronique	☐ 1 Oui	☐ 2 Non	ans
Emphysème	☐ 1 Oui	☐ 2 Non	ans
Asthme	☐ 1 Oui	☐ 2 Non	ans

Autre(s) affection(s) respiratoires, précisez:

a/ ans

b/ ans

Figure 1: Extract from the medical history questionnaire

All variables about respondents medical history are considered of type "P". As illustrated by Figure 1, respondents were asked by physicians whether they had being diagnosed heart disease or cancer.[6] Conditional on declaring the disease, respondents were asked the age of onset of the disease. This information is used to create a variable equal to '1' for all

[5]The AUDIT has been validated across genders and in a wide range of racial ethnic groups and is well-suited for use in primary care settings (WHO).

[6]While other diseases, such as respiratory disease, or digestive-related disease, are reported in the data, we intentionally focus on heart attack and cancer.

Table 2: Summary statistics on Constances' variables – health related

	No disease	Cancer	Heart disease
Proportion of sample	86.58%	4.02%	9.40%
Number of years in panel	9.15	10.21	10.16
Number of years in panel with disease		2.37	2.33
Age of onset of disease		44.73	47.22
Number of individuals	6180	287	671
Average number of Industries	1.84	1.54	1.61
Prior - health shock		1.67	1.66
After - health shock		1.09	1.46

Notes: The sample is limited to male blue-collar men aged between 20 and 59 years.

the years after the onset of the disease and '0' otherwise. As reported by table 2, during our period of analysis, 13.4% of our sample that reports having suffered from cancer or heart disease: 4% report cancer, and 9.4% report heart disease. The average number of years for which we have information per respondent is around 10 years. Healthy individuals report during 9.15 years, while individuals affected by a disease report 10 years. As compared with healthy individuals, affected individuals are older. At cancer onset, individuals are aged 44.7 years, while for heart disease, individuals are aged 47 years. Finally, individuals affected by a cancer or heart disease change industry less often than healthy individuals. In particular, between the year prior and the year after the onset of the disease, individuals' with cancer changed to 0.09 industries, while individuals with heart disease changed to 0.46 industries. Although not reported in the table, across the 10 year span, 60% of respondents changed at least one time of industry, and, conditional on changing, respondents switched industry at least twice. This is the variation that allows the identification of the compensation required for increases in fatal accident risks in our panel data specification.

Table 3 reports on respondents' working conditions. One such variable is perceived physical effort at work. Almost two thirds (=70%) of respondents declared that their perceived physical effort at work was somewhat high, 9% of respondents declared it to be light, and the rest declared it to be high. Another dimension captured by Constances is satisfaction at work. Nearly 40% of respondents declared being satisfied with their current work, while the rest was not. Similarly, 40% of respondents considered that they had a high chance of obtaining a promotion in the near future.

Table 3 also reports on three type "P" variables available from CNAV. The first variable is the type of contract an individual has at each period. For a large majority of observations (87%), individuals have a full-time contract, while the remaining observations comprise temporary, 4%, part-time, 4%, or other types of contracts, 6%. The second variable corresponds to the number of quarters in a year during which an individual contributed to the public retirement fund.[7]. For a quarter to be considered as valid, two conditions are required: a person needs to have contributed to the retirement fund; and needs to have earned at least 150 hours at the minimum wage for the going year. In special cases (i.e. maternity leave, unemployment, sickness...), a quarter may still be considered as valid even if no contributions are made. Finally, we only have information on individuals who contributed to the general social security.[8] However, if an individual migrates between schemes, we are only able to know that they contributed to this other scheme but we are not able to observe their salary at the moment of their contribution. Fortunately, only 2% of observations belong to this category.

3.2 Industry level: CNAMTS data

The data on mortality and morbidity risk measures come from the French National Health Insurance Fund. The dataset gathers information on around 29 million French workers covered by the National Technical Committee (NTC). This is a publicly available dataset, which contains information on the total number of workers, the number of hours worked, and the number of deaths on an annual basis per industry.[9]

A fatal accident is accounted for if a monetary compensation is (or could have been) given to persons close to the victim. Hence, a caveat of our fatality data is that the year the death is accounted for is directly linked with the year that the compensation is allocated. This implies a potential miss-reporting of actual fatalities caused by work-related accidents: some deaths occurring at the end of the year could in fact be assigned to following time period.

We use information from each industry for the years 2013 to 2016 to compute fatal risks. Industry related codes are available at the 4-digits level.[10] Fatal accident rates

[7]To benefit from a retirement plan in France, individuals need to have contributed for 160 to 172 quarters, depending on the birth date

[8]In France there are several health/retirement insurance schemes. The general insurance scheme, referred to in this paper, covers over 80% of the French population. It does not include self-employed or agricultural workers.

[9]The dataset is available at http://www.risquesprofessionnels.ameli.fr/statistiques-et-analyse/sinistralite-atmp/dossier/nos-statistiques-sur-les-accidents-du-travail-par-ctn.html [last visited on 9^{th} of July 2018 at 14h05]

[10]Since 2013, all statistics related to accidents follow the French National Institute of Statistics and Economic Studies (INSEE) classification: the *Nomenclature d'Activité Francaise* (NAF). NAF related codes divide the core activity of French firms into 720 categories. Unfortunately, it is not possible to have a one-to-one match between the code used prior to 2013 and the code used after 2013.

Table 3: Summary statistics on Constances' variables – work related

	Mean	Std. Dev.	Min	Max	Type
Physical effort at work is light	0.08	0.27	0.00	1.00	C
Physical effort at work is somewhat high	0.62	0.49	0.00	1.00	C
Physical effort at work is high	0.30	0.46	0.00	1.00	C
Satisfied with current work	0.51	0.50	0.00	1.00	C
Thinks that has a high chance for a promotion	0.49	0.50	0.00	1.00	C
Full-time contracts	0.87	0.34	0.00	1.00	P
Temporary contracts	0.04	0.19	0.00	1.00	P
Part-time contract	0.04	0.18	0.00	1.00	P
Other type of contracts	0.06	0.24	0.00	1.00	P
Contributed all 4 quarters	0.82	0.38	0.00	1.00	P
Contributed 3 quarters	0.06	0.23	0.00	1.00	P
Contributed 2 quarters	0.03	0.18	0.00	1.00	P
Contributed 1 quarter	0.03	0.16	0.00	1.00	P
Contributed 0 quarter	0.06	0.24	0.00	1.00	p
All quarters in the standard scheme	0.98	0.14	0.00	1.00	P
1 quarter reported in another scheme	0.00	0.07	0.00	1.00	P
2 quarters reported in another scheme	0.00	0.05	0.00	1.00	P
3 quarters reported in another scheme	0.00	0.05	0.00	1.00	P
4 quarters reported in another scheme	0.01	0.10	0.00	1.00	P

Notes: The sample is limited to male blue-collar men aged between 20 and 59 years. Physical effort at work is light, somewhat high, or high are variables equal to 1 if respondents considered it to be light, somewhat high, or high, respectively, and 0 otherwise.

are matched to individuals' working histories available in Constances, using the industry identifiers, which are available in both datasets.

The fatality rate in an industry j, FR_j, is computed by dividing the fatalities count in a given industry, N_j, by the number of total hours worked by all employees during the calendar year, H_j, as follows:[11]

$$FR_j = \frac{N_j}{H_j} \times 1607 \times 100,000.$$

The fatality rates are re-expressed in terms of 100,000 full-time equivalent (FTE) workers.[12]

In principle, one could use the equation above to compute blue-collar-specific fatality rates by replacing N_j and H_j with the corresponding blue-collar-specific values (Hersh, 1998). However, while the fatalities by blue-collar workers are provided in the CNAMTS data set, total hours worked by industry and occupation status are not available, at least in the web-provided dataset. Therefore, we assume that the fatality rate is proportional to the relative weight of blue-collar workers' deaths in the overall industry death count j. Based on this assumption, to approximate the fatality risk for blue-collar workers, we weight the average industry fatality rate, FR_j, by the share of blue collar deaths in industry j relative to the share of blue collar workers in industry j. Let FR_{kj} denote the fatality rate for blue collar workers in industry j, which we compute as follows:

$$FR_{kj} = \omega_{kj} \times FR_j = \frac{\frac{N_{kj}}{N_j}}{\frac{M_{kj}}{M_j}} \times FR_j,$$

where N_{kj} denotes the number of blue collar deaths in industry j, N_j the number of deaths in industry j, M_{kj} the number of blue collar workers in industry j and M_j the number of workers in industry j.

The information on the number of blue collar workers per industry originates from INSEE. The available information, however, only contains the number of blue collar workers for a 2-digit level of aggregation (in total 38 different industries), rather than the more dis-aggregated 4-digit level (in total 720 industries). We compute the weights, ω_{kj}, by counting deaths at the 2-digit level of aggregation, and assuming that each ω_{kj} is equal to all industries j sharing the same 2-digit level code. Our fatality risk measures are based on a four year average using fatality risk from 2013 to 2016. This four year average is intended to smooth out irregularities in the fatality rates for cells with small employment

[11] Hours-based fatality rates are more tailored to the length of the exposure to risk and thus are a more accurate reflection of the worker's risk (Gentry and Viscusi, 2016). An hours-based measure will be similar to the employment-based measure if the worker group includes mostly full-time workers.

[12] The legal duration of work in France is 151.67 hours, which corresponded to this computation : (35 hours - 52 weeks)/12 months = 151.67 hours. Annually, the maximal legal duration is 1,607 hours; see https://www.service-public.fr/particuliers/vosdroits/F1911 [last visited on July 1^{th} 2018]

levels, which sometimes lead to reporting zero fatalities in any given year (Gentry and Viscusi, 2016). We are able to match fatality rates to workers in specific industries using industry 4-digit level identifiers.

Table 4 in the Appendix reports the average fatality rates per industry on the final Constances-CNAMTS dataset.[13] Thus, the average fatality rates are weighted averages that depend on Constances respondents working history. The average fatality risk is around 5 per 100,000 full-time equivalent (FTE) workers, and there is significant variation across industries. The adjusted mortality risk measures, which only reflect the risk faced by blue-collar workers in each industry, are, unsurprisingly, higher for most industries with an average close to 6 deaths per 100,000 FTE workers. The highest fatality risk is recorded in the construction sector with 9 deaths per 100,000 FTE workers, and it reaches almost 11 after adjustment. As it involves more physical and riskier jobs, finding higher mortality risks in the construction industry is to be expected. In commerce, transport, accommodation and food services, the occurrence of fatal accidents after adjustment is of around 6 per 100,000 FTE workers and around 8 per 100,000 FTE. Mortality risk is close to 4 deaths per 100,000 FTE workers on average and around 5 deaths per 100,000 FTE workers when adjusting for blue-collar workers in the scientific and technical activities.

Government, health and education industry and the real estate industry incur smaller fatality risks, but given that most of the deaths within the industry come from blue-collar workers, the adjusted fatality risk increases markedly. On the contrary, in the financial and insurance industry, as well as in the information and communication industry, fatality rates decrease after adjusting for blue-collars workers exposure. The adjusted risk measures decrease due to the the relative small number of blue-collar workers deaths in those industries.

4 Empirical specification

This section describes the empirical specification used for our analysis. We first describe a hedonic wage model that only exploits cross-sectional variations. Next, we specify a hedonic wage model that exploits panel data information.

4.1 Exploiting cross-sectional variation

The form of the hedonic wage model that we adopt in this paper, in line with most of the related literature, is:

$$ln(w_i) = \alpha_0 + \alpha x_i + \beta_1 FR_{kj} + \gamma_d + \epsilon_{1i}, \quad (5)$$

[13] The fatality rates are computed on the 29 million workers in France, and then matched to each respondent in Constances. We report only the average fatality risk that Constance respondents faced during their working history.

Table 4: Average blue-collar fatal risks per industry in Constances

Industries	Fatality rate Unadjusted	Adjusted
Manufacturing	3.96	4.17
Construction	9.16	10.76
Commerce, transports, Hotel & restaurant	5.75	7.77
Information et communication	1.55	0
Financial and insurance	1.96	4.37
Real Estate	1.56	3.95
Scientific and technical activities	3.85	4.79
Government, health and education	1.37	4.02
Other services	1.69	2.67
Total	4.98	6.21

Notes: There are no Constances members working in the Agriculture, forestry & fishing industry. Mortality rates are based per 100,000 FTE workers. Mortality rates are averaged over 2013, 2014, 2015 and 2016 risks. The analysis covers all French industries and around 29 millions workers. The risks presented in this table are weighted by the number of years an individual in our sample belongs to an industry.

where w_i corresponds to individual i′s hourly wage; x_i is a vector of individual i′s demographic characteristics; γ_j corresponds to the industry fixed effects; FR_{kj} is the adjusted fatality rate in industry j; ϵ_{1i} rationalizes all other idiosyncratic variations. The coefficient of interest is β_1, which corresponds to the average fatal risk premium.

To assess the impact of each respondents' age and medical condition on the fatal risk premium, we use the following full-model specification:

$$ln(w_i) = \alpha_0 + \alpha x_i + \beta_z Z_i + \beta_1 FR_{kj} + \beta_2 FR_{kj} \times Z_i + \gamma_t + \gamma_j + \epsilon_{1i}, \qquad (6)$$

where $Z_i = \{Mcond_i; age_{i_{30;40}}; age_{i_{39;40}}; age_{i_{50+}}\}$ is a matrix $N \times 5$ containing all N respondents' medical conditions for the two diseases considered, and three age categorical variables.[14] The medical conditions considered in the cross-sectional analysis correspond to the conditions the respondent reported at the time of the cross-sectional analysis. The interpretation of β_1 in equation (6) differs from that in equation (5). In equation (6), both coefficients correspond to the main terms and are interpreted as the monetary compensation required by a healthy (and young) individual to accept a higher risk. The interaction coefficients, β_3 report on differences with respect to the main term.

4.2 Exploiting panel variation

A caveat of the cross-sectional estimation is that it imposes a strong assumption: conditional on observed controls, x_i, the error term ϵ_{1it} is uncorrelated with the fatal rates. There are two potential sources of individual unobserved heterogeneity that might be correlated with the fatality risks. On one hand, unobserved heterogeneity in personal safety

[14]The excluded category corresponds to respondents below age 30.

productivity might be positively correlated with wages. This effect leads higher-wage workers to select what appears to be riskier jobs because the true mortality probability for the individual is lower than the measured risk. On the other hand, unobserved heterogeneity in personal safety productivity might be negatively correlated with wages. This leads higher-wage workers to select safer jobs (Kniesner et. al, 2012). We relax this assumption by using panel data on workers to estimate the following model:

$$ln(w_{it}) = \alpha_0 + \alpha x_{it} + \beta_1 FR_{kj} + \gamma_t + \gamma_j + \theta_i + \epsilon_{2it}, \qquad (7)$$

where θ_i is an individual fixed effect that captures constant unobservable worker-specific characteristics that affect wages and may be correlated with fatal risks; x_{it} is a vector of individual i's time-varying demographic characteristics; ϵ_{2i} rationalizes all other idiosyncratic variations.

As our fatal risk measure is constant across years, the identification of β_1 comes from individuals switching jobs that have different fatal risks. We assume, however, that conditional on individual fixed effects and on time-varying observable characteristics, the fatal risks are exogenous to ϵ_{2it}. We are not modelling individuals' joint choice on wages and industry/occupation, changing from low-wage high-risk jobs, to high-wage low-risk jobs (Abowd, McKinney and Schmutte, 2015; Lavetti, 2018). Due to our limited sample on individual-job matches, we are not able to control for this source of endogeneity.

Similarly, to assess the impact of each respondents' age and medical history on fatal and non fatal risk premiums, we use the following full model specification:

$$ln(w_{it}) = \alpha_0 + \alpha x_{it} + \beta_6 Z_{it} + \beta_1 FR_{kj} + \beta_3 FR_{kj} \times Z_{it} + \gamma_t + \gamma_d + \theta_i + \epsilon_{2it}, \qquad (8)$$

where $Z_{it} = \{Mhist_{it}; age_{it_{30;40}}; age_{it_{39;40}}; age_{it_{50+}}\}$ is a matrix $N \times 5$ containing all N respondents' medical history on the two diseases considered, as well as 3 age dummies. The identification of β_3 and β_4 coefficients comes from differences between respondents' medical conditions and age, as well as changes in the medical history and the age within respondents. Similarly, the interpretations of β_1 and β_2 depend on whether there are interactions in the model or not.

4.3 Value per statistical life estimates

The hedonic-wage equation traces out the equilibrium points of tangency between firms' offer curves and workers' constant expected utility loci. That is, the VSL estimates reflect the joint influence of the supply and demand for potentially risky jobs. The VSL measures the responsiveness of wage to fatality risk.

As equation (5) has the natural logarithm of the wage as dependent variable, and since the fatality rate is measured in deaths per 100,000 FTE workers, VSL can be calculated by the following equation:

$$VSL = \hat{\beta}_1 \times \overline{wage} \times 1,607 \times 100,000 \tag{9}$$

where the coefficient is scaled-up by 100,000 FTEs multiplied by 1,607 hours worked.

5 Results

Estimates of equation (5) and equation (6) are presented in Table 5. An observation in the estimation is an individual-year. The cross-sectional sub-sample is constructed using the year when respondents were surveyed, thus using one observation per respondent.[15] This implies that the identification of the fatal and non fatal risk coefficients comes only from cross-sectional variation. As respondents answered the survey in different years, all columns control for the year of the survey. Also, all specifications include industry fixed effects.

Five models are reported in Table 5, the most comprehensive being model 1 and the least comprehensive being model 5.[16] All models include C-type demographic characteristics described in Table 1. Model 5 in Table 5 examines the effects of fatal risks rates on wages. The coefficient on fatal risks is significantly different from zero. Thus, the implied VSL from model 5 is 4.71 million euros.

Model 4 reported in Table 5 extends the analysis by including respondents' heart disease and cancer condition. This model does not distinguish between cancer or heart disease. It explores the heterogeneity around the VSL estimate by interacting respondents' reported diseases with fatality risk. As with model 5, the fatal risk coefficient is statistically different from zero. The interpretation of the coefficient, however, differs from that of model 5. The estimated VSL for a healthy individual is 5.4 million euros. As all other coefficients are not statistically different from zero, the estimated VSL for individuals reporting a disease is not statistically different from that of healthy individuals.

As with previous models, model 3 includes C-type demographic characteristics, but differs by also including interactions between fatality rate and respondents' age. The estimated VSL for a healthy respondent aged below 30 is 18.81 million euros. All age-related coefficients from the interactions are not statistically different from zero. The VSL estimates for individuals in their 30's, 40's and older than 50 are close to 0.63 million euros, 4.50 million euros, and 2.99 million euros, respectively. Although the VSL point estimates decrease with age, the decrease is not monotonic.

Models 2 and 1 report estimates after including interactions dis-aggregating heart and cancer diseases. As model 1 nests models 2, 3, 4, and 5, we find similar findings. The VSL

[15] The results are robust even if we split our sample into any other year. Nevertheless, we are not able to use the demographic variables reported by respondents if we use a different year than that when the survey was answered.

[16] Standard errors are clustered at the industry-city level.

estimate for a healthy individual below 30 is nearly 16 million euros. The VSL estimates for healthy individuals in their 30's, 40's and older than 50 are close to 1.79 million euros, 4 million euros, and 2.48 million euros, respectively. The interaction term between fatal risk, heart disease, and cancer are not statistically different from zero.

As previously discussed, these results potentially suffer from endogeneity. Therefore, in Table 6 we examine the results exploiting respondents' work history, while allowing for a fixed effect specification. Formally, this is expressed in equation (7) and equation (8). The fixed effects are aimed at capturing unobserved idiosyncratic variation that might be correlated with fatal risk. Evidently, this ereases a significant amount of the available variation. However, as can be seen from the standard errors, sufficient variation is left to identify the effect of fatality risk on wages. The sequence of specifications in table 6 follow the same pattern as in Table 5. Moreover, in all specifications of Table 6, we exploit all observations available for respondents. We have, on average, nine years of observations per respondent. All models include time-varying demographics characteristics reported in Table 1.

Similarly to model 5, model 10 in Table 6 is the least comprehensive model, and examines the effects of fatal risks on wages. Analyzing the respondents' work history introduces more identifying variability in the data, leading the coefficients on fatal rates to be estimated more precisely.[17] As a result, the coefficient on fatal risk is statistically different from zero and has a smaller variance. The estimated VSL for the average respondent is around 8.85 million euros.

As with model 4, interactions between respondents' medical conditions and fatal risks are introduced in model 9. The identification, however, differs from that of model 4. As we are using the respondents' medical history, rather than their conditions, identification is mostly coming from respondents' health shocks. We find a statistically significant coefficient. The estimated VSL for a healthy individual is around 8.7 million euros, while the estimated VSL for an individual suffering from a disease is 15.31 millions euros.

As with model 3, model 8 in Table 6 reports on the interactions between fatal risks and age, and between fatal risks and medical history. Following a similar pattern as in previous models, the coefficient on fatal risk is statistically different from zero. Results suggest that VSL estimates are decreasing with age. The VSL estimate for a healthy individual below 30 is nearly 17.5 million euros. The VSL estimates for healthy individuals in their 30's, 40's and older than 50 are close to 6 million euros, 8 million euros, and 7 million euros, respectively. The interaction term between fatal risk and medical history is statistically different from zero. The estimated VSL for individuals with a disease and below 30 is nearly 24.4 million euros.

Finally, model 6 reports on the estimates from the full model. This model includes all the interactions between respondents' age and medical history, and fatal risks. The results are similar to those reported for model 8, except for the relationship between fatal risk,

[17]Standard errors are clustered at the individual level.

heart disease and cancer. The interaction coefficient between fatal risk and cancer is not significantly different from zero. This might be due to the low number of industry changes observed for individuals with cancer, as compared to individuals with a heart disease.

6 Conclusion

In this paper, we analyze the effects of age and baseline health on individuals' trade-offs between mortality risks and wealth. As economic theory remains ambiguous about the impact of age and health on VSL, establishing the direction and magnitude of these effects remains an empirical question. This study uses a compensating wage differential approach, combining a rich population-based cohort with individual data on both work and medical history with a dataset on industry wide fatal risks in France.

Results suggest that the average VSL estimate is close to 8 million euros. We find that individuals with heart disease require nearly twice as much as healthy individuals for a similar exposure to mortality risk, leading to a VSL of 16 million euros. But we find weak evidence that VSL varies with cancer status. This is due to the lack of variation in job changes after cancer onset. VSL estimates vary positively with respect to worse health status. In addition, our results also suggest that VSL estimates vary with respect to age, ranging from 18, 6, 8 and 7 million euros for individuals below 30, between 30 to 39, between 40 and 49, and more than 50, respectively. These results contribute to the thin revealed preferences-based VSL literature in a European context, where the majority of the VSL literature has focused on stated preferences methods, such as Contingent Valuation Methods or Discrete Choice Experiments.

Moreover, while cost-benefit analysis is increasingly used in decision-making in France, there are very few estimates of French VSL (Hammitt and Herrera, 2016) and no studies, to the best of our knowledge, using RP approaches.[18] As a result, today's official VSL value used by the French administration (3 million euros in 2010 euros) is derived using a benefit transfer based on an OECD meta-analysis.[19,20] Given the value of 8 million identified by using French-based trade-offs, it might be the case that French preferences for mortality risk reductions are not adequately reflected by the value currently used by the French administration. Our results also suggest that VSL varies with respect to age, and health, implying lower VSL values for older individuals and higher VSL values for sicker individuals. These findings suggest opening up the discussion, not only on the

[18]The multi-annual French public budget programming bill of 2012 requires that all publicly funded investment should include a full socioeconomic evaluation before implementation.

[19]This value is notably higher than the previous one proposed by Boiteux, (1.5 million euros, in 2000) and seems closer to the empirical values found in the literature (Aldy et Viscusi 2004, Robinson and Hammitt 2011). However, it is still lower than those used in some countries such as North America.

[20]OECD values are derived by taking the mean of a set of studies that meet a certain standard for methodological reliability. Note that all of the studies included in the OECD analysis are based on stated preference methods.

magnitude of French VSL estimates, but more generally on the legitimacy of policies aimed at differentiating VSL estimates according to age or condition.

Table 5: Log wage regressions with fatality rates: cross-section

	Cross section				
	(1)	(2)	(3)	(4)	(5)
Fatality rate	0.00810***	0.00231***	0.00811***	0.00233***	0.00230***
	(0.00236)	(0.000742)	(0.00236)	(0.000742)	(0.000728)
Fatality rate X $Age_{30;39}$	-0.00733***		-0.00734***		
	(0.00281)		(0.00280)		
Fatality rate X $Age_{40;49}$	-0.00616**		-0.00615**		
	(0.00259)		(0.00259)		
Fatality rate X Age_{50+}	-0.00682***		-0.00680***		
	(0.00255)		(0.00255)		
Fatality rate X disease			-0.000725	-0.000977	
			(0.00315)	(0.00315)	
Fatality rate X cancer	-0.00123	-0.00165			
	(0.00533)	(0.00532)			
Fatality rate X heart disease	0.000708	0.000592			
	(0.00372)	(0.00369)			
Has had either disease ?			0.0615*	0.0644*	
			(0.0356)	(0.0356)	
Has had cancer ?	0.0822	0.0857			
	(0.0644)	(0.0643)			
Has had heart disease ?	0.0380	0.0402			
	(0.0406)	(0.0405)			
$Age_{30;39}$	0.247***	0.204***	0.247***	0.204***	0.204***
	(0.0288)	(0.0200)	(0.0288)	(0.0200)	(0.0200)
$Age_{40;49}$	0.280***	0.244***	0.280***	0.243***	0.244***
	(0.0276)	(0.0194)	(0.0276)	(0.0194)	(0.0194)
Age_{50+}	0.302***	0.261***	0.302***	0.261***	0.262***
	(0.0281)	(0.0202)	(0.0281)	(0.0202)	(0.0202)
C-type demographics	X	X	X	X	X
Industry FE	X	X	X	X	X
Year FE	X	X	X	X	X
Average hourly wage	14.43	14.43	14.43	14.43	14.43
Baseline VSL (in millions)	-	5.36	-	5.40	4.71
VSL- with either disease			25.86	3.14	
VSL- with cancer	15.93	1.53			
VSL- with heart disease	20.42	6.73			
VSL - Age less than 30	18.78		18.81		
VSL - Age btw 30 and 39	1.79		0.63		
VSL - Age btw 40 and 49	4.01		4.50		
VSL - Age 50 +	2.48		2.99		
Observations	7,202	7,202	7,202	7,202	7,202
R-squared	0.505	0.505	0.505	0.505	0.504

Table 6: Log wage regressions with fatality rates panel data

	Panel				
	(6)	(7)	(8)	(9)	(10)
Fatality rate	0.00798***	0.00398***	0.00797***	0.00397***	0.00404***
	(0.00207)	(0.00116)	(0.00207)	(0.00116)	(0.00116)
Fatality rate X $Age_{30;39}$	-0.00518***		-0.00518***		
	(0.00178)		(0.00178)		
Fatality rate X $Age_{40;49}$	-0.00504**		-0.00503**		
	(0.00206)		(0.00206)		
Fatality rate X Age_{50+}	-0.00564**		-0.00565**		
	(0.00226)		(0.00226)		
Fatality rate X disease			0.00318***	0.00302**	
			(0.00118)	(0.00118)	
Fatality rate X cancer	0.00148	0.00133			
	(0.00231)	(0.00231)			
Fatality rate X heart disease	0.00389***	0.00373***			
	(0.00130)	(0.00130)			
Has had either disease ?			-0.00923	-0.00837	
			(0.0134)	(0.0135)	
Has had cancer ?	0.000352	0.000531			
	(0.0266)	(0.0267)			
Has had heart disease ?	-0.0125	-0.0113			
	(0.0153)	(0.0153)			
$Age_{30;39}$	0.368***	0.339***	0.368***	0.339***	0.339***
	(0.0146)	(0.0106)	(0.0146)	(0.0106)	(0.0106)
$Age_{40;49}$	0.539***	0.511***	0.539***	0.511***	0.511***
	(0.0175)	(0.0126)	(0.0175)	(0.0126)	(0.0126)
Age_{50+}	0.671***	0.640***	0.671***	0.640***	0.640***
	(0.0194)	(0.0138)	(0.0194)	(0.0138)	(0.0138)
Individual FE	X	X	X	X	X
P-type demographics	X	X	X	X	X
Industry FE	X	X	X	X	X
Year FE	X	X	X	X	X
Average hourly wage	13.63	13.63	13.63	13.63	13.63
Baseline VSL (in millions)	-	8.72	-	8.70	8.85
VSL- with either disease			24.42	15.31	
VSL- with cancer	20.72	11.63			
VSL- with heart disease	25.80	15.42			
VSL - Age less than 30	17.28		17.46		
VSL - Age btw 30 and 39	5.94		6.11		
VSL - Age btw 40 and 49	6.24		8.26		
VSL - Age 50 +	4.93		6.90		
Observations	68,674	68,674	68,674	68,674	68,674
R-squared	0.70	0.70	0.70	0.70	0.70
Number of individuals	7,202	7,202	7,202	7,202	7,202

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