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The Value of a Statistical Life for Risk Averse and Risk Seeking Individuals

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Abstract

This paper estimates the Value of a Statistical Life (VSL) under the hedonic wage method accounting for individual risk preferences. This estimation is based on a unusual approach; it empirically uses two approaches to account for risk preferences in the estimation of the wage-risk trade-off and VSL estimation. First, risk aversion is directly measured using survey-measures of preferences toward hypothetical gambles, and second observed individual behaviors, that may proxy for risk preferences such as smoking status are used. The empirical results and the used of observed measures of risk aversion are reconciled with a theoretical model of economic behavior that predicts how the wage-risk trade-off changes as risk aversion differ across individuals. It also captures the effect of risk aversion across the wage distribution using quantile regressions to test for the modeling assumption that safety is a normal good. The VSL estimates range between 0.81 and 9.16 million dollars. The results using smoking behavior as proxies for risk attitudes are consistent with previous findings. However, directly measuring risk aversion corrects the wage-risk trade-off estimation bias in the opposite directions than when using smoking status. This suggests that, consistent with the literature that connects smoking behavior with labor market outcomes, smoking status could be capturing productivity effects due to poor health in addition to purely risk preferences. This paper contributes to the literature by mitigating potential bias that may appear due to individual rusk preferences using a novel approach.

Keywords: value of a statistical life, risk attitudes, elicited risk aversion, quantile regression.
JEL Classification: J17, J28, D81, C21

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1 Introduction

In this paper I estimate the Value of a Statistical Life (VSL) under the Hedonic Wage Method (HWM), accounting for an individual's risk aversion and observed risky behaviors. The VSL is a quantification of the price of a human life and is useful for cost-benefits analysis both in public and private settings when designing and evaluating policies associated with health and environmental trade-offs.

In an extensive review, Viscusi and Aldy (2003) report that for the U.S., the VSL is estimated to be between within 0.82 and 24.24 in millions of U.S. dollars.[1] More recent studies have used different parametric and nonparametric methods, and have estimated the American VSL to be between 6.20 and 91.79 in millions of U.S. dollars (Evans and Schaur, 2010; Kniesner et al., 2012). There are other estimations for developed countries such as Canada, the U.K., Switzerland, Austria, Spain, Australia, and Japan. The estimates range from 2.44 and 22.25 million U.S. dollars.[2] Fewer studies have been focused in developing countries. We can expect these estimates to be different due to different labor market structures, costs, and risks faced by workers. There have estimations for South Korea, Taiwan, Hong Kong, and India that report estimates in the range of 0.82 to 4.66 million U.S. dollars (Kim and Fishback, 1993; Liu and Hammitt, 1999; Siebert and Wei, 1998; Shanmugam, 2001). Under the hedonic wage method framework, not many calculations have been published for Latin American countries. Parada-Contzen et al. (2013) estimate a VSL for Chile using cross-sectional data. The estimates range from 5.38 to 14.95 million U.S. dollars.

The discussion in the literature have centered mainly around empirical issues (Kniesner et al., 2012). One of the concerns is the omitted variable bias caused by failing to capture individual attitudes toward risks. This is a relevant issue since an individual's level of risk aversion is defined by the individual's utility function, and as a result, it affects decisions and observed behaviors. Garen (1988) suggests that unobserved variables, such as the worker's cool-headness or the worker's productivity in risky environments should affect the results. He developed an instrumental variable approach for addressing this problem. The weakness of his approach is the standard instrumental validity critique. Parada-Contzen et al. (2013) include characteristics of other firms in the industry as exclusion restriction that should affect an individual's perceived risk, but not her wages following Timmins and Murdock (2007). Kniesner et al. (2012) propose that potential biases could arise from the unmodeled worker productivity and safety-related productivity. They account for this source of bias by using panel data estimation, which allows them to eliminate time-invariant individual effects and to instrument risks by using the dynamics of the model finding that, after accounting for individual unobserved characteristics, the VSL estimate decreases. This methods allows the authors to account for risk preferences if the assumption that risk aversion is time-invariant holds and when longitudinal data is available.

As it is difficult to have observed measures of risk aversion, the literature has used proxies for risky behaviors to test whether the wage-risk trade-off differ across individuals. Some common proxies used are observed behaviors such as the use of seat belts, smoking, preventative medical care consumption, or financial risk decisions (Hersch and Viscusi, 1990; Jianakoplos and Bernasek, 1998; Viscusi and Hersch, 2001; Eeckhoudt and Hammitt, 2004). Attempts to value the effect of risk aversion on the wage-risk trade-off and in the VSL estimates, have shown that the VSL increases as risk aversion increases (Viscusi and Aldy, 2003). Viscusi and Hersch (2001) develop a model in which workers are heterogeneous in smoking behavior as a way to capture variation in risk preferences, showing that the wage-risk trade-off might be different depending on the smoking's effect on wages. Empirically, they find that smokers select themselves in more risky jobs and have lower wage-risk trade-offs. For assessing the mortality cost of smoking, Viscusi and Hersch (2008) estimate the VSL for full-time workers by smoking status, age, and

[1] All values throughout this paper are expressed in dollars of 2015.

[2] See Marin and Psacharopoulos (1982); Weiss et al. (1986); Meng and Smith (1990); Kniesner and Leeth (1991); Cousineau et al. (1992); Siebert and Wei (1994); Miller et al. (1997); Baranzini et al. (2001); Font et al. (2007).

gender. They find a higher VSL for non-smokers than for smokers, consistent with the hypothesis that more risk averse individuals should have higher compensation, and they value life more highly. The wage-risk trade-off between smokers and non-smokers is similar for both groups, neverless they find that the marginal effect of a lost workday is higher for non-smokers, consistent with Viscusi and Hersch (2001). Interestingly, they find that the wage-risk trade-off is higher for smokers than for non-smokers for young individuals and similar as that for individuals starting at age 35.

A potential limitation of using observed risky behaviors as proxies for risk aversion is that there are confounded effects among general risk aversion, specific risky behaviors, and labor market outcomes. For instance, Berman et al. (2013) argue that smokers' productivity could be lower than for non-smokers due to excess absenteeism, smoking breaks, lower productivity as the result of nicotine addiction, among others. On the other hand, there is also evidence that general financial risk aversion may also affect a worker's productivity. Using self-reported, observed measures of risk aversion Bonin et al. (2007) and Le et al. (2011) find that risk attitudes significantly explain wages. In particular, as an individual's willingness to take risk increases as her perceived wage increases.[3] Additionally, even though there is evidence that proxies such as smoking status might capture an individual's risk preferences, Kaplow (2005) suggest that researchers should further explore individual discrepancies in risky behaviors in different contexts when estimating the VSL and its elasticities. Kaplow (2005) reconciles a model of economic behavior that incorporates individual preferences toward risks with the estimates of the VSL's income elasticity. The model predicts that the income elasticity should be as high as an individual's coefficient of relative risk aversion. Nevertheless, the empirical estimates found in the literature are not consistent with the rationalization of risk-taking behaviors. He suggests that this discrepancy might be due to variation in type of risky behavior. Following this line, Dohmen et al. (2011) find that smoking status is a good instrument for when other health measures of risk aversion are not available, but does not perform well when one wants to account for general risk preferences.

In this paper, I contribute to the discussion first by developing a wage-differential theoretical model that allows heterogeneity in financial risk aversion. I show that the wage-risk trade-off vary according an individual's level of risk tolerance depending on the effect of risk aversion on workers' productivity and whether the marginal effect of risk aversion is homogenous across good and bad states of the world. Second, as a novelty of this paper, I empirically classify individuals according to both their observed smoking status and according to their revealed risk aversion using survey measures for capturing individual risk preferences in general settings. To obtain reliable estimates, I classify individuals into different risk preferences categories using observed measures of risk aversion that come from hypothetical gambles toward lifetime income that have been validated by previous research.[4] As in Viscusi and Hersch (2008), I estimate separate wage equations for smokers and nonsmokers, as well as for individuals who show different levels of observed financial risk aversion. I also allow combinations of risk attitudes depending on these two classifications and estimates that vary according to the wage distribution. For the estimation, I use three waves (2004, 2006, and 2009) of the Chilean Longitudinal Survey of Social Protection (EPS) complemented with fatality risks measured as number of fatal accidentes reported over total number or workers per industry, given by the Chilean Safety Association (ACHS) for the same years.[5] Using sub-samples defined by an individual's risk aversion and smoking status, I estimate the wage-risk trade-off and empirically test the theoretical wage-risk trade-off predictions. I find that the estimation results are consistent with a model in which risk aversion negatively affects wages. Third, I contribute evidence to the scarce literature that estimate the VSL in Latin American countries under the

[3] A literature review on measures of risk aversion, and the effect of smoking and risk preferences in earnings is presented in Section 2.2.

[4] For references in survey measures of risk aversion see Andersen et al. (2006) and the references therein.

[5] The ACHS is one the three institutions in charge of managing health insurances for work accidents. More details in Section 4.

HWM and evidence on how the estimates vary across wealth levels for a developing economy.

This paper also contributes to the literature that accounts for variations in the wage distribution for addressing heterogeneity in the VSL and its income elasticity when estimating the wage-risk trade-off. It is expected that safety is a normal good, nevertheless most researchers have focused on one point of the wage distribution, which assumes that the variation across wages is small. This is a questionable assumption, especially for developing economies and countries with high wealth inequality. Following Evans and Schaur (2010) and Kniesner et al. (2010), I estimate the VSL for the different sub-samples while using quantile regression in order to account for the heterogeneity of VSL due to differences in wages and differences in the income elasticity of the VSL.

The theoretical model predicts that both the wage-risk trade-off and the VSL vary with general risk aversion. For the wage-risk trade-off, the results vary according to the effect of risk aversion on workers' productivity and whether I allow for heterogeneity on its marginal effect across good and bad states of the world. For instance, if one assumes that wages decrease with risk aversion, consistent with the empirical evidence, then the estimates are consistent with a model in which this marginal effect is homogenous across states. As a result the risk premium decreases as risk aversion increases. It is relevant to note that the opposite is true when using models that allows risk preferences to only vary in willingness to face health problems, as in Viscusi and Hersch (2001). In the same line, the empirical findings also support the hypothesis that more risk averse individuals are less productive in risky states, meaning that if individuals who are more risk averse lower their productivity as their jobs become more risky. If this change is bigger in the bad state, then they will be compensated less for risks than their counterfactual group.

With respect to the VSL, there are two confounded effects driving the differences due to risk aversion. First, as there is variation in the wage-risk trade-off, one can expect the VSL to be heterogeneous across groups. Second, importantly, even at a constant risk premium, the VSL varies due to wage differences across risk aversion groups. Generally, I find VSL estimates between 0.81 and 9.16 millions of U.S. dollars. The magnitude of the VSL estimate depends on whether I account for risk aversion or not, the observed measures for proxying for risk aversion, and the specific assumptions regarding the form of unobserved heterogeneity. The measure of risk aversion used is relevant as different measures predict different patterns of behavior and statistically different VSL estimates. For example, when using validated survey measures for capturing general risk preferences, the estimated VSL for risk averse individuals is 2.70 million dollars while the estimated VSL for risk averse individuals in smoking behavior is 3.79 million dollars (i.e., non-smokers). As predicted by the model and due to wage differences, the VLS is higher for generally non-risk averse individuals and lower for non-risk averse individuals in smoking status. The results suggest that smoking status can be capturing productivity effects not given by risk-management or "cool-headness"' reasons, but associated with lower productivity due to poorer health status especially in bad states, and as a result of addictive behaviors (e.g., longer breaks and higher absenteeism rates). Finally, I also capture the effect of risk aversion across the wage distribution using quantile regressions. Even at the same level of risk aversion, individuals could value risk differently, influenced by their wealth level. The theoretical model predict differences in wage-risk trade-offs as the marginal effect of risk preferences on wages, and its rate of change, is heterogeneous as wages increases. This result is supported by both measures of risk aversion. As in Evans and Schaur (2010), I find that for all risk aversion measures, there is an important income heterogeneity in the VSL as it increases as wages increases. This variation is due to differences in the estimated risk premium but importantly it is also considerably driven by the average wages used in the computation.

The rest of the paper is organized as follows. The next section presents the relevant literature on risk aversion, smoking behavior, and earnings. Section 3 presents the model and empirical specification; Section 4 presents the data source and descriptive statistics of key variables, such as risk aversion measures and fatality risks. Section 5 presents the results and finally Section 6 concludes.

2 Relevant literature

2.1 Survey measures of risk aversion

In classic economic theory, risk aversion has been measured following the models of Pratt (1964) and Arrow (1965). Since these theoretical measures of risk aversion and predictions on behavior appeared, several empirical papers have attempted to estimate them and to test the theoretical predictions (Eisenhauer and Ventura, 2003). In modern considerations, Bommier and Rochet (2006) expand the classic definition by introducing an individual intertemporal risk aversion measure using a lifetime utility function and by incorporating the horizon length of the individual dynamic optimization problem. This model predicts that risk aversion may change over time due to three effects: changes in wealth over the life-cycle, individual differences due to aging, and changes in the length of the planning horizon. Consistent with the dynamic models of risk aversion, there is empirical evidence that suggests that the variation in individual risk tolerance is based on observables is associated with time-varying attributes and due to persistent differences across individuals (Sahm, 2012).

There are generally three approaches for eliciting observed measures of risk attitudes: the investment portfolio approach, the lottery choice menu approach, and the pricing task approach (Holt and Laury, 2014). The investment portfolio approach asks respondents to choose among alternative financial gambles. One alternative is always less risky than the rest. The lottery choice menu builds the individual's risk attitude based on a structured list of binary choices between safe and risky gambles. The pricing task approach asks respondents to name a certainty equivalent money amount for a gamble. Risk attitude is inferred using this value and the expected value of the gamble. The most common used observed measure of risk aversion in the literature is the Holt-Laury measure where individuals are presented with lottery choice tasks in an experimental setting under both hypothetical and real conditions (Holt and Laury, 2002). In this experiment, individuals have typically have a set of 10 choices between two lotteries where one is always riskier than the other one. When one individual chooses a safer lottery, then it is possible to define her level of risk aversion.

Additionally, representative surveys have also included lottery choice questions in their questionnaires to assess an individual's risk attitude. In these questions, individuals are presented with hypothetical choices between jobs with a certain lifetime income level and risky jobs with variable income. Depending on individuals' responses, they can be classified into risk aversion categories. The first survey to include these questions was the American Health and Retirement Study (HRS) in 1992, and repeated in 1994, 1998, 2000, and 2002. Other examples are the National Longitudinal Survey of Youth 1979 (NLSY79) given in 1993 and 2002; and the German Socio-Economic Panel Study (SOEP) with waves in 2004, 2006, 2008, 2009, 2010, and 2011. Some surveys, such as the Dutch Household Survey (DNB), 1993-2011, include investment scenarios and measures a less general financial risk aversion. Although the number of surveys that incorporate these questions have been increasing, longitudinal data of risk aversion is scarce and almost non-existent for developing countries. The few that exists includes the EPS for Latin America and the Ukrainian Longitudinal Monitoring Survey (ULMS) waves 2007 and 2012 for transitioning economies.

Typically a respondent is asked: *what do you prefer, a job with a certain lifetime-stable salary or a job where you have* p *chances of earning* λ_1 *of your lifetime income or* $(1-p)$ *changes of earning* λ_2 *of your lifetime income?* where $\lambda_1 \geq 1$ and $0 < \lambda_2 < 1$. Economists design and model these survey answers as resulting from an expected utility calculation . Assuming U is the utility function and c the permanent consumption (equal to lifetime stable salary), then the indifference point between options solves: $p \times U(\lambda_1 c) + (1-p) \times U(\lambda_2 c) = U(c)$. Some authors assume a static framework using a CRRA form for U and directly compute the relative risk aversion parameter by normalizing wealth, replacing the survey information, and solving for the indifference coefficient of relative risk aversion (Barsky et al., 1997).

An advantage of these type of survey measures is that they are constructed over the individual's willingness to gamble his lifetime income rather than gambling small stakes like in laboratory settings, which may lead to issues with the scaling of risk aversion due to miscalibration of the expected-utility theory (Rabin, 2000). Accordingly, it avoids the problem in the existing literature where experiments have little effect on an individual's lifetime resources, i.e., there there is risk premium. Additionally, individuals are asked to gamble over their family income which eliminates the potential problem that a respondent might be more likely to gamble with their spouse's income (Spivey, 2010). Nonetheless, a critique in the literature is that individuals may value their job for more than pecuniary reasons. In such a case, they could choose the safe option because they do not want to leave their current job (Barsky et al., 1997; Spivey, 2010). However, the questions do not suggest that the individuals should choose between their current job and the potential gamble job.

The evidence from survey data indicates that most individuals select themselves into the most risk averse categories. There is also evidence that observed risk aversion evolves over time. For instance, using data from the HRS, Sahm (2012) finds that at least 60% of individuals belong to the most risk averse categorization while around 10-16% of individuals are in the least risk averse category. Over time, almost 70% of individuals did not move from the most risk averse category while only between 15-26% of individuals stay in the least risk averse categories and between 56-75% of individuals move to more riskier categories. Spivey (2010) uses two waves of the NLSY79 showing that individuals tend to cluster in the most risk averse categories, while 25% and 18% of individuals belongs to the least risk averse category for the years 1993 and 2002 respectively. The transition probabilities are not presented since the samples do not necessary overlap in both waves, but he notes that fewer individuals are willing to take big risks as they age.[6]

Survey measures of hypothetical gambles have been validated by correlating elicited risk aversion and observed behaviors that may also capture risk attitudes (Anderson and Mellor, 2009). For instance, Barsky et al. (1997) find that elicited risk aversion from hypothetical gambles predicts risky behaviors including smoking, drinking, investing in risky assets, among others. There is also evidence that more risk averse individuals predicts insurance acquisition. In particular for smoking behavior, they find that individuals who have never smoked are more risk averse than those who have smoked and current smokers. Dohmen et al. (2011) find that smoking status is positively correlated with willingness to take risks in general settings and particularly willingness to take risks in driving, financial matters, sports, career, and health. The empirical literature has not been conclusive with respect to how differences in risky scenarios may drive differences in revealed risk preferences and observed behaviors. For instance, Dohmen et al. (2011) - despite finding that the best predictor for smoking status is a question about willingness to take health risks, rather than a general risk question - suggest that a useful all-around measure for risk aversion is asking for global assessment of willingness to take risks. He also finds that smoking status can be used as a proxy for risk aversion in health matters, but it is an imperfect instrument for general risk aversion.

2.2 Wages, risk aversion, and smoking behavior

Some empirical evidence exists on how risk aversion affects labor market allocations and outcomes. The main approach has been to use a risk aversion measure as a right-hand side variable to test how it affects outcomes such as earnings, entrepreneur status, occupation selection, and migration status, among

[6] For details, see Tables B1 and B2 in Appendix B.

others. With respect to earnings, Bonin et al. (2007) study the role of risk attitudes on occupational sorting and earnings using an observed measure of self-reported willingness to take risks that takes values from 0 to 10 from a cross-section of the German Socio-Economic Panel.[7] They find that general risk attitudes significantly explains higher wages. Le et al. (2011) analyze how risk aversion affects wages and its role in the gender payment gap using Australian Twin Study of Gambling data set (2004-2007). They add an observed measure of risk aversion that takes values from 1 to 10 and captures self-reported attitudes toward risk as an additional right-hand side variable to explain earnings.[8] They find that individuals who tolerate higher economic risks are associated with having higher earnings. A different approach to account for risk attitudes is to model individual unobserved heterogeneity. Kniesner et al. (2012) use a first difference estimator in a Mincerian equation to address individual time-invariant unobserved heterogeneity. Risk attitudes could be one of these unobserved individual characteristics. If we think of it as a time-invariant component from the unobserved heterogeneity distribution, then following this approach we could unbiasedly estimate coefficients in a Mincerian equation and compare the estimated coefficients with the ones obtained when levels are estimated. Pollmann et al. (2013) study wage dispersion per occupation category using German administrative wage data and the German Socio-Economic Panel. They find that willingness to take risk is positively correlated with an individuals occupation specific wage dispersion.

There is evidence that smoking negatively affects earnings through deteriorating health and behavioral effects. Levine et al. (1997) was one of the first papers to quantify this effect finding that smoking reduces wages by between 4% to 8%. In the same line, Van Ours (2004) finds a negative effect of smoking in males (10% reduction) and no statistical effect for females; while Auld (2005) estimate that smokers earn 8% less than non-smokers. However, after correcting for endogeneity, he finds that smokers earn up to 24% less than non-smokers. By exploring a longitudinal data set and therefore accounting for potential bias due to individual unobserved heterogeneity, Schwarze and Heineck (2003) find that male smokers between 25 and 35 years old earn 2.5% more than their non-smoking counterparts. This result is justified by arguing that young males have high time preferences rates and therefore they do not account for future health problems and select into jobs with flatter lifetime earnings, while non-smokers start in jobs with lower starting wages while they become established and then move to jobs with higher earnings profiles. When exploring the cross-section nature of the data, they find consistent results with the previous literature. Generally there are not any effects from smoking for females and losses in the 2% to 8% range for males. Studies for developing countries are scarce.. For instance, Lokshin and Beegle (2011) find that for Albania, there is a 20% wage penalty for smokers.

There are several hypothesis that try to explain this effect. First, smoking reduces worker productivity due to longer breaks, higher absenteeism rates, and poorer health status and therefore their perceived wages are lower. Second, there could be discrimination from non-smokers against smokers as some employers have established their own smoking policies. Additionally, if employers expect smokers to be less productive than non-smokers there could be also be statistical discrimination. Third, smokers can also be more costly than non-smokers to employers due to higher insurance premiums while smokers may choose jobs that provide better health insurance (Levine et al., 1997). Finally, an smoker's behavior may impact their human capital accumulation as it has been shown that there is a positive correlation between health status and smoking, between smoking behavior and cognitive ability, and because smokers may have a low discount of the future (Grafova and Stafford, 2009; Heckman et al., 2014).

[7]Specifically, individuals are asked: "*How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: completely unwilling to take risks and the value 10 means: fully prepared to take risks*"

[8]Specifically, individuals are asked: "*On a scale of 1 to 10, with 1 meaning no risk, and 10 meaning extremely high risk, how much risk are you willing to tolerate when deciding how to invest your money?*"

Most studies that analyze smoking behavior focus on cross-sections of information making it hard to study smoking status transitions over time. These transitions and trends are consistent with the evidence in EPS as I will show in Section 4. For instance, Bondy et al. (2012) analyze longitudinal smoking behavior and find that in three consecutive semiannual interviews, 20% of smokers (daily and occasional) quit. In particular, 5% of daily smokers become occasional smokers and 29% of occasional smokers quit completely. From former smokers, 10% start smoking daily and 15% start smoking occasionally. Using waves 1 and 2 (2002 and 2003) from the International Tobacco Control Four Country Survey for Australia, Canada, the UK and USA, Hyland et al. (2006) find that on average for all four countries, 8% of daily smokers in wave 1 quit by wave 2, and 22% of weekly or monthly smokers in wave 1 quit by wave 2. The transition probabilities for weekly/monthly smokers vary across countries, for instance transitions represent a 23% for the US, 27% for Canada, 17% for the UK, and 20% for Australia. Tindle and Shiffman (2011) find that 13% of daily smokers quit while 18% and 27% of non-daily/intermittent smokers (depending on whether they smoked daily before or not) quit.

3 Risk aversion, smoking behavior, and the wage-risk trade-off

3.1 Wage differential theory and risk aversion

Following the standard formalization for models of compensating differentials, let p be the job risk that the worker endogenously face, $0 \leq p \leq 1$, and $w(p)$ the wage rate that depends on p. Each worker maximizes her expected utility over two states, a good outcome $U^1(w(p))$ with probability $(1-p)$, and a bad outcome $U^2(w(p))$ where the individual suffers a work injury with probability p. It is assumed that workers prefer not to have an accident $(U^1(w(p)) > U^2(w(p)))$ and that the marginal utility of income is positive in both states and decreases with wealth (i.e., $U^1_w(w(p)) > 0$, $U^2_w(w(p)) > 0$, $U^1_{ww}(w(p)) < 0$, $U^2_{ww}(w(p)) < 0$). From the utility maximization, each worker chooses from potential wage-risk combinations in the market locus $w(p)$. Each worker has a utility locus that satisfies $V = (1-p)U^1(w(p)) + pU^2(w(p))$. By differentiating V, we can get the wage-risk trade-off along the worker's curve:

$$\frac{dw}{dp} = w_p = \frac{U^1(w(p)) - U^2(w(p))}{(1-p)U^1_w(w(p)) + pU^2_w(w(p))} \tag{1}$$

Typically the literature assumes that workers are homogenous in preferences and therefore one assumes that the utility function captures preferences of a representative worker. Viscusi and Hersch (2001) extends this analysis by incorporating heterogeneity in workers preference toward smoking as a measure of risk aversion against unhealthy states. They assume that wages are a function of smoking status so the worker's locus is represented by $w(p, s)$ and that the utility in the bad state is a function of smoking (and in particular the marginal loss in smokers utility due to an injury is less than for non-smokers'), $U^2(w(p, s), h(s))$. The model's theoretical predictions depend on the marginal effect of smoking on the wage-risk trade-off. Empirically, they find that the smoker's risk premium is lower than for non-smokers and that the wage offer curves are smoking-status specific.

In this paper, I continue with the analysis of heterogeneous preferences by incorporating general risk aversion toward financial losses. Unlike Viscusi and Hersch (2001), I assume that financial risk aversion capture preferences toward general risks related with income variations and not only with respect to health outcomes. General risk aversion still incorporates aversion toward unhealthy states through variations in financial wealth due to, for example, wage losses or higher medical expenditures. Therefore, an individual who is more risk averse will be less willing to face health risks than an individual who is less risk averse. Aversion toward being unhealthy for non-financial reasons is not captured in the measure of general risk aversion but in the specific utility level associated with each health state.

Let's consider a simple setting in which individuals only differ in their level of (financial) risk aversion, denoted by θ, meaning that the curvature of their utility function varies. In order to capture the "cool-headness" hypothesis, it is assumed that risk aversion has an effect on an individual's wages (i.e., wages are a function of p and θ, $w(p,\theta)$) due to productivity effects. The marginal effect of risk aversion in productivity is $w_(p,\theta) = \frac{dw(p,\theta)}{d\theta}$ and it could be positive, negative, or equal zero. If it equals zero then we have the standard model. One could also assume that the marginal effect of risk aversion on wages differs across states. To allow for this possibility, I denote w_θ^1 for the marginal effect of risk aversion on wages in the good state and w_θ^2 for the marginal effect of risk aversion on wages in the bad state. Note that the marginal of income $(U_w\left(w(p,\theta)\right))$ is higher in the good state for any level of w (i.e., $U_w^1\left(w(p,\theta)\right) > U_w^2\left(w(p,\theta)\right)$), and both marginal effects decrease with wealth $(U_{ww}^1\left(w(p,\theta\right) < 0)$ and $U_{ww}^2\left(w(p,\theta\right) < 0)$. Therefore, the wage-risk trade-off in expression 1 is now also a function of risk aversion and becomes:

$$\frac{dw}{dp} = w_p = \frac{U^1(w(p,\theta)) - U^2(w(p,\theta))}{(1-p)U_w^1\left(w(p,\theta)\right) + pU_w^2\left(w(p,\theta)\right)} \tag{2}$$

and the marginal effect of risk aversion is given by the following expression:[9]

$$\frac{dw_p}{d\theta} = w_{p\theta} = \frac{\left[U_w^1 w_\theta^1 - U_w^2 w_\theta^2\right]\left[(1-p)U_w^1 + pU_w^2\right] - \left[U^1 - U^2\right]\left[(1-p)U_{ww}^1 w_\theta^1 + pU_{ww}^2 w_\theta^2\right]}{\left[(1-p)U_w^1 + pU_w^2\right]^2} \tag{3}$$

As the denominator is always positive, then $w_{p\theta}$ is positive if the following condition holds:

$$\left[U_w^1 w_\theta^1 - U_w^2 w_\theta^2\right]\left[(1-p)U_w^1 + pU_w^2\right] > \left[U^1 - U^2\right]\left[(1-p)U_{ww}^1 w_\theta^1 + pU_{ww}^2 w_\theta^2\right] \tag{4}$$

We know that both the second and third terms in equation 4 are positive. Therefore, the sign of $w_{p\theta}$ depend on the sign of w_θ, on the heterogeneity of the marginal effect across states and the relation between terms in equation 4. The different scenarios for positive and negative marginal effects of risk aversion on wages and with heterogeneity of its effects in each state are summarized in Table 1. As presented in Section 2, the evidence from the previous literature suggests that $w_\theta < 0$, so the total effect depends on whether heterogeneity in the marginal effect of risk aversion across states is allowed. If the effect is homogeneous, then we can expect the risk premium to decrease as financial risk aversion increases (row one of Table 1). Following the "coolheadness" hypothesis first proposed by Garen (1988) one could argue that as risk aversion increases, the (absolute value) of the marginal productivity is lower in the bad state (i.e., $\left|w_\theta^1\right| < \left|w_\theta^2\right|$). In such a case, the wage-risk trade-off might be positive or negative. For instance, if $U_w^1 w_\theta^1 < U_w^2 w_\theta^2$ then the risk premium decreases with risk aversion. As I will find later, the estimated risk premium is higher for less risk averse individuals. This empirical result is consistent with a model in which the conditions from rows 1, 2, 3, and 5 hold, shown in Table 1.

One could also expect the wage-risk trade-off to vary through the wage distribution. Evans and Schaur (2010) develop a model that predicts that if we allow wages to depend on a component that is unrelated to the job's riskiness and if the *dead-anyway* effect proposed by Pratt and Zeckhauser (1996) dominates any other effect, then the VSL increases as wages increases.[10] In this result there are confounding effects, as the wage-risk trade-off varies, and there is also an effect of the wage used to compute the VSL. In this paper, I allow a general framework with variation in risk attitudes. To quantify how the risk premium changes as wages increase, we need to compute $dw_{p\theta}/dw$. The sign of that effect is at first unknown as it

[9] I omit the arguments of the functions for simplicity.

[10] The dead-anyway effect is such that an individual facing serious health threats is willing to pay more for a small risk reduction than an individual facing a less serious health pressure.

Table 1: Variation in risk premium due to financial risk aversion

Parameters		$\left[U_w^1 w_\theta^1 - U_w^2 w_\theta^2\right]$	$\left[(1-p)U_{ww}^1 w_\theta^1 + pU_{ww}^2 w_\theta^2\right]$	$w_{p\theta}$
$w_\theta < 0$	$\lvert w_\theta^1\rvert = \lvert w_\theta^2\rvert$	< 0	> 0	< 0
$w_\theta < 0$	$\lvert w_\theta^1\rvert < \lvert w_\theta^2\rvert$	?	> 0	?
$w_\theta < 0$	$\lvert w_\theta^1\rvert > \lvert w_\theta^2\rvert$	< 0	> 0	< 0
$w_\theta > 0$	$\lvert w_\theta^1\rvert = \lvert w_\theta^2\rvert$	> 0	< 0	> 0
$w_\theta > 0$	$\lvert w_\theta^1\rvert < \lvert w_\theta^2\rvert$	?	< 0	?
$w_\theta > 0$	$\lvert w_\theta^1\rvert > \lvert w_\theta^2\rvert$	> 0	< 0	> 0

depends on the utility levels in both states, the sign of the marginal utility, the change in the marginal utility with respect to wealth (U_{www}) on the effect of risk aversion on wages (w_θ), on its marginal change through the wage distribution ($w_{\theta w}$), and on the weights of the different components of the derivative.[11] Depending on the magnitudes, as wages increases, the wage-risk trade-off through the wage distribution could increase or decrease. As I will find later, the empirical results show that the effect of wages in the risk premium is heterogeneous across the wage distribution, but the total effect in the VSL show that as wages increase, the VSL increases for any measure of risk aversion.

3.1.1 Extension: Wage differentials with financial risk aversion and smoking behavior

It is possible to extend the model with financial risk aversion to jointly incorporate the effect of smoking behavior as in Viscusi and Hersch (2001). The wage-risk trade-off in that case becomes:

$$\frac{dw}{dp} = w_p = \frac{U^1(w(p,\theta,s)) - U^2(w(p,\theta,s), h(s,\theta))}{(1-p)U_w^1\,(w(p,\theta,s)) + pU_w^2\,(w(p,\theta,s), h(s,\theta))} \tag{6}$$

where s represents smoking intensity and is zero for non-smokers and increases as the intensity increases, and $h(\cdot)$ represents willingness to entail health risks which increases with s. As health risks also entail financial risk one could also extend $h(\cdot)$ to be a function of financial risk aversion, expecting that as financial risk aversion increases, the willingness to hazard health risks decreases as wealth uncertainty and wealth outcomes change. This general specification allows wages to depend on smoking intensity and financial risk aversion. Based on the empirical evidence, one could argue that $\frac{dw(p,\theta,s)}{d\theta} < 0$ and $\frac{dw(p,\theta,s)}{ds} < 0$. Note that these two effects go in opposite directions, while more risk averse individuals in general risk aversion earn less; more risk averse individuals defined by smoking intensity (non-smokers) earn more. The total effect of financial risk aversion and smoking intensity on the wage-risk trade-off depends on the cross-effects between these two effects on wages, health-risk-tolerance, the marginal utilities, and their rate of change.[12]

[11] Formally, the effect of an increase in wages on the wage-risk trade-off is given by:

$$\frac{dw_{p\theta}}{d_w} = \frac{d}{dw}\left[\frac{U_w^1 w_\theta^1 - U_w^2 w_\theta^2}{(1-p)U_w^1 + pU_w^2}\right] - \frac{d}{dw}\left[\frac{U^1[(1-p)U_{ww}^1 w_\theta^1 + pU_{ww}^2 w_\theta^2]}{[(1-p)U_w^1 + pU_w^2]^2}\right] + \frac{d}{dw}\left[\frac{U^2[(1-p)U_{ww}^1 w_\theta^1 + pU_{ww}^2 w_\theta^2]}{[(1-p)U_w^1 + pU_w^2]^2}\right] \tag{5}$$

[12] In particular, the total effect on the risk premium of financial risk aversion interacting with smoking intensity will be given by $\frac{d^2 w_p}{d\theta ds}$.

3.2 Empirical model

The standard model in the HWM is an extension of the classic Mincer's model. I estimate a semi-log wage equation to capture the wage-risk trade-off following the recommended approach in the literature (Viscusi and Aldy, 2003). The empirical specification is presented in equation 7.

$$lnw_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \varphi p_{it} + \epsilon_{it} \tag{7}$$

where w_{it} is wage of agent i at time t, X_{it} are individual characteristics of agent i at time t, Z_{it} are job characteristics of agent i at time t, p_{it} is the industry fatal risk faced by agent i at time t, and ϵ_{it} is an stochastic shock. α, β, γ, and φ are the parameters to estimated. Note that φ is the estimated wage-risk trade-off. The estimated VSL can be obtained by $\widehat{\varphi} \times \overline{w} \times 4 \times 12$ where $\overline{w}$ is the mean hourly wage of the sample (Viscusi and Aldy, 2007).

4 Data source and definition of variables

4.1 Data source and sample selection

For individual characteristics, I use three waves (2004, 2006, and 2009) of Chilean Survey of Social Protection (EPS). This is a longitudinal data representative of the whole adult population in Chile after a sample expansion with respect to the first wave (2002). The EPS is a validated data set administered by the Ministry of Labor and Social Security and is one of the pioneer longitudinal surveys in Latin America (and Mexico). Its design, implementation, and partial funding was provided by the University of Pennsylvania. The EPS was constructed to evaluate retirement and social security policies and following the experience of the Health and Retirement Survey from the University of Michigan. In particular, the methodological design and the survey application was supervised by the Institute for Social Research of the University of Michigan.

An important feature of the EPS and why it fits this research is that it contains questions to capture preferences toward hypothetical gambles which allows one to elicit individual risk aversion over time. The inclusion of these questions was inspired by the growing literature that models observed risk aversion over time. The use of observed measures of risk attitudes have been increasing over the past 10 to 15 years, and researchers included them to explain heterogeneity in individual behavior due to differences in preferences (Holt and Laury, 2014). The measures contained in the EPS are similar to the ones included in other longitudinal representative surveys.

The fatality risk measures are constructed using reported accidents provided by the Statistics Yearly Report of the Chilean Safety Association (ACHS). ACHS is one of the three non-profit institutions in Chile that manage the mandatory work accident social insurance. It provides information on the total number of fatal and non-fatal accidents, and number of workers by 1-digit industry classification. Although Chile has reliable and robust data available compared to other Latin American countries, disaggregated information according to additional digits, occupational variation, or exogenous individual characteristics is not available. Still the advantage of this research is that it incorporates variability in the fatality measure by industry, attributable to the same individuals over time, and measures of risky behaviors. The mean fatality rate for the sample is in similar magnitudes than other non-U.S. studies, and in the mean between risk reported by government and by non-government sources (Viscusi and Masterman, 2017). It is higher than statistics from the U.S. Kniesner et al. (2012) for instance, report annual and average three-year fatality risks over 100,000 workers of 6,415 and 6,260 respectively.

The final sample includes all the individuals who have information for the control variables for years 2004, 2006, and 2009. Table 2 presents the summary statistics for the regression variables for the research sample. Table 2 presents the summary statistics for the regression variables for the research sample.

Table 2: Summary statistics for control variables for the research sample

Variable	Mean	Std. Dev.	Min	Max
Monthly wage	589.74	862.69	0.01	36,384.61
Hourly wage (in logs)	0.76	1.52	-10.10	5.35
Annual fatal risk	10.44	9.44	0.00	35.74
Three-year fatal risk	10.62	9.65	3.07	48.25
Age	42.88	11.99	16.00	89.00
Schooling	10.76	3.88	0.00	24.00
Male	0.61	0.49	0.00	1.00
Married	0.51	0.50	0.00	1.00
Union	0.15	0.36	0.00	1.00
Occupation category				
Managers	0.03	0.18	0.00	1.00
Professionals	0.08	0.27	0.00	1.00
Technicians and associate professionals	0.08	0.27	0.00	1.00
Clerical support workers	0.11	0.31	0.00	1.00
Service and sales workers	0.16	0.37	0.00	1.00
Skilled agricultural, forestry and fishery workers	0.06	0.23	0.00	1.00
Craft and related trades workers	0.16	0.37	0.00	1.00
Plant and machine operators, and assemblers	0.10	0.31	0.00	1.00
Elementary occupations	0.22	0.41	0.00	1.00
Geographical location				
Region 1	0.02	0.15	0.00	1.00
Region 2	0.03	0.17	0.00	1.00
Region 3	0.02	0.13	0.00	1.00
Region 4	0.05	0.21	0.00	1.00
Region 5	0.10	0.31	0.00	1.00
Region 6	0.06	0.23	0.00	1.00
Region 7	0.07	0.25	0.00	1.00
Region 8	0.11	0.32	0.00	1.00
Region 9	0.05	0.22	0.00	1.00
Region 10	0.08	0.27	0.00	1.00
Region 11	0.01	0.08	0.00	1.00
Region 12	0.01	0.09	0.00	1.00
Region 13	0.40	0.49	0.00	1.00
Observations	24,055			

4.2 Key variables

4.2.1 Risk variable

For the risk variable I use an objective measure of risk defined by the ratio between the number of fatal accidents and the number of workers per industry. These statistics are provided by the Chilean Safety Association which is one of three mutual institutions in Chile that manage social-work accident insurance. The ACHS is a non-profit organization regulated under the code #16,744 of the Chilean regulation for the mandatory social insurance for work accidents and professional illnesses established in 1968. Under Chilean labor law, employers have to get work accident insurance for their employees. The insurance prince is fully funded by the employer for all dependent workers and for independent workers under some job categories, and is voluntary for the rest of independent workers. The law makes it so it is in everyone's best interest to report the accident so that the medical cost is covered by the social insurance. In case of an accident (in the workplace or in the worker's commute), the employee needs to report the accident directly to the employer or through the health care center, and the employer reports to the mutual security in which it is subscribed so that the worker can receive health care. In this context, the ACHS is the biggest security in the system as it covers more than half of affiliated workers and around half of employers subscribed to the system. The ACHS has collected data of all firms enrolled to the organization since 1969 and it has provided public yearly statistics since 2002.

The EPS and ACHS use the same 1-digit industry classification, which allows for the matching of both samples. The standard classification used in VSL estimates allows comparability across studies. A disadvantage of the ACHS statistics is that it is provided at the 1-digit industry classification and does not include further detail. This does not allows me to account for measurement error in industry imputation. Nevertheless, this data availability is still an advantage with respect to other developing countries. Table 3 presents the descriptive statistics of the risk variable per year and for the 3-year-average as a ratio per 100,000 workers, while Table 4 presents the transition probabilities across 1-digit industry categories. These risk rates are higher than the ones reported for the U.S. (see Viscusi and Aldy (2003); Kniesner et al. (2012)), but in similar magnitudes as in other non-U.S. studies with government sources (see Viscusi and Masterman (2017)). The riskiest sectors are transportation, communication, and storage and construction. The safest sectors iare retail trade and service. It is expected that workers in more dangerous sectors would received a higher risk premium than those in retail trade or services. Most individuals tend to stay in their same industry over time, with services the most inelastic. However, there is a substantial share of individuals (around 30 to 40% for some industries) who move across industries over time. This additional variability in the risk measure is one of the gains of using longitudinal data sets.

Table 3: Fatality risk per industry (annual rates and 3-years-average)

Sector	Annual rates			3-year-average rate		
	2004	2006	2009	2004	2006	2009
Agriculture, Forestry, and Fisheries	16.43	9.86	16.77	14.60	13.62	17.98
Mining	13.07	35.74	20.54	27.82	48.25	25.51
Manufacturing	15.19	5.84	4.39	11.69	11.00	7.72
Electricity, Gas, and Water	16.41	0.00	28.89	18.78	16.07	24.87
Construction	33.88	24.26	21.64	33.46	25.55	20.55
Retail trade	3.83	5.76	2.64	3.07	3.91	3.21
Transportation, Communication, and Storage	28.26	29.44	24.49	28.35	28.89	23.27
Services	4.23	4.06	3.32	3.20	4.03	4.16

Note: (a) The risk variable is constructed as the ratio between total number fatal accidents and total number of workers in that industry. The ratio is presented per 100,000 workers.(b) The 3-years-average rates considers 2002, 2003 and 2004, 2004, 2005, and 2006; and 2007, 2008, and 2009 for the years 2004, 2006, and 2009, respectively.

Table 4: Transition probabilities for sector of economic activity

time $t-1$	*time* t								
	Ag.	Mi.	Ma.	El.	Co.	Re.	Tr.	Se.	Total
Ag.	67.87	0.30	6.56	0.45	4.83	11.09	2.56	6.33	100.00
Mi.	0.65	64.05	10.46	1.31	9.15	4.58	5.23	4.58	100.00
Ma.	6.65	1.45	54.41	0.53	7.97	12.58	3.95	12.45	100.00
El.	4.55	1.52	3.03	50.00	9.09	13.64	4.55	13.64	100.00
Co.	4.11	2.43	7.89	1.34	67.28	3.36	4.03	9.56	100.00
Re.	3.83	0.72	7.53	0.36	2.97	68.23	4.33	12.03	100.00
Tr.	3.16	0.87	4.58	0.33	4.58	8.18	66.74	11.56	100.00
Se.	1.65	0.67	3.20	0.19	2.79	6.01	2.46	83.04	100.00
Total	10.68	1.78	11.81	0.73	10.64	19.29	8.32	36.76	100.00

4.2.2 Risk aversion measures

Hypothetical gambles for financial risk aversion

A key variable in this paper is measuring risk aversion using survey hypothetical questions. Each wave of the EPS has a question that asks individuals their preferences toward hypothetical lotteries in which they are asked to gamble their potential lifetime income. In particular, I focus on a question that is in the waves from 2004, 2006, and 2009. The hypothetical scenarios are common for all three waves with the exact same wording and survey structure. The translation of the question from Spanish is as follows:

> *Suppose that you are the only income earner in the household. You need to choose between two jobs. Which option do you prefer? (Option A) a job with a stable and certain salary over your lifetime or (Option B) a job where you have the same chances of doubling your lifetime income or earning only 1/4 of your lifetime income.*

The respondent is asked if he prefers a lottery (p) or a certain payment(x) smaller than the expected value of the lottery ($E_p(x)$). That is: $x \leq E_p(x) \leq p$. If the agent prefers x to the lottery, then she is more risk averse than an agent that chooses the lottery. An expected utility maximizer will choose the 50-50 gamble if: $\frac{1}{2}U(2c) + \frac{1}{2}U(\lambda c) \geq U(c)$ where $\lambda = \frac{1}{4}$. An important feature of the risk aversion question in EPS is that it is a reliable and validated question, based on the seminal measures of risk aversion by Holt and Laury (2002), and that considers validation characteristics proposed by Barsky et al. (1997), Rabin (2000) and Spivey (2010) as discussed in Section 2 .

Based on the above, I construct a categorical variable where if an individual who chooses the certain payment x is more risk averse than an individual than one who chooses the gamble. For the estimation I split the sample into two sub-samples: the risk averse group and the non-risk averse group.[13] Tables 5 and 6 present the share of individuals in each category and the probability of transitioning between groups from one period to the next. As found in the literature, most individuals select themselves into the most risk averse category, in each period 80% of individuals are in the risk averse category. As in Sahm (2012), most individuals in the risk averse category stay in that classification over time, and most individuals in non-risk averse categories move to risk averse groups.[14].

Table 5: Share of Individuals in each financial risk attitude category per year

Category	Number			Share		
	2004	2006	2009	2004	2006	2009
Risk Averse	7,007	6,776	5,604	80.45	80.94	80.37
Non-risk Averse	1,703	1,596	1,369	19.55	19.06	19.63
Total	8,710	8,372	6,973	100.00	100.00	100.00

Note: (a) An individual that prefers x to the lottery is more risk averse than a agent that chooses the lottery.

[13]We could also named it “most risk averse” and “least risk averse”. Through the paper I keep the “risk averse” and “non-risk averse” labeling for simplicity’.

[14]See Appendix B for details in Sahm (2012) and Spivey (2010)

Table 6: Transition probabilities for financial risk aversion

time $t-1$	*time* t		
Category	Risk Averse	Non-risk Averse	Total
Risk Averse	82.02	17.98	100.00
Non-risk Averse	75.71	24.29	100.00
Total	80.81	19.19	100.00

Note: (a) An individual that prefers x to the lottery is more risk averse than a agent that chooses the lottery.

Smoking behavior

In every wave of the EPS, each individual is asked whether she smokes or not, and if so, how many cigarettes monthly. Using this information, I construct the main measure for smoking status as a self-reported categorical variable that takes the value of 1 if the individuals reports smoking and 0 otherwise. In terms of risk attitudes, a non-smoker is considered to be risk averse (in smoking behavior) and a smoker non-risk averse. For robustness, I also use alternative definitions of smoker status using the self-reported, average number of cigarettes smoked monthly by individuals who report smoking. In this setting, I create two alternative definitions. In the first I classify individuals into three group: non-smoker (if the individuals reports not smoking), light smoker (smokes on average 100 cigarettes monthly or less) and heavy smoker (smokes on average more than 100 cigarettes per month). In the second I classify individuals into two groups: smoker (if the individual reports smoking, and has reported to smoking average more than 100 cigarettes per month in at least one wave) and non-smoker (if the individual reports not smoking or is smoking, on average, less than 100 cigarettes per month up to period t). The objective of these classifications is to test whether the results are sensitive to smoking intensity.

Table 7 presents the summary statistics of smoking status under the baseline definition and the alternative categories for smoking status, and Table 8 has the transition probabilities. Under the baseline definition and the first alternative definition, there are 62% are non-smokers. Meanwhile the number of light smokers and smokers is similar (18% and 19% respectively.) The second definition adds conditions for being considered a smoker, and as a result 78% of the sample are non-smokers.

Most individuals do not change their smoking behavior. The transition probabilities vary across definitions and states. For instance, under the baseline definition, 24% of smokers quit, similar to the 22% using the second alternative definition. The second definition also sees 30% of smokers becoming light smokers. On the other hand, under the baseline a 10% starts smoking opposed to a 5% in the second alternative definition. Twenty-six percent of light smoker intensify their smoking.

With respect to other countries, Chile has high smoking prevalence rates. It ranks second in smoking rates in Latin America after Cuba and second among the OECD countries after Greece (Müller and Wehbe, 2008; OECD Indicators, 2015). In Table C1 I compare the smoking prevalence rates in EPS with those from other Chilean surveys. The smoking prevalence rate reported in EPS is slightly smaller than statistics from other national statistics for the same period of time and similar to Latin American statistics for Chile.[15] The cross-section nature of other national data sets does not allows one to study

[15] In particular, I use the National Survey of Health 2009-2010 (or ENS by its acronym in Spanish from Encuesta Nacional de Salud) and the cross-sections for 2002, 2004, 2006, 2008, 2010, and 2012 from the statistics of drugs and tobacco use from the Ministry of the Interior and Public Security of Chile (or SENDA by its Spanish reference). I complement this comparison with the PATIOS (2005) survey from the Pan American Health Organization (PAHO) for Chile. The smoking prevalence rate in the EPS is 40 percent for the wave of 2004, while in ENS (2003) is 42% and 44% for SENDA. According to the PAHO data, Chile's smoking prevalence was 37% in 2005. The decrease in smoking rates over time in EPS follows the same pattern than

transitions in smoking behavior over time for the same individual. According to the second wave of ENS, 22% of individuals are former smokers, 17% of individuals quit smoking more than one year before the second ENS wave and 4% less than 6 month before the survey.

Table 7: Number and share of individuals in each smoker category per year

Definition	Number			Share			
	2004	2006	2009	2004	2006	2009	Total
Baseline							
Non-smoker	5,256	5,281	4,483	60.34	63.08	64.29	62.44
Smoker	3,454	3,091	2,490	39.66	36.92	35.71	37.56
Alternative 1							
Non-smoker	5,256	5,281	4,483	60.34	63.08	64.29	62.44
Light Smoker	1,420	1,662	1,330	16.30	19.85	19.07	18.34
Heavy Smoker	2,034	1,429	1,160	23.35	17.07	16.64	19.22
Alternative 2							
Non-smoker	6,676	6,568	5,610	76.65	78.45	80.45	78.38
Smoker	2,034	1,804	1,363	23.35	21.55	19.55	21.62
N	8,710	8,372	6,973	100.00	100.00	100.00	100.00

Note: (a) Under the baseline definition, a smoker is an individual who reports to smoke (independently of the number of cigarettes) and a non-smoker is an individual that reports not to smoke. Under Alternative 1, a smoker is an individual that reports to smoke and to smoke on average more than 100 cigarettes per month; a light smoker is an individual that reports to smoke and to smoke on average less or equal than 100 cigarettes per month, and a non-smoker is an individual who reports not to smoke. (b) An agent that does not smoke is considered to be more risk averse than an agent that does smoke.

observed in the repeated cross-sections in ENS and SENDA.

Table 8: Transition probabilities for smoking behavior

time t − 1	*time t*		
Baseline	Non-Smoker	Smoker	Total
Non-Smoker	89.50	10.50	100.00
Smoker	23.86	76.14	100.00
Total	64.01	35.99	100.00
Alternative 1	Light Smoker	Heavy Smoker	Total
Light Smoker	74.18	25.82	100.00
Heavy Smoker	30.42	69.58	100.00
Total	48.44	51.56	100.00
Alternative 2	Non-smoker	Smoker	Total
Non-smoker	94.91	5.09	100.00
Smoker	21.66	78.34	100.00
Total	78.27	21.73	100.00

Note: (a) Under the baseline definition, a smoker is an individual who reports to smoke (independently of the number of cigarettes) and a non-smoker is an individual that reports not to smoke. Under Alternative 1, a smoker is an individual that reports to smoke and to smoke on average more than 100 cigarettes per month; a light smoker is an individual that reports to smoke and to smoke on average less or equal than 100 cigarettes per month, and a non-smoker is an individual who reports not to smoke. (b) An agent that does not smoke is considered to be more risk averse than an agent that does smoke.

4.2.3 Wage variable

I use the reported after tax monthly wage and the reported number of hours typically worked weekly multiplied by four to compute the hourly wage. Table 9 presents the average monthly wage per industry (1-digit level) and per risk attitude classification. A fundamental difference between the two measures of risk aversion is different wage levels associated with the groups defined by smoking behavior or by preferences towards the lottery income. From Table 9 one can see that when using the lottery preferences, earnings for more risk averse individuals are less than the non-risk averse individuals for every industry. On the other hand, when using smoking status, earnings for more risk averse individuals (non-smokers) are higher in almost every industry except for agricultural activities and mining. These statistics are consistent with the literature that explores the labor costs of smoking and the literature that studies the effect of risk preferences on earnings. Depending on the estimated risk premiums, this is an important consideration when calculating the VSL.

Table 9: Mean monthly wage per industry and per risk attitude classification

Sector	Hypothetical Gambles		Smoking Status (base)	
	Risk Averse	Non-risk Averse	Non-smoker	Smoker
Agriculture, Forestry, and Fisheries	350	393	350	372
Mining	1,042	1,112	918	1,284
Manufacturing	566	781	622	588
Electricity, Gas, and Water	912	1,327	1,216	775
Construction	561	680	610	555
Retail trade	461	597	498	481
Transportation, Communication, and Storage	674	737	723	636
Services	645	753	670	653
All industries	567	687	597	578
Sample Size	19,387	4,668	15,020	9,035

Note: (a) An agent that prefers x to the lottery is more risk averse than a agent that chooses the lottery (b) An agent that does not smoke is more risk averse than an agent that does smoke.

5 Results

In the first set of estimations, I present the VSL using pooled ordinary least squares and robust standard errors for the whole sample and for every sub-sample. Each sub-sample is defined according to one of the two classifications of risk attitudes (i.e., preferences towards potentially gambling with lifetime income and smoking status) and for combinations. Two sets of estimates are presented: one set where the annual fatality rate is used and a second where the three-year-average fatality rate is used to avoid the influence of random fluctuations in fatalities due to small number of accidents.

In the second set of estimations, I estimate the wage-risk trade-off for each sub-sample using quartile regressions in order to capture variation on the estimates at different points of the wage distribution. All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. The VSL is then estimated using the coefficient on the fatality measure for each regression and the average wage for the corresponding sub-sample.

5.1 VSL according to revealed risk attitudes

The estimated wage-risk trade-off and the estimated VLS using pooled OLS for each sub-sample are presented in Table 10 and Table 11. The regression results for the whole sample are presented in Table D1 in the Appendix D. The pattern across risk aversion groups is different depending on the measure: the wage-risk trade-off is higher for less risk averse individuals in lottery income and lower for less risk averse individuals in smoking behavior. The estimated wage-risk trade-off for each sub-sample are statistically different from each other and with respect to the estimates for the whole sample at the 1% level. The only exception is the estimate for those who are less risk averse in the lottery question but risk averse in terms of smoking status. That group is statistically different to the whole sample estimator at 5%. Generally, the wage-risk trade-off is higher when three-year-average for fatality rates are used as it avoids rates that might be randomly low for some period. The pattern across sub-samples holds.

I first discuss the results by smoking status. When using smoking status as a proxy for risk aversion, the wage-risk trade-off is higher for risk averse individuals (i.e., non-smokers). This is consistent with evidence in the literature and with the theoretical model developed by Viscusi and Hersch (2001) that predicts smokers face a flatter market offer curve relative to non-smokers. For robustness check, I estimate the wage-risk trade-off for different sub-samples defined by smoking status and smoking intensity. The two alternative definitions presented in Section 4 are used to divide the sample. The general pattern holds across definitions, meaning that the estimated wage-risk trade-off is higher for non-smokers (and light smokers) than for (heavy) smokers. The results are similar between non-smokers and light-smokers, which is consistent with the evidence that labor market outcomes are affected by smoking behavior through health and productivity avenues and with models where the marginal effects of smoking increase with intensity. An important finding is that differences in estimated wage-risk trade-off happen between heavy smokers and the rest of the individuals. These results are presented in Table 12.

Secondly, when using survey measures on hypothetical gambles, the estimated wage-risk trade-off is higher for non-risk averse individuals. At first this may look surprising. Nevertheless, these results are consistent with the previous evidence of the effect of risk aversion on wages and with a model where the marginal effect of risk aversion on wages is negative. According to the model presented in Section 3 both homogenous and heterogeneous marginal effects across risk aversion groups are consistent with the empirical results. Due to the difference in wages between these groups, it is possible to frame the results in a model where the marginal effect of risk aversion on wages in the bad state of the world is greater (in absolute value) than in the good state of the world. This result shows the relevance of the risk aversion measure one uses for allowing heterogeneity in the estimation of risk premiums. As in Kaplow (2005), differences between models of the rationalization of risk-taking behaviors and these empirical results can be due to heterogeneity in behavior in different risky markets for the same group of individuals. In this line, a general measure of risk aversion allows one to capture the effect of global risk attitudes especially in scenarios where different effects can be interacting.

Both the difference in the estimated risk premiums and in wages across groups drives the variation in VSL estimates (Table 11). For the entire sample, the estimated VSL is 3.41 million U.S. dollars. For smokers and non-smokers, the estimated VSL is 3.79 and 3.01 million, respectively; while for the risk averse and non-risk averse in lotteries the estimated VSL is 2.70 and 6.83 million dollars respectively. These estimates are lower than others reported in the literature for Chile under the HWM and higher than VSL estimates that rely on other methods. Parada-Contzen et al. (2013) find estimates in the range of 5.38 to 14.91 million U.S. dollars using the same fatality measure for 2006 and a cross-sectional representative Chilean survey for the same year (CASEN). Other estimates for Chile, based on extrapolations of VSL from North American, European, and Asian countries and correcting for GDP, range between 0.88 and 1.33 million U.S. dollars (Miller, 2000; Bowland and Beghin, 2001). There is a vast literature that estimate the VSL for Chile using stated preferences methods that came from different risk causes, such as road safety and air pollution. These estimates outside the HWM report values between 0.33 and 6.31 million U.S. dollars.[16]

Table 10: Pooled OLS estimated wage-risk trade-off using annual and 3-years-average fatality risk

Sample	Annual risk	3-years-average risk
Whole sample	0.00483***	0.00515***
	(t =4.96)	(t =4.84)
Preference toward lotteries		
Risk averse (no lotteries)	0.00396***	0.00436***
	(t =3.55)	(t =3.68)
Non-risk averse (lotteries)	0.00828***	0.00839***
	(t =4.29)	(t =3.46)
Smoking status		
Risk averse (non-smoker)	0.00529***	0.00552***
	(t =3.79)	(t =3.69)
Non-risk averse (smoker)	0.00434***	0.00487***
	(t =3.46)	(t =3.48)
Combinations		
Risk averse in lotteries and	0.00386*	0.00426**
risk averse in smoking status	(t =2.43)	(t =2.59)
Risk averse in lotteries and	0.00436**	0.00487***
non-risk averse in smoking status	(t =2.95)	(t =3.00)
Non-risk averse in lotteries and	0.01080***	0.01054***
risk averse in smoking status	(t =3.76)	(t =2.95)
Non-risk averse in lotteries and	0.00432*	0.00491*
non-risk averse in smoking status	(t =2.06)	(t =1.84)

Note: (a) t-value in parentheses. (b) All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. (c) For the preferences toward lotteries, an agent that prefers x to the lottery is more risk averse than a agent that chooses the lottery. For the smoking status, an agent that does not smoke is more risk averse than a agent that does smoke. (d) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

The higher VSL for non-smokers is consistent with the prediction that less risk averse individuals should be more highly compensated to accept a higher fatality risk. However it is also consistent with the productivity side of the trade-off between wages and risks. Smokers could be willing to accept a lower compensation for facing higher fatality risks because they are less productive due to health reasons and not because they are able to perform better in risky environments. On the other hand, agents with high tolerance to lotteries have a higher estimated VSL. One could consider an individual risk averse

[16]See for instance Dios Ortúzar et al. (2000), Rizzi and de Dios Ortúzar (2003), Iragüen and de Dios Ortúzar (2004), Hojman et al. (2005), and GreenLabUC (2014)

in preferences toward lotteries and smoking status to be in the most risk averse category. I find that this estimate is the lowest from all the sub-samples, suggesting that relatively, the effect of financial risk aversion is dominant over the effect of smoking status.

Table 11: VSL using different samples

	Annual risk		3-years-average risk	
	VSL	95% interval	VSL	95% interval
Whole sample	3.41	[3.29; 3.55]	3.65	[3.52; 3.77]
Preference toward lotteries				
Risk averse	2.70	[2.56; 2.83]	2.96	[2.83; 3.09]
Non-risk averse	6.83	[6.50; 7.16]	6.92	[6.60; 7.25]
Smoking status				
Risk averse	3.79	[3.61; 3.97]	3.96	[3.78; 4.13]
Non-risk averse	3.01	[2.85; 3.17]	3.38	[3.21; 3.54]
Combinations				
Risk averse in lotteries and risk averse in smoking status	2.64	[2.45; 2.83]	2.92	[2.73; 3.10]
Risk averse in lotteries and non-risk averse in smoking status	2.92	[2.74; 3.09]	3.26	[3.08; 3.44]
Non-risk averse in lotteries and risk averse in smoking status	9.16	[8.66; 9.66]	8.90	[8.41; 9.40]
Non-risk averse in lotteries and non-risk averse in smoking status	3.41	[3.06; 3.77]	3.89	[3.55; 4.23]

Note: (a) Prices in million U.S. dollars (2015). (b) Clustered standard errors in parentheses. (c) C.I. = 95% confidence interval. (d) All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. (d) For the preferences toward lotteries, an agent that prefers x to the lottery is more risk averse than a agent that chooses the lottery. For the smoking status, an agent that does not smoke is more risk averse than a agent that does smoke. (e) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.

Table 12: Pooled OLS using alternative definitions of smoking status

Definition	Annual risk		3-year-average	
	Coeff.	VSL	Coeff.	VSL
Alternative 1				
Non-smoker	0.00529***	3.79	0.00552***	3.96
	($t = 3.49$)	[3.61; 3.97]	($t = 3.69$)	[3.78; 4.13]
Light Smoker (≤ 100)	0.00559***	3.81	0.00597***	4.07
	($t = 2.65$)	[3.61; 3.97]	($t = 2.85$)	[3.83; 4.30]
Heavy Smoker (> 100)	0.00365*	2.57	0.00425**	2.99
	($t = 1.89$)	[2.35; 2.80]	($t = 2.24$)	[2.78; 3.21]
Alternative 2				
Non-smoker	0.00548***	3.88	0.00577***	4.09
	($t = 4.24$)	[3.73; 4.03]	($t = 4.52$)	[3.94; 4.23]
Smoker	0.00310*	2.18	0.00355**	2.50
	($t = 1.70$)	[1.97; 2.39]	($t = 1.97$)	[2.29; 2.71]

Note: (a) t-value in round parentheses. 95% confidence interval in square parentheses. (b) All the models control for age, age squared, categorical dummy for working region, categorical dummy for 1-digit occupation, for marital status, for gender, for union status, and for year effect. (c) For the smoking status, an agent that does not smoke is more risk averse than a agent that does smoke. (d) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

5.2 Capturing the effect of risk aversion across the wage distribution

For capturing the variation at different points of the wage distribution I estimate the VSL for the same specification and sub-samples using quantile regressions. To estimate the wage-risk trade-off only at one point of the wage distribution assumes that the variation across the wage distribution is small, which is a questionable assumption (Evans and Schaur, 2010). This is important because even if we have the same degree of risk aversion across a group of individuals, these agents could value risk differently because of their position in the wage distribution. Additionally, the marginal effect of risk aversion and smoking behavior on wages could be different across the distribution. It is important to pay close attention to these variations when estimating values for developing economies where inequality rates are higher than in developed countries and where smoking status tends to also be higher than in developed countries. Table 13 and 14 presents the estimated wage-risk trade-off and VSL, respectively, using quantile regression at the mass points at 25%, 50%, and 75% of the distribution. As in Evans and Schaur (2010) there are two effects driving the results for the VSL estimates. We can observe from Table 14 that as wages increase, the VSL increases, driven by the differences in the estimated wage-risk trade-off and, importantly, due to differences in earnings across groups.

For the sub-sample by smoking status, as we evaluate the wage-risk trade-off at different mass points of the wage distribution, we can observe that the estimated wage-risk trade-off is higher for non-risk averse individuals (smokers). This shows that the previous finding, where non-smokers need to be compensated more than smokers for accepting higher risks, only holds at the mean of the distribution. There are several hypothesis that may explain this effect. For example, it could be the case that individuals with higher earnings have more bargaining power and are able to obtain higher wages as their budget constraints are different and may incur higher medical care expenses due to deteriorated health, while non-smokers do not need this additional amenity.

This compensation pattern is more consistent when using preferences toward lotteries as measure of risk aversion. The exception to the previous findings is at the median of the wage distribution, where more risk averse individuals have higher compensation than their counterparts. This result is within the framework developed in Section 3 where I allow heterogeneous effects of risk aversion on wages across the wage distribution. Specifically, the empirical results presented here are consistent with a model in which the marginal effect of risk aversion on wages and its rate of change vary across the wage distribution and market offer curves differ across groups.

Table 13: Estimated coefficients for fatal risk

Sample	Pooled OLS	Quantile Regression		
		25 percent	50 percent	75 percent
Whole sample	0.00483***	0.00284***	0.00405***	0.00408***
	(t =4.96)	(t =5.71)	(9.13)	(7.02)
Preference toward lotteries				
Risk averse	0.00396***	0.00263***	0.00416***	0.00405***
	(t =3.55)	(t =4.32)	(8.30)	(6.60)
Non-risk averse	0.00828***	0.00345***	0.00347***	0.00517***
	(t =4.29)	(t =3.54)	(3.44)	(3.83)
Smoking status				
Risk averse	0.00529***	0.00269***	0.00372***	0.00385***
	(t =3.79)	(t =3.66)	(6.77)	(4.94)
Non-risk averse	0.00434***	0.00280***	0.00530***	0.00422***
	(t =3.46)	(t =3.62)	(7.54)	(5.02)
Combinations				
Risk averse in lotteries and	0.00386*	0.00236**	0.00362***	0.00427***
risk averse in smoking status	(t =2.43)	(t =3.15)	(6.06)	(5.25)
Risk averse in lotteries and	0.00436**	0.00328***	0.00547***	0.00405***
non-risk averse in smoking status	(t =2.95)	(t =4.43)	(t =8.56)	(t =4.33)
Non-risk averse in lotteries and	0.0108***	0.00459**	0.00352***	0.00579***
risk averse in smoking status	(t =3.76)	(t =3.27)	(t =2.65)	(t =4.67)
Non-risk averse in lotteries and	0.00432*	0.00165	0.00371***	0.00567***
non-risk averse in smoking status	(t =2.06)	(t =1.33)	(t =2.80)	(t =2.77)

Note: (a) t-value in parentheses. (b) All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. (c) For the preferences toward lotteries, an agent that prefers x to the lottery is more risk averse than a agent that chooses the lottery. For the smoking status, an agent that does not smoke is more risk averse than a agent that does smoke. (d) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 14: VSL estimates using quantile regression

	Quantile 25%		Quantile 50%		Quantile 75%	
Sample	VSL	C.I.	VSL	C.I.	VSL	C.I.
Whole sample	0.99	[0.96; 1.02]	1.92	[1.89; 1.96]	3.35	[3.27; 3.42]
Preference toward lotteries						
Risk averse	0.92	[0.88; 0.95]	1.97	[1.93; 2.01]	2.80	[3.09; 3.17]
Non-risk averse	1.23	[1.17; 1.28]	1.81	[1.73; 1.90]	4.51	[4.32; 4.71]
Smoking status						
Risk averse	0.94	[0.89; 0.98]	1.76	[1.72; 1.80]	3.15	[3.05; 3.26]
Non-risk averse	0.97	[0.93; 1.02]	2.51	[2.45; 2.56]	3.23	[3.13; 3.34]
Combinations						
Risk averse in lotteries and risk averse in smoking status	0.83	[0.78; 0.86]	1.68	[1.64; 1.72]	3.38	[3.28; 3.49]
Risk averse in lotteries and non-risk averse in smoking status	1.15	[1.10; 1.18]	2.59	[2.54; 2.64]	2.99	[2.88; 3.10]
Non-risk averse in lotteries and risk averse in smoking status	1.62	[1.55; 1.71]	1.84	[1.72; 1.96]	5.21	[5.04; 5.40]
Non-risk averse in lotteries and non-risk averse in smoking status	0.61	[0.53; 0.68]	1.96	[1.84; 2.07]	4.70	[4.42; 4.97]

Note: (a) Prices in million U.S. dollars (2015). (b) Standard errors in parentheses. (c) C.I. = 95% confidence interval. (d) All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. (e) For the preferences toward lotteries, an agent that prefers x to the lottery is more risk averse than a agent that chooses the lottery. For the smoking status, an agent that does not smoke is more risk averse than a agent that does smoke. (f) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.

6 Conclusion

In this paper I address the effect that individual risk aversion and risky behaviors have on wage-risk trade-off and in estimates of the VSL for developing countries. First, I develop a theoretical model for capturing the effect of risk aversion measured based on the curvature of the utility function on the wage-risk trade-off. I then test the theoretical predictions of the model. Different from the previous literature I use two different measures for risk aversion. The first one relies on financial risk aversion according the classical economic definition of preferences toward lotteries; and for this measure I use validated survey measures of reported preferences toward hypothetical labor market scenarios. Following the previous literature in the hedonic wage method, I also use smoking status as a proxy for risk attitudes.

Generally, I find estimates between 0.81 and 9.16 million U.S. dollars. The magnitude of the VSL estimator depends on whether or not I account for risk aversion and the assumptions regarding unobserved heterogeneity. The measure of risk aversion is statistically important since different measures gave different behavior patterns and statistically different VSL estimates. The results suggest that smoking status - which is a common risk aversion measure - could be capturing different productivity effect influenced by addictive behavior and health status. I find that dividing the samples according to more than one category of risk aversion could help in finding estimates that account for unobserved risk preferences. A limitation of this research is, that in the data used, that the fatality risk measures are only available at 1-digit industry level disaggregation. However the fatality measure comes from an institution that has been managing social health insurance for almost 60 years. These reliable fatality measures and additionally the observed measures of risk aversion and the longitudinal nature of data used in this research contribute to the scarce research for environmental and health valuations in developing countries, specifically, in Latin American under the hedonic wage framework.

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Appendix

A Dictionary of Variables

Wage: reported after tax monthly wage transformed into an hourly wage by dividing it by the reported number of hours typically worked in a week multiplied by 4. In 2015 US$.

Fatal risk: Rate between the number of fatal accidents per sector and the number of workers in that particular sector. Matched using the reported sector of work (1-digit industry classification).

Age: reported in years.

Schooling: years of schooling completed.

Male: 1 if individual is male, 0 otherwise.

Married: 1 if the individual is married, 0 otherwise.

Union: if the individual reported to be affiliated with a workers union, 0 otherwise.

Occupation: set of dichotomous variables created using the 1-digit occupational classification (ISCO): managers; professionals; technicians and associated professions; clerical support workers; service and sales workers; skilled agricultural, forestry and fishery workers; craft and related trades workers; plant and machine operators, and assemblers; and elementary occupations. In the estimation, elementary occupations is the omitted category.

Geographical location: set of dichotomous variables based on the reported region where the individual works using the old Chilean administrative division which labels regions from 1 to 13. Region 1 = de Tarapacá, Region 2 = de Antofagasta, Region 3 = de Atacama, Region 4 = de Coquimbo, Region 5 = de Valparaíso, Region 6 = del Libertador General Bernardo O'Higgins, Region 7 = del Maule, Region 8 = del Bío Bío, Region 9 = de la Araucanía, Region 10 = de los Lagos, Region 11 = de Aysén del General Carlos Ibáez del Campo, Region 12 = de Magallanes y de la Antártica Chilena, and Region 13 = Metropolitana de Santiago. In the estimation, Region 13 is the omitted category.

Smoking status: a categorical variable for sample definition that takes the value of 1 if the individuals reports smoking and 0 otherwise. For alternative definition 1, there are three categories: non-smoker (if the individuals reports not smoking), light smoker (if he reports smoking 100 cigarettes or less per month), and heavy smoker (if he reports smoking more than 100 cigarettes per month). For alternative definition 2 there are two categories: smoker (if the individual reports smoking and has reported smoking on average more than 100 cigarettes per month in at least one wave) and non-smoker (if the individual reports not smoking or smokes on average less than 100 cigarettes per month up to period t).

Preferences toward lotteries: categorical variable used for sample definition. It is created using survey answers to questions toward hypothetical lotteries in which individuals are asked to gamble their potential lifetime income. If the individual chooses the certain payment x over the lottery, then she is classified into the risk averse category.

B Risk attitudes distribution and transition probabilities in the literature

Table B1: Risk attitude distribution in the literature (%)
(Based on Spivey (2010) and Sahm (2012))

Author	Risk aversion distribution (%)		
	Most Risk averse	Intermediate	Least risk averse
Spivey (2010)	*Very Strongly and Strongly*	*Moderate*	*Weakly*
1993	58	17	25
2002	66	16	18
Sahm (2012)	*Groups 1 and 2*	*Groups 3 and 4*	*Groups 5 and 6*
1992	65	23	13
1994	62	29	10
1998	58	26	16
2000	64	23	12
2002	62	26	13

Note: (a) The number of risk aversion categories vary according to the number of questions considered. Spivey (2010) classifies individuals into 4 categories. Sahm (2012) classifies individuals into 4 categories for the first wave and 6 categories for the later four waves).

Table B2: Transition Probabilities for Risk attitude in the literature (%)
(Based on Sahm (2012))

time $t-1$	*time t*			
Category	*1–2*	*3*	*4*	*5–6*
1–2	68	13	9	10
3	56	24	10	10
4	54	17	15	15
5–6	47	15	13	26

Note: (a) Sahm (2012) classifies individuals into 4 categories for the first wave and 6 categories for the later four waves).

C Smoking prevalence rate

Table C1: Smoking prevalence evidence from cross-sections

Source	Prevalence rate (%)
ENS (Cross-section 2003)	
Smoker	42.0
Non-Smoker	58.0
ENS (Cross-section 2009-2010)	
Smoker	40.6
Smoker with high dependence	33.2
Non-Smoker	59.4
Smoking quitting rates	
Former Smoker over total population	21.6
Former smokers over total population (for $<$ 6 months)	3.5
Former smokers over total population(for $>$ 6 months)	18.1
Former smokers over total population (for $>$ 1 year)	16.7
Former smokers over current smokers	53.2
SENDA (Cross-sections)	
Smoker (2002)	43.6
Smoker (2004)	43.6
Smoker (2006)	42.4
Smoker (2008)	41.2
Smoker (2010)	36.0
Smoker (2012)	34.0
PATIOS - 2005	
Smoker	37.0

Note: (a) ENS = National Survey of Health (Encuesta Nacional de Salud in Spanish), SENDA = Survey from the National Service for drug and alcohol prevention and rehabilitation dependent from the Ministry of the Interior and Public Security of Chile (Servicio Nacional para la Prevención y Rehabilitación del Consumo de Drogas y Alcohol in Spanish) , PATIOS = Survey from the Pan American Health Organization.

D Regression Results

Table D1: Estimation results for the whole sample

Variable	Coefficient	St.Dev	p-value
Fatal risk	0.005***	0.001	0.000
Age	0.024***	0.005	0.000
Age squared	-0.000***	0.000	0.000
Schooling (years)	0.051***	0.003	0.000
Married	0.081***	0.018	0.000
Union	0.228***	0.023	0.000
Male	0.198***	0.020	0.000
Occupation			
Managers	0.399***	0.082	0.000
Professionals	0.829***	0.047	0.000
Technicians and associate professionals	0.488***	0.044	0.000
Clerical support workers	0.248***	0.033	0.000
Service and sales workers	-0.005	0.028	0.862
Skilled agricultural, forestry and fishery workers	-0.201***	0.039	0.000
Craft and related trades workers	0.107***	0.026	0.000
Plant and machine operators, and assemblers	0.101***	0.031	0.001
Geographical location			
Region 1	-0.272***	0.079	0.001
Region 2	0.070	0.051	0.170
Region 3	-0.216**	0.095	0.024
Region 4	0.007	0.028	0.813
Region 5	-0.147***	0.031	0.000
Region 6	-0.004	0.029	0.901
Region 7	-0.359***	0.044	0.000
Region 8	-0.085***	0.026	0.001
Region 9	-0.208***	0.035	0.000
Region 10	-0.060*	0.033	0.065
Region 11	0.160*	0.092	0.081
Region 12	-0.160	0.140	0.252
Year			
2006	0.125***	0.010	0.000
2009	-0.414***	0.028	0.000
Constant	-0.651***	0.107	0.000

Note: (a) t-value in parentheses. (b) All models control for fatal risk, age, age squared, years of schooling, marital status, union status, gender, occupational category (1-digit classification), geographical location, and for year effects. Elementary occupations and Region 13 are the omitted categories for occupational category and geographical location. (c) The estimation sample is constructed by all the individuals who have information for all the variables including both measures of risk aversion.

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.