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ESSAYS ON JOB-RELATED RISKS AND WORKER SORTING

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ESSAYS ON JOB-RELATED RISKS AND WORKER SORTING

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics at the University of Kentucky

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ABSTRACT OF DISSERTATION

ESSAYS ON JOB-RELATED RISKS AND WORKER SORTING

This dissertation examines heterogeneity in the value of a statistical life (henceforth VSL) stemming from employer-provided health insurance (henceforth EHI) and worker sorting. The dissertation consists of three essays.

In the first essay (Chapter 2), I investigate the effect of health-driven productivity on the wage compensation for mortality risk, and how EHI influences VSL using the US labor market data. In this chapter I build a framework showing that the level of job risks influences the incentive of employers to provide EHI. The basic notion of the framework is that health insurance is an investment in health and health is a form of general human capital. Employers are willing to invest in employees' health and pay the associated costs as long as they can recoup the costs of health investment. Occupational hazards, however, are harmful to health; productivity gains from health tend to decline as risk increases, resulting in lower health investment made by employers. As a result, the workers in risky jobs have to contribute more to their health investment in the form of lower wages than do workers in safe jobs. This behavioral response pushes down the wage offer curve of the insured in high risk occupations. Consequently, workers with health insurance, on average, accept a lower risk premium, leading to a lower VSL. Empirical findings from this dissertation suggest evidence of heterogeneity in VSL due to health insurance status : the estimated VSL for workers with health insurance is lower than those without one.

In the second essay (Chapter 3), I extend the framework of the second chapter into the United Kingdom (the UK) labor market. Different from the US, the UK has universal health care system in which all eligible individuals (almost all the UK citizens) are covered by publicly-provided health care. This chapter also provides evidence that private medical insurance in the universal health care system affects the risk premium. Despite the fact that the UK and the US have different institutional settings in health coverage, findings from the UK are, to some extent, qualitatively similar to the US.

A major issue in estimates of VSL is that people are not randomly assigned to jobs. That is, heterogeneous people would sort into jobs based on their preferences on risk and safety-related skills. Thus, failure to account for heterogeneity in both risk preferences and safety-related skills will bias the estimated VSL. In the third essay (Chapter 4), I discuss worker sorting and how it may affect the mortality risk premium. In this chapter, I focus on the role of personality traits in safety-related skill and their influence on worker sorting based on job risk. I use Five-Factor Model of personality or also known as the Big Five personality traits. The big 5 personality traits are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. In my framework, these personality traits are inputs and the technology of skill formation transforms the traits into safety-related skill.

KEYWORDS: Value of Statistical Life, Employer-Sponsored Health Insurance, Worker Sorting, Personality Traits, Big Five

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ESSAYS ON JOB-RELATED RISKS AND WORKER SORTING

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To my family, Atri, Adrian, and Brigitta

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Chapter 1 Introduction

Different occupations exhibit vastly different job-related likelihood of death and injury. Certain jobs expose workers to high probabilities of injury, such as construction laborers or truck drivers. Despite these risks, some people are voluntarily willing to bear the risks for higher wages in return, holding other things constant. This observed behavior in the labor market is the key prediction of the compensating differential theory that individuals must be compensated by higher than average wages to induce them to take unfavorable jobs. Based on the theory, economists have developed a method to quantify individuals' willingness to accept fatal risk at workplace—i.e. the tradeoff rate between monetary compensation and fatal injury risks, or what is known as the value of statistical life (henceforth VSL).

Over the last three decades, a vast body of research has documented various estimates of VSL (Viscusi and Aldy, 2003). Earlier research focused attention to the precision and accuracy of VSL. However, these studies produced a wide range of estimated VSLs (Viscusi and Aldy, 2003). As such, these estimates hardly offer a precise benchmark for policy evaluations. This raised skepticism that VSL could provide a guideline for policies (see Leigh (1995) for example). Nevertheless the availability of new data and more refined measures of risks allow economists to have better estimates of VSL. Recent research using panel data from the US labor market data has narrowed down estimates of VSL that are robust to various specifications (Kniesner et al., 2012).

Recently, research in VSL has shifted its attention to explore heterogeneity in VSL. It is obvious that individuals' valuation of risk depends on their characteristics, such as income, age and other demographic factors. Thus, one would expect that VSL may differ for different populations under study. For instance, the VSL tends to be higher among high income individuals (Kniesner et al., 2010), and thus, higher income countries tend to have higher VSL that do poor countries (Viscusi and Aldy, 2003). Relatively older individuals are more likely to have lower VSL than are middle aged individuals (Aldy and Viscusi, 2008). This heterogeneity in VSL across different populations would have policy implications. As policies reducing mortality risk would be costly, heterogeneity in VSL suggests that different populations value differently the benefits of risk reduction. Thus, a single estimated VSL may be too high or low than what society is willing to pay for risk reduction. Consequently, policies intended to reduce risks may fail to improve welfare.

Heterogeneity in VSL may also stem from workplace characteristics or other policies as well. In states where workers receive generous workers' compensation, they accept a lower wage premium for risk of injury (Viscusi and Moore, 1987). This essentially suggests evidence of compensation transfer. In particular, employers compensate workers for risks they are taking either with wage payments (i.e. *ex ante* compensation) or workers' compensation benefits (i.e. *ex post* compensation). A lower risk premium that is associated with generous workers' compensation suggests that the employer transfers compensation from wage compensation to workers' compensation benefits. Yet there is a wide array of compensations and the employer may use them to attract workers as well. Thus, it is plausible that other noncash compensations, such as health insurance, play role in affecting VSL (Dorsey, 1983).

In this dissertation, I investigate the influence of employer-provided health insurance (henceforth EHI) on the wage compensation for fatal risk. Thus so far the literature has no extensive discussion yet on this issue.[1] However, there is policy relevance for taking into account heterogeneity in VSL stemming from health insurance coverage. As workplace safety in most developed countries has improved substantially over decades, the rate of fatal accident at work has declined to an unprecedented level. Overall, occupational mortality rates in developed countries are much lower than they were in previous decades.[2] But at the same time, the costs of illness and other health risks increase substantially. Accordingly, individuals may be willing to accept a lower risk premium in return for health insurance.

The policy relevance of employer-provided health insurance in the estimated VSL is also related to a recent trend and variation in health coverage across occupations. In the US, employer-sponsored health insurance continues to be the major source of health coverage for the nonelderly population.[3] Health insurance coverage varies substantially across sectors, yet workers who lack health insurance are concentrated in occupations considered blue-collar, and in industries associated with high rates of fatal injury, such as, agriculture, mining, and construction. So, if VSL differs by health coverage status and uninsured are concentrated in particular industries, a single benchmark VSL used for policy evaluations may be too high or low for workers in different sectors.

Conceptually, health insurance would have an impact on the estimated VSL when

[1] I am only aware one paper that discusses the role of fringe benefits, including health insurance on the wage premium for risk, that is, the paper of Dorsey (1983).

[2] In the US, the overall fatality rate is 3.4 per 100,000 workers (BLS 2014). It is 1.2 in the United Kingdom (UK HSE 2014).

[3] It was estimated that 67.8 percent of workers ages 18-64 received EHI in 2012 (Fronstin, 2013).

workers' valuations on health insurance differ across different levels of job riskiness. If job safety is normal good, more productive workers would seek safer occupations. However, more productive workers that tend to earn higher incomes may value more health insurance than are less productive workers. On the other hand, workers who go to riskier occupations reveal that they are more tolerant to risks, and, may value less the benefits of health insurance. At the same time, working environments where risks to human health are high make the costs of health insurance are high too. Thus, both employers and workers in risky occupations are less willing to purchase health insurance. Consequently, as workers in riskier occupations tend to prefer full wage compensation, we may expect that workers with health insurance—mostly are located in safe jobs—would accept lower wage premium for risk than do workers without health insurance.

I proceed the dissertation as follows. Chapter 2 discusses the role of employer-provided health insurance on the VSL using the US labor market data. In this chapter I build a framework showing that the level of job risks influences the incentive of employers to provide EHI. I view that health insurance is an investment in health and health is a form of general human capital. Employers are willing to invest in employees' health and pay the associated costs as long as they can recoup the costs of health investment. Occupational hazards, however, are harmful to health; productivity gains from health tend to decline as risk increases, resulting in lower health investment made by employers. As a result, the insured in risky jobs have to contribute more to their health investment in the form of lower wages than do the insured in safe jobs. This behavioral response pushes down the wage offer curve of the insured in high risk occupations. Since VSL is estimated through the slope of the wage offer curve, it implies that workers with health insurance, on average, accept a lower risk premium, leading to a lower VSL. Empirical findings from this dissertation suggest evidence of heterogeneity in VSL due to health insurance status: the estimated VSL for workers with health insurance is lower than those without one.

Chapter 3 extends the framework of the second chapter into the United Kingdom (the UK) labor market. The US is unique among developed countries as it has a strong link between health insurance and employment. Different from the US, the UK has universal health care system in which all eligible individuals (almost all the UK citizens) are covered by publicly-provided health care. Despite the low coverage of private medical insurance, private health insurance, which majority is employer-provided, is growing in the UK. Thus, research on the effect of employer-provided health insurance on VSL is warranted. This chapter provides evidence that private medical insurance in the universal health care system affects the risk premium. Despite the fact that the UK and the US have different institutional settings in health coverage, findings from the UK are, to some extent, qualitatively similar to the US.

A major issue in estimates of VSL is that people are not randomly assigned to jobs. Indeed, the central implication of the compensating differential theory is that heterogeneous people would sort into jobs based on their preferences on risk. Shogren and Stamland (2002) note that an individual who chooses to work in a riskier occupation reveals that "he is more tolerant to risk or has personal ability to reduce risk of death or both". Hence, failure to account for heterogeneity in both risk preferences and safety-related skills will bias the estimated VSL. Findings from Chapter 2 and 3 confirm that controlling for the latent variable reduces the estimated VSL, suggesting that the estimated VSL using OLS is upward bias.

Chapter 4 discusses worker sorting and how it may affect the mortality risk premium. In this chapter, I focus on the role of personality traits in safety-related skill and their influence on worker sorting based on job risk. I pursue a pragmatic approach by which I use measures of personality traits that have been developed by personality psychologists and, recently, widely used by economists. Specifically, I use Five-Factor Model of personality or also known as the Big Five personality traits (Borghans et al., 2008). The big 5 personality traits are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. In my framework, these personality traits are inputs and the technology of skill formation transforms the traits into safety-related skill.[4]

Using data from the United Kingdom Household Longitudinal Study (the UKHLS), I find evidence of worker sorting based on personality traits. I particularly find that conscientious and extravert individuals tend to be employed in riskier jobs (i.e. jobs with high rate of fatal and nonfatal injury). On the other hand, I also find that agreeableness, openness, and neuroticism are negatively associated with risk of injury—i.e. individuals with these traits are inclined to choose safer jobs.

Finally, Chapter 5 concludes the dissertation and discusses extension for further research.

[4]This notion is similar to that of Heckman et al. (2006). Yet I use a simpler approach in which I directly employ measures of personality traits to observe worker sorting.

Chapter 2 Employer-Sponsored Health Insurance and Wage Compensation for Risk

2.1 Introduction

Despite a declining trend since 2000, employer-sponsored health insurance (EHI) continues to be the major source of health coverage for the nonelderly population in the US.[1] Health insurance coverage varies substantially across sectors, yet workers who lack health insurance are concentrated in occupations considered blue-collar, and in industries such as, agriculture, mining, and construction. In 2012, the uninsured rate in these sectors was 38.9 percent (Fronstin, 2013). These jobs are also associated with high rates of fatal injury. Thus, the empirical observation seems to suggest that the riskier the job, the less likely the worker will be covered by EHI. At the same time, we also observe that the insured workers typically earn higher wages and receive better fringe benefits than do observationally similar workers who lack health coverage.[2]

The concentration of desirable job attributes—e.g. jobs offering higher wages and health coverage—in safe jobs is expected to have an impact on the structure of wages, and consequently, the valuation of risk of injury. This paper investigates the impact of employer-provided health benefits on wage premiums for mortality risk at workplace—i.e. usually is expressed in terms of value of a statistical life (VSL).[3] The link between health insurance coverage and wage premiums for risk rests on the incentive of employers—which is determined by the level of job riskiness—to provide health coverage, and, the structure of wages between jobs with and without health coverage. If safe jobs are more likely to provide health coverage than are risky jobs, and that health coverage is associated with higher wages, EHI would affect both wage levels and the choice of job risk. In turn, it has an impact on the wage compensation for mortality risk.

The premise that lies at the heart of this paper is that EHI is an investment in

[1]It was estimated that 67.8 percent of workers ages 18-64 received EHI in 2012 (Fronstin, 2013).

[2]Earlier empirical papers do not find evidence of negative relationship between EHI and wages (Currie and Madrian, 1999). Lehrer and Pereira (2007) find that the provision of EHI has contributed to wage inequality. Particularly, the wages of workers in jobs with EHI have increased by 50 % over decades.

[3]The wage premium for fatal risk represents the fatal risk-wage tradeoff. It is also known as the value of statistical life.

health, and that healthy workers are more productive.[4] I model health as a form of general human capital. Employers are willing to invest in employees' health if they can recoup the associated costs of health investment. Yet, the elevated risk of death at work reduces the level of health investment made by employers. The reason is that hazardous working conditions have deleterious impacts on health such that productivity gains from health decline.[5] The insured in dangerous jobs then have to pay more than do the insured in safe jobs for the health investment in the form of lower wages; they trade the risk premium for health insurance. Accordingly, this behavior affects the wage structure of the insured, and thus, the provision of EHI reduces the wage premium for risk.

I provide empirical evidence consistent with the model using Panel Study of Income Dynamics (PSID). The empirical strategy of this paper is designed to deal with several prominent issues in the literature on the wage compensation for fatal risk or value of statistical life (VSL). The first issue is the potential endogeneity of job riskiness. People are not randomly assigned to jobs. Hence, there may be unobserved individual heterogeneity that affects both wage levels and the choice of job risk (Garen, 1988). Therefore, failure to control for unobservables results in biased estimates of compensating differentials for risk. I deal with this issue by exploiting the capabilities of panel data to control for individual-specific heterogeneity. Another key issue is measurement error in the fatality risk variable. Many studies in the VSL use the aggregate measure of fatality risk by major industry groups.[6] The aggregate measure of risk ignores substantial variation in risks across occupations within industry groups. More importantly, it may not be pertinent to workers in relatively safe occupations but in industries perceived dangerous, for example, an office-based manager in a construction firm. To address this problem, I follow Kniesner et al. (2012) to construct the risk variable by occupation-industry groups. The measure of

[4]The improved productivity can be in the form of higher ability in avoiding work-related injuries. Empirical papers in the literature generally assume that risks are independent of individual actions. In fact, some individual actions affect the likelihood and the magnitude of danger. For example, two workers in the same workplace, but one is more attentive to their working condition and always uses protective gears (e.g. a hard hat), would face different probabilities of injury. That is, despite facing the same working condition, the risks of injury of these two workers are different (i.e. the risks are endogenously determined by individual behaviors). A more relevant example to this paper, workers taking regular medical checkups would have less vulnerability to health risks leading to injuries. Some papers explore how individual actions determine the valuation of risk (Ehrlich and Becker, 1972; Berger et al., 1987; Shogren and Crocker, 1991; Shogren and Stamland, 2002).

[5]Evidence suggests that high occupational hazards are also associated with high risk of fatal injury.

[6]Viscusi (2004) and Kniesner et al. (2012) use the fatality risk based on occupation-industry groups.

fatality risk based on occupation-industry cells is expected to provide a more refined fatality risk variable.

I find that an increase in the mortality risk leads to a lower probability of EHI coverage. The effect of risk on EHI coverage is statistically significant but modest. This suggests that employer-provided health coverage is less sensitive to the elevated mortality risk. Given that observed health coverage reflects an equilibrium condition—i.e. supply of and demand for health coverage, the low responsiveness of EHI to mortality risk changes is likely to be driven more from the demand side: demand for health coverage continues to increase despite increasing risk. Thus, the workers in dangerous jobs would have to accept substantial lower wages to compensate for EHI coverage. The results from hedonic wage model with health insurance status support this theory.

I also find that controlling for unobserved heterogeneity leads to a reduction in the wage compensation for fatal risk by more than 53%—i.e in terms of the value of statistical life (VSL). With the baseline model accounting of individual heterogeneity, the estimated value of statistical life (VSL) is $ 7.68 million. Inclusion of health insurance in the baseline model leads to a slightly increase in the estimated VSLs by 2.5-7.2 %. The increase in VSLs in the model with health insurance suggests that the VSL is likely to be biased downward when we omit health insurance status from the standard model. However, the bias seems to be small due to the low responsiveness of EHI to mortality risk at work.

Salient evidence from this paper is heterogeneity in the estimated VSLs stemming from EHI coverage status. I find that workers with employment-based health coverage accept lower wage premium for risk, implying a lower VSL. Particularly, the estimated VSL of those with health coverage reduce by 26-37 %, depending on econometric specifications. From the specification accounting of unobservables, the implied VSL of the insured is $ 4.87 million. This confirms the model that the insured trade the wage-risk premium for health insurance, resulting in the lower VSL. Yet, I also find that the VSL of the uninsured is $ 20.87 million. The considerable increase in the VSL of the uninsured cannot be explained merely by the rate of tradeoff between the risk premium and health insurance. As I investigate further, I find that the high VSL of the uninsured is driven by uninsured married men. This may be because uninsured married men exhibit greater aversion to financial risk and require a substantially high wage premium to attract them to risky jobs.[7] Particularly,

[7]Eeckhoudt and Hammitt (2004) posit that a positive correlation between mortality risks and financial risk increases VSL.

health insurance minimizes catastrophic financial shock due to unexpected medical expenditures. Thus, the uninsured are at greater risk to financial loss, and, those displaying strong aversion to financial risk require relatively higher risk premium as precaution.

This paper makes several contributions. First, the paper provides a mechanism and evidence that health insurance provision has an impact on VSL. Specifically, I explore the effect of health-driven productivity on the wage compensation for mortality risk. Thus far there has been no extensive discussion on this subject in the wage-risk relationship literature. Second, the paper provides insight into how risk of job-related death coupled with labor market frictions affects firms' decision to invest in workers' health. This paper reveals the role of job characteristics (i.e. the risk of fatal injury) in explaining a health coverage gap across occupations.[8]

The findings also have some policy implications. Numerous government agencies such as, the U.S. Environmental Protection Agency (U.S. EPA), have long used observational labor market data to estimate wage-risk premiums for policies on workplace health and safety (Cropper et al., 2011). The estimates of risk premium depart from the canonical hedonic wage model that tends to ignore heterogeneity in the estimated VSL across jobs with different levels of non-pecuniary benefits. It also does not account for a possibility that workers use risk premium to purchase various desirable job attributes such as, health insurance. I show that failure to account of heterogeneity in VSL stemming from employer-sponsored health coverage status may overestimate (or underestimate) the benefits of risk reduction at workplace if the benchmark VSL is too high (or too low). In this paper, I also provide evidence that workers trade the wage-risk premium for health coverage. This behavior affects the structure of wages, and, determines the valuation of mortality risk reduction. Policy evaluations then should take into account possible tradeoffs between wage-risk premium and job amenities in estimates of wage compensation for mortality risk at work.

Finally, the remainder of the paper is organized in the following way. Section 2 discusses related literature while section 3 discusses analytical framework and model. Section 4 derives econometric implications derived from the basic model. Section 5 covers the estimation results and conclusion is in section 6.

[8]The finding is complementary to findings in Currie and Yelowitz (1999); they find that the low rate of health insurance coverage among some workers is partly driven by the employer side.

2.2 Related literature

This paper is closely related to papers that focus on heterogeneity in the value of statistical life (VSL). Empirical papers in VSL suggest that estimates of wage premiums for risk range between $ 5- 12 million with the median estimate at $ 7 million (Viscusi and Aldy, 2003). However, there is variation in VSLs that can be attributed to both unobserved and observed variables. On issues pertaining to unobserved characteristics, some papers show that failing to take account of unobserved worker characteristics results in biased estimates of premiums for risk. Using an instrumental variables approach in order to address this concern, Garen (1988) finds a twofold increase in the mortality risk premium from the standard hedonic model with OLS.

Although there is consensus that the inability to control for unobserved heterogeneity can bias estimates of compensating differentials for risk, there is disagreement over the direction of the bias. Hwang et al. (1992) argue that the hedonic wage model may underestimate the premium of mortality risk if the model does not control for unobserved labor productivity. In contrast to Hwang et al. (1992), Shogren and Stamland (2002) argue that heterogeneity reflects more safety-related productivity than general unobserved productivity; some workers possess skills—typically are unobserved—that help them to avoid injuries. Thus, the inability to control for unobserved skills in the hedonic model will overestimate wage premiums. Recent studies employing longitudinal data confirm the theoretical findings in Shogren and Stamland (2002). Kniesner et al. (2012) find a significant reduction in the risk premiums associated with a method accounting for unobservables.

Brown (1980), and Dorsey (1983) consider the effect of non-pecuniary benefits on the money-risk tradeoff in a way that is similar to the one which I explore. With inclusion of non-pecuniary benefits into the hedonic wage model, Brown (1980) finds no evidence of the wage premium for mortality risk. Using the survey of employers' expenditures for employee compensation, Dorsey (1983) finds heterogeneity in VSLs when the cash-equivalent of non-pecuniary benefits is included in the model. He also finds that the elevated risk of death is negatively associated with EHI provision. While obviously complementary, there are several important differences between this paper and that of Dorsey (1983). Dorsey (1983) assumes that a dollar value of fringe benefits is equivalent to one dollar in wage. I do not assume this as health insurance has, indirectly through health, a productivity effect. In particular, I provide a mechanism showing that health insurance could affect the structure of wages, and in turn, it affects wage premiums for risk.

Another related literature explores human capital investment. Under the competitive wage theory with no friction, workers take all the returns to their general human capital investment (Becker, 1964). Accordingly, no employer is willing to pay for general human capital investment. Yet, the conjecture of the competitive wage theory does not confirm the empirical observation that firms often bear the costs associated with the general training of their employees. Acemoglu and Pischke (1999) show that with labor market friction, firms may be willing to pay for general trainings. Friction leads to "wage compression" that transforms "technologically" general skills into *de facto* "specific" skills. This gives an incentive for firms to invest in their employees. Fang and Gavazza (2011) apply the framework of Acemoglu and Pischke (1999) to explore dynamic inefficiencies of employment-based health insurance system. They find that employment-based health coverage leads to underinvestment in health during working years and, consequently, increasing medical expenditures in the retirement period (Fang and Gavazza, 2011).

The literature on the impact of health insurance on health is extensive. Many studies share the findings that health insurance improves health (see Levy and Meltzer (2004) for a thorough survey). There is a wide range of measures of health, yet some health issues are precursors to occupational injuries. For example, many papers show that visual impairment strongly contributes to occupational injuries (Zwerling et al., 1996; Legood et al., 2002). Stress and depression have also long been associated positively with work-related accidents (Johnston, 1995), and productivity loss (Lerner et al., 2004). Ample evidence suggests that health coverage benefits substantially people with these health problems (Newhouse and The Insurance Experiment Group, 1993; Baicker et al., 2013), and also increases survival rates due to better treatments (Doyle Jr, 2005).

My paper views that improvements for health measures considered precursors to injuries are similar to improvements in workers' skill. That is, these health improvements basically increase workers' ability to cope with dangerous working conditions, and accordingly, workers become more productive. Tompa (2002) provides a survey showing evidence on the positive effect of health on productivity. Pinheiro and Dizioli (2012) show a direct link that health coverage reduces work absenteeism, which can be translated into higher productivity for workers with health insurance. They find that a worker with health coverage loses, on average, 55 % fewer workdays per year than does a similar worker without health insurance. An indirect effect of health insurance on productivity can also be found in Lehrer and Pereira (2007). Lehrer and Pereira (2007) find that returns to a college education in jobs with health insurance increase by almost 30 percent. This suggests that health coverage has an impact on productivity and wage levels.

2.3 Analytical Framework

The main objective of the following framework is to provide some intuition and a mechanism through which the health investment affects wage structures and the wage-risk tradeoff. I develop a static model that adapts labor market frictions of Acemoglu and Pischke (1999) and Fang and Gavazza (2011) into the standard model of hedonic prices.

2.3.1 Assumptions

My model is a two-period model without discounting. In period 1, workers are endowed with an initial stock of health, denoted by h^1. Workers or employers can make health investment. I denote m as the total amount of health investment with a unit cost of c. Allowing contribution from the worker or the firm, we have $m = m_w + m_f$, where m_w and m_f are the worker's and the firm's contribution, respectively. m can be interpreted as health insurance, since it allows workers to access medical services, which are essentially the same as investment[9]. Health investment in the first period increases workers' health stock in the second period. Following Fang and Gavazza (2011), the evolution of worker health stock is assumed as follows

$$h^2 = k(h^1, m) \tag{2.1}$$

h^2 is health stock in period 2 and $k(.,.)$ is the health production function for worker. I assume that the health production function is homogenous across workers. $k(.,.)$ is assumed to be a well-behaved health production function: $k(.,.)$ is continuous and increasing in h^1 and m-i.e. $\partial k/\partial h^1 > 0$ and $\partial k/\partial m > 0$. When there is no health investment, $h^2 = h^1$.

As in Figure 2.1, workers and firms set the level of health investment simultaneously.[10] After that, workers decide the level of risk they are willing to accept for two

[9] In this paper, I use health insurance and health investment interchangeably. Many studies show that people with health insurance utilize more health service (Currie and Madrian, 1999). Fang and Gavazza (2011) find that workers with health insurance spend higher medical expenditures than those without health coverage.

[10] Both workers and firms do not know who is going to die or survive in period 2. As such, firms cannot select and invest in the health of individuals who are perceived to survive in period 2. This is a critical assumption as I concern with statistical lives and "not identified lives" (Viscusi, 2008; Blomquist, 2015).

periods. Let p denote the risk of fatal injury, where $0 \leq p \leq 1$. The risk for each period is assumed to be independent from one another. In the beginning of period 2, the worker either stays with the current firm or quits and works at another firm with probability q where $q \in (0, 1)$. When the worker quits, he receives an exogenous outside offer, $v(h^2, p)$ (i.e. the external wage).

The firm's production is a function of risk and health stock. I assume that each worker produces output, $f(h^t, p)$, where t is time period in which $t =$ 1, 2. The current firm offers wage rates that are equal to the worker's productivity, $w^t(h^t, p) = f(h^t, p)$. Firms must pay additional wage payments to attract workers to bear extra risk—i.e. wage premiums for mortality risk. Formally, this can be written as $f_p(h^t, p) = w_p^t(h^t, p)$, where $f_p = \partial f(., .)/\partial p$, and, $w_p^t = \partial w^t(., .)/\partial p$. The assumption suggests that marginal costs of safety improvements, w_p^t, should be equal to marginal benefits from additional outputs due to the increased risk, f_p. Wage premiums for risk, w_p^t, are positive, and thus, f_p will be positive as well (i.e. $f_p > 0$). Health adds output, so $f_{h^2} > 0$, and $f_{h^1} > 0$.

In addition, the necessary second-order condition of production function requires that $f_{pp} < 0$, $f_{h^2h^2} < 0$, and $f_{h^1h^1} < 0$. It is also assumed that safety increases health productivity, and assuming symmetric condition, I have $f_{h^2p} = f_{ph^2} < 0$. The assumption of negative cross-productivity, $f_{h^2p} < 0$ also means that health stock and risk of accidents are substitutes.[11] To give an example on this assumption, a well-functioning worker may not be able to work optimally due to poor visibility brought by air pollution at the worksite. As the pollution increases, the worker's additional output would eventually decline.

Labor market friction is important to this framework, and in the spirit of Acemoglu and Pischke (1999), I assume that worker productivity is higher than the external wage offer, that is, $f(h^2, p) > v(h^2, p)$. The assumption tells us that the worker is not paid at his full marginal product of labor if he moves to another firm. However, it is important to note that the worker is equally productive in the current firm and the outside firm, that is, $f(h^2, p)$. The assumption of friction implies that $f_{h^2}(h^2, p) > v_{h^2}(h^2, p)$. Acemoglu and Pischke (1999) provide several institutional settings creating such frictions. For instance, frictions may be caused by costly-job searching which creates monopsony power of firms. With monopsony power, firms are then able to capture a fraction of the higher output due to the worker's higher productivity.

[11] This is a similar assumption as in Thaler and Rosen (1976).

2.3.2 Equilibrium

I follow Acemoglu and Pischke (1999) non-cooperative regime under which health investments by the firm and the worker are chosen non-cooperatively. Under this regime, the worker and the firm set simultaneously the amount of resource they want to allocate for health investment. The worker may pay for his health investment with the period 1's wage; the first period wage is then $w^1 = f(h^1, p) - cm$.[12] Health investment in period 1 increases the worker's productivity in period 2. If the worker does not quit in period 2, there will be a productivity surplus, $f(h^2, p) - v(h^2, p)$. $f(h^2, p)$ is the output produced by the worker in period 2, and $v(h^2, p)$ is the wage that the worker receives if he quits from his current job. The productivity surplus, $f(h^2, p) - v(h^2, p)$, is shared between the worker and the firm according to the Nash bargaining solution. Let β represents the worker's bargaining power, $\beta \in (0, 1)$. With the probability $1 - q$ the worker stays with the current firm and receives $w^2(h^2, p)$. Otherwise, the worker quits and get $v(h^2, p)$ with probability q. Let $\mathbb{E}(w^2)$ be the expected second period wage. Hence, the worker's maximization problem can be described as [13]

$$W = \mathbb{E}(w^2) + w^1$$

$$W = v(h^2, p) + (1 - q)\beta(f(h^2, p) - v(h^2, p)) + f(h^1, p) - cm \tag{2.2}$$

Similar to the worker, the firm selects the level of health investment that maximizes profit. The firm may also pay for the worker' health investment; the firm's first-period profit is $\pi^1 = f(h^1, p) - w^1(h^1, p) - cm$. The profit maximization problem can be written as the sum of the profits in two periods.[14]

$$\Pi = \mathbb{E}(\pi^2) + \pi^1$$

$$\Pi = (1 - q)(1 - \beta)(f(h^2, p) - v(h^2, p)) + f(h^1, p) - w^1(h^1, p) - cm \tag{2.3}$$

[12] On the other hand, if the firm pays full costs of health investment or there is no health investment, the worker receives full wage $w^1 = f(h^1, p)$.

[13] To be more detailed, with probability $(1 - q)$, the worker stays at the current firm and receives $w^2(h^2, p) = v(h^2, p) + \beta[f(h^2, p) - v(h^2, p)]$. If he quits, he takes the outside offer, $v(h^2, p)$. Thus, $\mathbb{E}(w^2) = (1 - q)[(1 - \beta)v(h^2, p) + \beta f(h^2, p)] + qv(h^2, p)$.

[14] The intuition is similar. By probability $1-q$, the firm gets the surplus $(1-\beta)[f(h^2, p)-v(h^2, p)]$ and with probability q the firm gets surplus 0.

The worker maximizes equation 2.2 by choosing $m_w \geq 0$ and takes m_f as given. Thus, the optimal contribution to health investment can be found by taking first order condition of 2.2 with respect to m_w.

$$\begin{aligned} \left[v_{h^2}(h^2,p) + (1-q)\beta\left(f_{h^2}(h^2,p) - v_{h^2}(h^2,p)\right)\right]\partial k/\partial m_w - c &= 0 \text{ if } m_w > 0 \\ &\leq 0 \text{ if } m_w = 0 \end{aligned} \quad (2.4)$$

The firm also selects the optimal level of health investment, m_f, by taking the worker's contribution, m_w, as given. So the first order condition of 2.3 with respect to health investment is

$$\begin{aligned} (1-q)(1-\beta)(f_{h^2}(h^2,p) - v_{h^2}(h^2,p))\partial k/\partial m_f - c &= 0 \text{ if } m_f > 0 \\ &\leq 0 \text{ if } m_f = 0 \end{aligned} \quad (2.5)$$

Expressions 2.4 and 2.5 suggests that either the worker or the firm that pays all costs of health investment. The intuition is that the firm's and the worker's contributions to health investment are perfect substitutes. Let $\widehat{m}_f$ be the level of health investment that holds the equality condition of 2.5, and, $\widehat{m}_w$ is the solution to the equality condition of 2.4. If $\widehat{m}_f > \widehat{m}_w$, the firm bears all the costs, and as a result, $m_w = 0$. On the other hand if $\widehat{m}_w > \widehat{m}_f$, then it is the worker who pays all the costs of health investment. From this inspection, it is clear that within-industry variation in health coverage from the empirical observation is due to heterogeneity in the desired levels of health investment of the firm and of the worker.

Furthermore, Proposition 1 explores the effect of mortality risk on the equilibrium level of health investment made by the firm. As we will see, the utilization of health as an input depends substantially on the risk produced by the firm. Health becomes far less productive in high hazard working environments, and thus, the elevated mortality risks reduces the firm's incentive to invest in the worker's health. Consequently, the worker with health coverage in risky job bears health investment in the form of lower wage: he trades the risk premium for health insurance.[15] This also rationalizes the low rates of EHI coverage among workers in risky jobs.

[15] In addition to the firm technology, a decrease in the firm's contribution when risk of death increases may be related to the possibility of accidents, and thus, the firm cannot recoup the costs of health investment. Recall that the health investment is made in the period 1. If in period 2, a substantial number of workers die due to job-related accidents, the firm cannot recover the costs and lose the potential surplus. Of course this is an extreme case yet it plausibly affects firms' decision to invest in their employees.

Proposition 1. *An increase in the job-related death decreases equilibrium health investment made by the firm.*

The firm makes health investment. The equilibrium health investment of the firm implies $m_f^* > 0$, and hence, the equality condition of 2.5 holds. From the expression, let us define $\lambda(p, m_f^*)$ as follows.

$$\lambda(p, m_f^*) = (1-q)(1-\beta)(f_{h^2}(h^2, p) - v_{h^2}(h^2, p))\partial k/\partial m_f - c$$

Applying the implicit function theorem, we have

$$\frac{\partial m_f^*}{\partial p} = -\frac{\partial \lambda(p, m_f^*)/\partial p}{\partial \lambda(p, m_f^*)/\partial m_f^*} < 0$$

Proof is as follows.

$$\frac{\partial \lambda(p, m_f^*)}{\partial p} = D(f_{h^2 p} - v_{h^2 p})\partial k/\partial m_f < 0$$

Furthermore, the necessary second-order condition of the equation 2.6 is

$$\frac{\partial \lambda\left(p, m_f^*\right)}{\partial m_f^*} = D\left\{(f_{h^2h^2} - v_{h^2h^2})\left(\frac{\partial k}{\partial m_f}\right)^2 + (f_{h^2} - v_{h^2})\left(\frac{\partial^2 k}{\partial m_f^2}\right)\right\} < 0$$

Where $D = (1-q)(1-\beta)$. Therefore, we have that $\partial m_f^*/\partial p < 0$.

Figure 2.2 describes the idea of my model, and, depicts the relationship between wages and risk of death at work. Person 2—his utility is $\widehat{u}_2$—is willing to take a relatively high risk job (i.e. p_2), and thus, he chooses firm 2—the firm 2's wage offer curve is $\widehat{o}_2$. Person 1 prefers to work in safe job—i.e. his utility is $\widehat{u}_1$ and firm 1's wage offer curve is $\widehat{o}_1$. A risky job pays premium, that is, $\widehat{w}_2 > \widehat{w}_1$. Under a perfectly competitive market, no firm is willing to invest in the workers' health. If workers are less willing to invest in their health too—for the reason that the surplus will be disproportionately captured by the firms—we only observe the wage locus of jobs without health insurance, $\widehat{w}_{no\ HI}$. The wage premium for mortality risk is then $\Delta\widehat{w}/\Delta p$.

Under imperfect labor market, workers are less mobile, and, given that health increases productivity, firms are willing to unilaterally invest in their workers' health—i.e. now we observe the wage locus of jobs with health insurance, $\widetilde{w}_{HI}$. As the probability of death is low, let say below p^*, health is productive—making health investment then attractive to the firms. Thus, some of type 1 workers are covered by health insurance, and, as health insurance improves health and productivity, he is paid by higher wage—i.e. $\widetilde{w}_1 > \widehat{w}_1$. Yet, the increasing risk of injury reduces health investment made by the firms, and consequently, the insured workers in risky jobs (i.e. $\widetilde{u}_2$) bear the costs of the investment; their wage is lower than the wage of worker without health insurance, $\widetilde{w}_2 < \widehat{w}_2$. Thus, the wage-risk premium for the insured worker is $\Delta\widetilde{w}/\Delta p$. It is clear that the risk premium of the insured will be lower than that of the uninsured—i.e. $\Delta\widetilde{w}/\Delta p < \Delta\widehat{w}/\Delta p$.

2.3.3 Testable Implications

The previous discussion results in several testable predictions that can be derived from the above framework. I summarize them as follows

1. Workers in high risk occupations are less likely to be covered by employment-based health insurance. The harmful effect of job hazards reduces the incentive to invest in workers' health.

2. The insured workers in dangerous jobs have to pay the associated costs of health benefits in the form of lower wages. Hence, we should observe the wage-health insurance tradeoff among workers in risky jobs.

3. The risk premium for the insured will be relatively lower than that of the uninsured. Implication 2 suggests that the increased mortality risk reduces the wages of the insured workers relative to the wages of the uninsured workers; the mortality risk compresses the wages of the insured workers. Accordingly, the wage-risk slope of the insured workers will be flatter than that of the uninsured.

2.4 Data and Econometric Specifications

2.4.1 Data

The main dataset is the Panel Study of Income Dynamics (PSID). The PSID consists detailed information on workers' characteristics and health insurance. The advantage of using of panel data is that it permits us to reduce bias from individual unobserved variables. Information on employment covers the employment conditions in the current and the previous survey year. But information on health insurance refers to the two-previous years of the survey year.

Beginning in 2003, industry and occupation codes in the PSID data changed. As controlling for industry and occupation has been a standard approach in hedonic wage model, the changes could create a complication. To deal with changes in these codes, I split the PSID into two periods: before and after 2003. Prior 2003, industry classification in the PSID is based on the 1987 Standard Industrial Classification (SIC 1987). After 2003, the industry classification is based on the Census 2002. In order to match with the fatality data where industry and classification codes *after* 2003 is based on the 2002 NAICS, I recode industry classification in the post-2003 PSID into the 2002 NAICS. Given that I use three-year average fatality rate, classification changes in both the PSID and fatality data lead me to drop the 2001 PSID (I will discuss more detailed on the fatality data in the following section). Yet, I take the information of health insurance in the survey year of 2001 as it refers to the health insurance coverage in 1999. The final sample consisting both employment and health insurance information, is then composed from the surveys of 1997, 1999, 2003, 2005, and 2007.[16]

In constructing the sample, I follow Kniesner et al. (2012) by restricting the sample in the following way 1) heads of households ages 18-60 in the Survey Research Center. 2) They worked for hourly and salary pay. 3) not permanently disabled or institutionalized, 4) not working in agriculture or the armed forces, 5) have a real hour wage between $2 and $100, and have no missing data on wages, education, region, industry and occupation. This sample includes both full-time and part-time workers.[17]

Table 1 exhibits the summary statistics of the sample. Real hourly wage in the sample is $23.44 in the 2005 dollar. The 3-year average fatality rate is 4.23 per 100,000 workers. Based on the PSID data, we see that 82 percent of workers reported that they have been, at least, covered by employer health insurance in the past two-years before the survey year.

Fatal Data

The focal variable in this model is the risk variable. In this paper, I use reported fatal injury as a measure for risk perceived by workers. The key assumption of using reported fatal injury is that subjective risks perceived by workers and employers are reflected through the objective measure of fatal risk represented by the rate of fatal injury. The assumption has also been at the heart of many studies on VSL

[16] Meanwhile controlling for occupations is important in the hedonic wage equation. I follow Bollinger and Hirsch (2006): I create dummy variables for occupation codes in different periods.

[17] the PSID does not distinguish jobs into full-time and part-time jobs. We could possibly identify part-time jobs from types of their pay, that is, whether the respondent is paid by hourly pay by which most of part-time workers are paid

(Kniesner et al., 2012). Moreover, Viscusi and Aldy (2003) collecting from various studies suggest that there is a strong correlation between workers' subjective risk assessments and reported injury rates. Hence, it is plausible that the reported injury rates render workers and employers about the nature of the job, and thus, workers use this information to form risk beliefs. Therefore, we expect that the rates of injuries could serve as a proxy for the subjective risk beliefs.

To construct the risk variable, I use the reported public version of fatality data from the Census of Fatal Occupational Injuries (CFOI). The CFOI defines fatal injury at workplace and thus includes the injury in the data when such injury satisfies following criteria (Bureau of Labor Statistics, 2015). First it is a traumatic injury defined, among other things, as any wound or damage to the body due to exposure to heat, electricity, or impact from a crash or fall. Sudden death due to some causes, such as heart attacks or strokes, are excluded from CFOI. But, if a traumatic injury involves, the resulting injury, including death, is included in the data. Second, an injury is considered workplace injury when such injury occurs on the employers premises—e.g. such as building, parking lots, facilities, and so on —and the injured person was there to work. A workplace injury may occur off the employers premises. But as long as the injured person was there to work and the causes of injury were related to his job or status as an employee, it is a workplace injury and thus included in the data.

I constructed fatality data from 1992-2010. The CFOI data report the total number of annual fatalities by various categories such as industry, occupation, and causes. The dataset does provide fatality rates nevertheless. Thus, I calculate the fatality rate by taking the ratio of fatalities in any occupation-industry group from the CFOI data to that group's average employment from monthly Current Population Survey (CPS) over a year.

Previously, similar to the PSID, industry and occupation classifications in the CFOI also changed in 2003. To cope with this issue, I split the fatality data into two periods:1) 1992-2002 and 2) 2003-2010. Following Kniesner et al. (2012), I construct the fatality rate based on occupation-industry groups. Prior to 2003, the fatality rate is constructed from 720 occupation-industry groups consisting of 72 two-digit the 1987 Standard Industrial Classification (SIC 1987) and 10 one-digit code occupations. Prior to 2003, both the CFOI and PSID use SIC 1987, so I can match both datasets directly. For the 2003-2009 CFOI data, I construct 900 occupation-industry groups containing 90 three-digit the 2002 North American Industrial Classification System (NAICS) and 10 one digit code occupations. I recode the 2002 census-based industry and occupation classifications of the PSID into the 2002 NAICS. By doing so I can match the 2003-2007 PSID with the 2003-2010 CFOI data. After this step, I merge back all the datasets.

As fatal accidents are rare events, even in occupations perceived as high risk jobs, there may be large swings in fatality rate from year to year. In order to avoid this, I use 3-year average fatality rate.[18] The 3-year average fatality rate is calculated by averaging three year forward annual fatality rates (e.g. for the fatality rate in 2003, I average fatality rates in 2003, 2004, and 2005). I use the average forward fatality rate is because industry and occupation classifications changed in 2003 for both PSID and the CFOI data. Thus, I cannot create continuous occupation-industry fatality rates covering periods before and after 2003. As I match the PSID and the CFOI data based on occupation-industry groups, calculating mean fatality rate forward allows a higher sample size of PSID. This is also the reason why I drop the 2001 PSID from the sample.

Health Insurance Data

Started in 1999, the PSID individual data has asked respondents whether they were covered by any health insurance in the two calendar years before the survey year. For instance, the 2009 PSID asked health insurance coverage in 2007 and 2008. If they reported having had coverage, the interviewer further asked types of coverage with up to four mentions allowed. Table 2.2 provides types of coverage asked in the PSID.

The health insurance variable is a binary variable coded as 1 if a respondent has employer-sponsored health insurance and 0 otherwise. Individuals having no insurance or those having other types of health coverage are coded as 0—i.e. non employer-provided health insurance would be coded as zero. This distinction fits with the proposed framework. Recall that the proposed framework views health insurance as health investment intended to improve worker productivity. Labor market frictions, moreover, create an incentive to the firm to share the productivity gains from the investment. Thus, the shared productivity gains from health would be reflected in wages. Other types of health coverage also improve worker productivity. But the firm is able to capture those productivity gains without paying the costs and sharing the gains. Consequently, other types of health insurance theoretically should have no effect on wages, and thus, the wage offer of workers with non EHI coverage may be the same as the ones without health insurance.

[18] Kniesner et al. (2012) provide a valid case of averaging fatality rate over some periods.

A major issue with the health insurance question in the PSID is that the PSID does not distinguish between policy holder and dependent. This creates a problem when the head of household is covered through his spouse's employment. Thus, one could falsely think that he gets health insurance through his own employer. To address this problem, I include marital status and a dummy variable indicating whether or not spouse is working. While this is not ideal, I expect that marital status and spouse's working status could pick up the effect of spouse's employer-sponsored health insurance if the head of household is in fact covered by his spouse. In addition, I also split the sample into married and single men and estimate the wage model separately. Thus, we are able to get a relatively clean identification of EHI coverage through the sample of single men. Given that single men may be systematically different from married men and the difference may be correlated with EHI coverage, in the following robustness check I split the sample of married men. In particular, I distinguish married men into 1) married men whose spouse is working and 2) married whose spouse is not working. The observed EHI coverage from the later sample tells us that people in this group get health coverage from their own employers.

Moreover, the question on health insurance is multi responses, allowing respondents to report more than one types of health insurance coverage. Without the specific date of coverage, I am not fully able to identify respondents who switch types of health insurance (e.g. from private health insurance to public within this two-year survey interval), and reference years in which they change the coverage. Despite these limitations, Levy (2007) notes that the PSID estimates of the population with private coverage are very accurate. Levy (2007) suggests PSID users to rely on respondent reports of "any private coverage" for estimating respondents with private coverage. In constructing the health insurance coverage variable, I pursue Levy's (2007) algorithm. Respondents are considered having employer health insurance if they report having had "any employer health insurance".

Since the health insurance question is retrospective, I need to align demographic and employment variables with health insurance variable. To be specific, I match health insurance information collected in the current survey with the previous survey. For example, information on health insurance in the survey year 2009 is matched with employment information in the 2007 survey. So, for employment and demographic variables in the 2003-2009 period, I practically use three surveys (i.e. 2003, 2005, and 2007).

2.4.2 Econometric Specifications

In this section, I set up econometric specifications aimed at testing the main implications of the framework. I begin with implication 1, that is, the elevated risk of death leads to lower health investment made by firms. To empirically test this implication, I specify the following regression equation:

$$H_{ijkt} = c_i + \delta Z_{jkt} + X_{ijkt}\beta + \varepsilon_{ijkt} \tag{2.6}$$

H_{ijkt} is a binary variable indicating health insurance status (i.e. $H_{ijkt} = 1$ covered by EHI, 0 otherwise) for worker i (i = 1,. . . , N) in industry j (j =1,. . . ,J) and occupation k (k = 1,. . . ,K) at time t (t = 1,. . . , T). ; Z_{jkt} is the industry and occupation specific fatality rate.; X_{ijkt} refers to a vector consisting demographic variables: education, age, age squared, race, union status, marital status, industries, occupations and states of residence. The error term is denoted by ε_{ijkt}, and c_i is unobserved individual heterogeneity.

A challenge to the identification of model 2.6 is a non-random selection of jobs. Worker characteristics induce workers' decision on the choices of job risk and of job amenities, such as health insurance. As an example, workers with relatively high ability may go to safe jobs that provide health insurance as well. If these characteristics are unobserved—as is in ability —the estimated δ will be biased. I utilize the panel component of PSID to deal with this selection problem and employ methods accounting of person-specific heterogeneity. To get information on the size of the bias, however, it is useful to compare results that control and do not control for individual heterogeneity (Wooldridge, 2010).

I start with Probit to estimate the model. Here I do not control for the individual-specific heterogeneity, c_i. Next, I estimate the above model with Linear Probability Model with panel fixed-effects estimator to control for individual heterogeneity. Finally, I estimate the model with Chamberlain-Mundlak device (i.e. Correlated Random Effects, CRE). CRE probit model allows to preserve a non-linearity structure of the model while controlling for individual heterogeneity.

To empirically test implications 2 and 3, I use the standard econometric framework of hedonic wage equation used in the literature on the wage-risk relationship. I begin with a baseline specification in which I do not include the health insurance variable. The hedonic wage equation is described by

$$\ln w_{ijkt} = c_i + \alpha_1 Z_{jkt} + X_{ijkt}\beta + \varepsilon_{ijkt} \tag{2.7}$$

$\ln w_{ijkt}$ denotes the natural log of the hourly wage rate and, the same as before, c_i is unobseved heterogeneity. The main coefficient of interest is α_1 that measures the rate of the wage-risk tradeoff.

In the following econometric model, I investigate whether the inclusion of health insurance in the hedonic wage model affects risk premium. I include health coverage status as an additional control variable to specification 2.7.

$$\ln w_{ijkt} = c_i + \alpha_1 Z_{jkt} + \alpha_2 H_{ijkt} + X_{ijkt}\beta + \varepsilon_{ijkt} \tag{2.8}$$

If health insurance is negatively associated with risk but positively correlated with wage, as what we observe empirically, α_1 in specification 2.7 will suffer a downward bias. Consequently, the inclusion of health insurance increases the estimated VSL—α_1 in model 2.8 will be larger than α_1 in model 2.7.

In model 2.8, I assume that the slope of wage offer curve of the insured is the same as that of the uninsured, although they may have different levels of wages. The assumption may not hold. Indeed, the model predicts that jobs providing health insurance differ from jobs not providing one such that the wage offer slope of the insured will be lower than that of the uninsured. Specifically, risk affects the wage structure of the insured. To capture the impact of health insurance on the structure of wages, I interact the variable of risk of fatal injury and the indicator of health insurance coverage. Thus the specification 2.8 becomes

$$\ln w_{ijkt} = c_i + \alpha_1 Z_{jkt} + \alpha_2 H_{ijkt} + \alpha_3 Z_{jkt} \times H_{ijkt} + X_{ijkt}\beta + \varepsilon_{ijkt} \tag{2.9}$$

Different from model 2.8 and 2.7, α_1 in model 2.9 measures the rate of the wage-risk tradeoff when the health coverage variable is zero (i.e $H_{ijkt} = 0$). In other words, α_1 is the risk premium for the uninsured workers. Moreover, the new feature of model 2.9 is the interaction between the risk variable and EHI status (i.e. $Z_{jkt} \times H_{ijkt}$). The coefficient of the interaction, α_3, provides evidence whether health insurance coverage has an impact on the wage structures of the insured and the uninsured—i.e the slopes of wage offer locus are different between jobs with and without health coverage. Based on the framework, we expect that α_3 is negative. It reflects that workers trade wage-risk premiums for health insurance. The negative coefficient of interaction also suggests that health and risk are substitutes. Here, I do not directly measure health in the above hedonic wage equation. Yet, since health insurance improves health (i.e. a positive relationship between health insurance and health), and if health and risk are substitute, the coefficient of the interaction between risk and health insurance will be negative.

Similar to the health insurance and risk relationship, there is a major issue pertaining to the identification of the hedonic wage models in equations 2.7, 2.8 and 2.9, namely, selection problem. That is, workers are not randomly allocated to jobs. Thus, unobserved heterogeneity, such as ability or unobserved productivity associated with risk is correlated with fatal injury and the health insurance coverage in jobs they choose. The implication is that the estimated coefficients of interest (i.e. α_1, α_2, and α_3) will be biased.

To better understand the magnitude of the bias due to unobservables, I use various econometric methods. First, I use models accounting of heterogeneity. In particular, I use panel fixed effects estimator—the most preferred specification—and panel random effects. Despite controlling for unobserved heterogeneity, in random effects model, I impose an assumption that the unobserved individual heterogeneity is not correlated with the risk variable. I compare the models with cross-section estimators: Pooled OLS (POLS) and between effects. Here I assume strict exogeneity in explanatory variables and no individual heterogeneity.

The preferred specification, fixed-effects model, permits us to control for person-specific heterogeneity by employing within-transformation of data. However, within-transformation of data plausibly leave little variation in the fatality rate and as such, we may not be able to identify credibly the fatality parameter. Table 3.4 shows that between-group variation exceeds within-group variation. However, for all sample, the within-variation in the fatality rate is sufficiently large—i.e. it is about 45 % of the between variation. Thus, using fixed effects model is feasible to estimate VSL. Furthermore, the decomposition of variation by job switch status suggests that job switchers are the one that contributes substantially to within-group variation—, that is, the within variation of job switcher is 59 % of the between variation. Table 3.5 displays variation in employer health insurance coverage. We see that within-group variation in EHI status in the total sample is sufficient to identify the health insurance parameter (about 48 % of the between variation). Similar to fatality risk, a large fraction of within-group variation in EHI status is driven by job switching. I exploit this evidence to address potential endogeneity in risk and health insurance by estimating the fixed-effects model with the sample of job changers.

Furthermore, the implied value of a statistical life at the level of wages, $\bar{w}$, can be calculated as follows

$$\text{VSL} = [(\frac{\partial w}{\partial Z} = \alpha_1 \times \bar{w}) \times 2,000 \times 100,000] \tag{2.10}$$

Here the fatality risk is per 100,000 workers and I assume a fixed annual hours point of 2000. I also use the same formula to estimate VSL for the uninsured workers in models 2.7 and 2.8. To estimate VSL for the insured workers, however, I use the following formula

$$\text{VSL}_{\text{HI}} = [(\frac{\partial w}{\partial Z} = (\alpha_1 + \alpha_3) \times \bar{w}) \times 2,000 \times 100,000] \tag{2.11}$$

VSL_{HI} is the value of a statistical life for the insured workers. When workers covered by EHI, the coefficient of the interaction, α_3, is not zero. I calculate standard error of the estimated VSL for the insured workers by simply computing the standard error of linear combinations between α_1 and α_3.

Moreover, inclusion of health insurance on the hedonic wage function permits us to estimate "wage premiums" for health investment. If I set Z_{jk} to zero (i.e. jobs with zero mortality risk), then α_2 is the wage premiums for health coverage of workers in very safe jobs. What it becomes clear to us is that the elevated risk decreases the wage premiums for health coverage—as α_3 is negative—and, at some point of fatal risk, workers with health coverage receive lower wages. We can see this as follows

$$\text{WP}_{\text{HI}} = (\alpha_2 + \alpha_3 \times \bar{Z}_{jk}) \times \bar{w} \times 2,000 \tag{2.12}$$

WP_{HI} is the wage premium for health insurance. A negative value of the wage premium for health insurance suggests the wage-health insurance tradeoff, that is, the worker pays for health insurance in terms of lower wages. In general, equation 2.12 measures the changes in the wage-health insurance tradeoffs as risk of fatal injury increases.

2.5 Empirical Results

This section provides empirical results. Before addressing the effect of EHI on the wage-risk gradient, I first investigate the effect of mortality risk on EHI coverage.

2.5.1 Health insurance and mortality risk

I estimate the likelihood of health insurance coverage conditional on mortality risk with Linear Probability model (LPM) with fixed effects, Probit, and Probit with Correlated Random Effects (CRE). The results are shown in Table 2.5. Column 1 of the table exhibits the result of LPM while the column 2 and 3 report marginal effects (evaluated at the mean of all variables) of Probit and Probit CRE respectively. It is instructive to note that the observed health insurance coverage reflects the equilibrium condition between health insurance offer from the firm side and the worker decision.

Thus, in general, we can interpret the coefficient of risk in Table 2.5 as the equilibrium condition.

I find that the elevated risk of death is associated with lower EHI coverage. The coefficient of fatality rate is negative and statistically significant in both LPM and Probit. With panel fixed effects estimator, a one unit increase in fatality rate per 100,000 workers is associated with a reduction in probability of EHI coverage by 0.16 percent. From Probit estimate, the marginal effect of risk is a little bigger, that is, 0.18 percent. A concern regarding Probit model arises due to a possible correlation between the risk variable and unobserved heterogeneity, which potentially leads to biased estimate of the risk coefficient. Yet, the estimates of LPM with fixed effects accounting of unobservables and probit model apparently are similar, suggesting that the magnitude of the bias appears to be small.

All specifications—both with and without controlling for individual heterogeneity—exhibit a similar pattern. Thus, individual heterogeneity does not seem to have a substantial impact on the risk-health insurance relationship. However, it is plausible that firm heterogeneity affects both risk levels and decision to provide health insurance, and, inability to account of firm heterogeneity results in biased estimates of the risk coefficient. Unfortunately, the data do not permit us to control for firm heterogeneity. However, Dorsey (1983) uses data on employers' contribution to employee non-wage compensation, and finds a negative association between fatal injury and the probability of providing health insurance.[19] Meanwhile Dorsey (1983) employs data on the employer side. His findings are qualitatively similar to my finding using labor data. Thus, we can conclude that both workers and firms respond in a similar way regarding employment-based health coverage as the mortality risk increases.

Overall, the finding on the risk-health insurance relationship is fairly consistent with the proposed framework that workers in jobs with high mortality risk are less likely to receive EHI. As discussed previously, firms' decision on the health investment of employees is determined by the firm production technology tied to external risks. At higher level of risk, health improves incrementally at which firms see no incentive to provide health investment. Accordingly, workers would incur the associated costs. Unless they are unconstrained financially or willing to take lower wages for health insurance, we will observe the low rate of health insurance coverage among these workers.

[19] Dorsey (1983) uses a different measure of the fatality variable. So I cannot make a direct comparison between his result and mine. But, relative to other variables in his model, the effect of mortality risk on the probability of providing EHI in Dorsey (1983) is also relatively small.

However, it is worth noting that the magnitude of the risk coefficient is rather moderate. Apparently, employer-provided health coverage is less sensitive to the elevated mortality risk. If the low responsiveness of EHI to mortality risk changes is much more driven from the demand side—demand for health coverage is high despite increasing risk, it is then likely that the workers in dangerous jobs have to accept lower wages to compensate for EHI coverage. Thus, the wages of the insured grow much less as the mortality risk increases. As I discuss later, the results from hedonic wage model with health insurance status confirm this assertion.

2.5.2 Health insurance and the wage-risk relationship

Here I investigate the effect of health insurance on the money-risk tradeoff. I start with the baseline model 2.7, and the empirical results are presented in Table 2.6. For brevity, I only report the coefficient of risk. Table 2.6 provides the coefficient of risk based on various econometric models. Comparisons between panel fixed effects and other estimates inform us the magnitude of the bias in estimates of wage-risk premiums. Furthermore, I also calculate the implied value of a statistical life based on equation 2.10.

With fixed-effects model, the most preferred specification, the estimated wage-risk premium for an increase in deaths per 100,000 workers is 0.16 %, and accordingly, the implied VSL is $ 7.68 million. The implied VSL with fixed-effect estimator is in the median of estimated VSLs from many studies. When I use random effects specification, the estimate of the wage premium for risk is slightly higher, and, the implied VSL is $10.52 million.[20] We notice here that unobserved heterogeneity has a substantial impact on estimates of compensating differentials for risk. Models accounting of heterogeneity (i.e. Random and fixed effects) reduce the estimated VSL by about 66 % relative to models ignoring heterogeneity. Estimates of VSL from the cross-section models assuming no heterogeneity (i.e. POLS and between effects) yield high implied VSLs. With POLS model, the implied VSL is around $22.6 million. Overall, the implied VSLs are close to estimates in Kniesner et al. (2012) that use PSID and panel econometric model.

The substantial difference in estimates of VSL with heterogeneity versus without heterogeneity confirms the theoretical conjecture of Shogren and Stamland (2002). Shogren and Stamland (2002) argue that failing to control for unobserved skill will overestimate the VSL. In particular, the reduction in the estimated VSLs after con-

[20]Random effects assume that heterogeneity is distributed normally and not correlated with the variable of interest. If the assumption is violated, the estimate will be biased.

trolling for individual-specific heterogeneity suggests that heterogeneity reflects more safety-related productivity and risk preferences than general unobserved productivity in the context of Hwang et al. (1992).

In the following discussion, I examine the impact of health insurance on the hedonic wage function. From Table 2.5, I find that fatal injury leads to lower probability of EHI coverage. If EHI coverage affects both wage levels and job riskiness, omitting health insurance status from the hedonic wage model results in a downward bias in the estimated VSLs presented in Table 2.6. Results from the hedonic wage models including health insurance are presented in 2.7. I find that the estimated VSLs in Table 2.7 are higher than are the estimated VSLs in models without health insurance. This is consistent with the notion that health insurance is positively correlated with wages but is negatively related with risk, leading to underestimated VSLs in models ignoring EHI as a control variable. However, we also notice that EHI coverage is less responsive to risk changes—i.e. this is a suggestive of small bias. Thus, the bias from omitting health insurance in the hedonic models seems to be small: we see here that differences in the estimated VSLs between models with and without health coverage are rather small. Additionally, I still observe a consistent pattern that models accounting of person-specific heterogeneity yield lower VSLs.

The framework, furthermore, suggests that risk affects the structure of wages between jobs providing and not providing health benefits: heterogeneity in estimates of compensating wage differentials for mortality risk may arise due to employment-based health coverage. This implies that health insurance has an impact on the wage-risk gradient. Results of model 2.10 are, then, shown in Table 2.8. In general, models with the interaction between EHI and fatality risk increase wage-risk premiums relative to the standard model. Particularly, the coefficient of risk increases by 51-63 %, depending on the specifications, relative to models without health insurance. Given that the coefficient of risk in these specifications actually measures the rate of the wage-risk tradeoff for the uninsured workers (i.e. $H_{ijkt} = 0$), this evidence suggests that the uninsured workers receive higher wage premium for risk of death at work than do the average workers (i.e. the wage-risk premium for all sample).

Columns 2 and 4 of Table 2.8 report estimates from the panel random-effects and the fixed-effects estimators respectively. The fixed-effects estimator produces the implied VSL of the uninsured at $ 20.87, which is far larger than the estimated VSL in the hedonic model without health insurance. Columns 1 and 3 of Table 2.8 present the results of the cross-sections estimators. In contrast to specifications controlling for person-specific heterogeneity, these specifications produce considerably high wage premiums for risk—about 0.91-0.99 %, and the implied VSLs are around \$ 42.7-44.7 million.

I estimate the risk premium for the insured from the sum of the risk coefficient and the coefficient of the interaction term between the risk and health insurance (i.e. $\alpha_1 + \alpha_3$).[21] I find that, inclusion of health insurance status and controlling for heterogeneity, the estimated VSLs decline by 34-37%. Specifically, with models accounting of individual-specific heterogeneity, the implied VSLs of the insured are around \$4.87-\$6.91 million, despite being statistically insignificant at 95 % confidence level. On models ignoring heterogeneity, the implied VSLs of the insured range between \$ 15.7-17.5 million. These empirical findings are consistent with the conjecture of the model: the insured workers receive lower mortality risk premiums than do the uninsured.

Striking evidence from Table 2.8 is that the coefficient of the interaction between mortality risk and health insurance is negative and statistically significant in all specifications. This reflects that risk and health insurance are substitutes. Health investment improves health and increases productivity. But hazardous working environments have deleterious impacts on health such that health investment improves little employees' health. This reduces the level of health investment made by firms with high occupational hazards.

Another economic intuition to the lower VSL of the insured is because the insured trade the risk premium for health insurance. The low health investment made by the firm is compensated by the contribution of the insured worker in the form of lower wage: The insured workers basically are willing to accept relatively lower risk premium to get health insurance. The model predicts that this would be the case of the insured in dangerous jobs. However, it may occur among the insured in safe jobs as well. If there is heterogeneity in mortality risk such that the wage-risk premium of safe jobs is lower than is the wage-risk premium of dangerous jobs, workers in safe jobs would have a strong incentive to give up premiums for risk of death—which is very small—in order to get health coverage provided by employers. The productivity impact of health investment is then the pull-factor that attracts workers to give up the wage-risk premium for health coverage. Also notice that from the coefficients of risk, health insurance, and the interaction between them in Table 2.8, the insured workers in relatively safe jobs (i.e. low fatality rates) earn high wages than the uninsured workers.

However, we should be cautious in interpreting it as solely the tradeoff between

[21] That is, I set $H_{ijkt} = 1$

risk premium and health insurance or the worker productivity effect. The substantial gap in the implied VSLs indicates that other factors are at play. There could be true inter-industry wage differences between jobs with and without health insurance, and those jobs providing health insurance are locating in industries with low rate of fatal injury. Another plausible explanation is worker aversion to other types of risks that affect the estimates of VSLs. In the next section, I investigate how aversion to financial risk may explain the wide gap in the estimated VSLs between the uninsured and the insured.

It is useful to put the findings presented in Table 2.8 into the context of theoretical predictions in Hwang et al. (1992) and Shogren and Stamland (2002). The substantial difference in estimated VSL with individual-specific heterogeneity versus without individual-specific heterogeneity in the model reaffirms the theoretical emphasis of Shogren and Stamland (2002). That is, latent individual heterogeneity is likely to represent unobserved skill related to personal ability to avoid injury, and risk preferences. Accordingly, failure to control for unobserved skill leads to a potentially substantial upward bias in the estimates of compensating differentials for fatal risk. However, job characteristics inducing labor productivity are also important to control in the hedonic wage function, and particularly, if these characteristics vary with the level of mortality risk (i.e. health insurance). We see that employment-based health insurance induce, indirectly, worker productivity and omitting health insurance status from the hedonic wage model leads to a potentially substantial downward bias in the estimated VSL. This evidence lends support to the theoretical conjecture in Hwang et al. (1992).

2.5.3 Risk aversion, family structure, and the wage-risk premium

The lower VSL estimates of the insured relative to that of the average workers can be attributed to the fact that the insured trade the wage-risk premium for health benefits. However, the substantial difference in the implied VSLs between the insured and the uninsured cannot be explained merely by productivity differential or the tradeoff between wage-risk premium and health insurance. It is then natural to think that the high estimate of VSL for the uninsured workers may be related to other types of risks—in particular, financial risk.

Eeckhoudt and Hammitt (2004) show that aversion to financial loss leads to an increase in VSL. Some individuals exhibit greater aversion to financial risk, and accordingly, they need to get higher mortality-risk premiums. Specifically, a married man derives his utility from—in addition to his own consumption—the consumption of his spouse (e.g. bequest model). When a work-related accident occurs, his utility decreases. But it decreases further when income loss due to accident reduces his spouse's consumption. The same argument applies to health insurance. Health insurance reduces financial risk. The uninsured could face catastrophic financial shocks—both in terms of the monetary value of working time losses and the direct costs of illness—when they are sick. Accordingly, married men, and particularly, uninsured married men whose utility depends on their spouse's utility would require higher wage premium for mortality risk than do single men.

To empirically test this, I split the sample into two groups: married men and single men. I then estimate wage-risk premiums separately for these two groups with models 2.9 and 2.10 and use the fixed-effects estimators to control for individual heterogeneity. The results are presented in Table 2.9. The implied VSLs for both groups are calculated using the formula 2.11, using the average wage for each group instead of the mean wage for the full sample. The results are presented in columns 1 and 2 of Table 2.9.

Despite being statistically insignificant, the point estimate of risk premium for married men is, on average, greater than that of single men. The implied VSL for married men is $ 9.26 million, which is higher than that of single men (i.e. $ 5.91 million). When I compare the implied VSL for married men to the estimated VSL of the average worker in Column 4 of Table 2.7, the estimated VSL of married men is higher than that of the average workers. This evidence may show that married men are more risk averse: they require higher wage compensation than do single men to attract them to dangerous jobs.

Columns 3 and 4 of Table 2.9 report the results for married and single men respectively when I include health insurance. In general, I observe a similar pattern to the baseline model in which married men receive higher wage premium for risk than single men do. However, I observe a striking difference in the implied VSL for uninsured married men. The implied VSL of uninsured married men is $ 29.05 million, which is far larger than that of any group. The considerable increase in the estimated VSL following the inclusion of health insurance status apparently is driven by uninsured married men group. This group may exhibit strong aversion to financial risk due to the absence of health insurance. This finding lends support to the theoretical emphasis in Eeckhoudt and Hammitt (2004).

Previously we are concerned on how employer health insurance is measured. In particular, the PSID does not allow us to distinguish policy holder and dependent. Thus if the health insurance coverage is mismeasured—e.g. the observed coverage is actually the coverage from spouse's employment, the positive coefficient on EHI plausibly reflects the fact that the respondent whose health insurance is covered by his spouse does not pay for EHI. The EHI for single men, however, should provide a better measure of employer health coverage. Column 4 of of Table 2.9 provides the estimate of EHI and I find the coefficient on EHI is positive. It suggests that the positive coefficient on EHI on wage may not be driven by the imperfect measure in health insurance. However, mismeasurement in health insurance might have an effect, despite small. Particularly, when we compare the coefficient on EHI between the sample of married and single men, we find positive, slightly larger and statistically significant effect of EHI on wage among single men. Meanwhile among married men the coefficient is not statistically significant at conventional significance level. This may be some individuals get their coverage from their spouses and thus, the coverage has limited effect on wage.

2.5.4 Robustness Checks

In this section, I focus on robustness checks for previous estimates. There are two things that I address here. First is the selection problem that causes both the observed risk and health coverage are endogenous. However, having two endogenous variables in a single model may complicate the interpretation of risk and health insurance parameters. In addition, we may lack valid instrumental variables that affect wages only through the choice of risk and health insurance. Hence, to address this issue, I use the sample of job switchers. The underlying assumption is that instrumental variables, if there is a valid one, should shift both the risk measure and EHI coverage. Thus, although we do not have valid instrumental variables, changes in the risk measure and EHI coverage occur, at least, when people change their jobs (or lose their jobs). Consequently, using the sample of job changers might partially solve endogeneity issue. The second issue that we discussed previously is potential error in EHI reporting—that is, we are unable to separate policy holder and dependent. In previous section, I estimate separate the sample between married and single men with a notion that the EHI coverage of single men should provide a clean identification of EHI. However, single men and married men may be systematically different and the difference could be related to EHI coverage. To tackle this problem, I focus on married men and estimate separately the sample of married men with working and non-working spouses. The observed EHI coverage among married men with non-working spouse suggests that they are policy holders.

Fixed Effects Estimator Specification Checks

Fixed-effects model permits us to control for person-specific heterogeneity by employing within-transformation of data. However, it comes at the cost of eliminating cross-sectional variation that provides important information on wage differentials across occupation-industry groups—i.e. variation that reflects true differences in job riskiness. Under fixed-effects model, the main source of identification relies on within-group variation that arises from 1) changes in fatality risk in a given occupation-industry group and 2) job changes resulting in the changes of fatality risk—i.e. workers move to different occupation-industry cells over some periods. Variation coming from changes in the occupation-industry specific fatality risk could confound estimates of risk premiums if these changes are not systematically reflected in wage levels. That is, over time workplace safety tends to improve (i.e. fatality risks fall), and, at the same time, real wages are more likely to increase. I attempt to control for these trends with year dummies in the model. However, if year dummies do not fully control for the trends, we may indeed observe a negative relationship between fatality risk and wage. Another possible confounding factor in fixed-effects model is that individuals may learn about risks on the job over some periods and switch if wage compensation for risk is inadequate.[22]

On health insurance, workers generally stay in jobs that provide health coverage, and, the effect of health coverage on real wages could also be confounded by the general trend of increased wage levels.[23] Again, year dummies are expected to absorb this trend. With the panel structure of data, however, the identification of the effect of EHI on wages comes mainly from changes in health insurance status—i.e. workers who gain or lose health coverage. Thus, it is likely that health insurance gainers/losers are also those who change jobs.[24]

This implies that the fixed effects model—despite controlling for heterogeneity—potentially underestimates VSLs. This is driven by failure to control trends of increased wages and falling fatality risks. The effect of the confounding factors on the relationship between health coverage and wages is less clear nevertheless. If more productive workers are more likely to move to jobs providing health insurance

[22]Another possibility is that over time workers may accumulate skills that enable them to cope with risk of injury

[23]Despite mixed evidence, some papers show that EHI reduces worker mobility; this phenomena is called as job-lock.

[24]It is also plausible that an employee who works with the same employer loses health coverage because of health care costs—e.g. rising health insurance premiums. Yet, Baicker and Chandra (2006) find that increases in health premiums are compensated with lower wages instead of dropping off health coverage.

and higher wages, the effect of EHI coverage on wages in the previous fixed effects estimator is also biased downward. In this section, I investigate the importance of job changing status for the wage-risk premium estimates in Tables 2.6 and 2.8. Specifically, first I estimate risk premiums for job changers while I still control for unobserved heterogeneity (Schaffner and Spengler, 2010; Kniesner et al., 2012).[25] I then compare the estimated VSLs for job changers with that of workers who never change jobs. The results are presented in Table 2.10.

Columns 1 and 2 of Table 2.10 exhibit estimates of risk premiums based on job change status from the baseline model. Columns 3 and 4 present compensating wage differentials for the insured and uninsured among job changers. The implied VSL of job changers in the baseline model is around $ 3 million higher than the estimated VSL with the standard model presented in Table 2.6. Furthermore, the estimated VSL of job changers in jobs providing health insurance follows the same pattern as in the baseline model with the sample of job changers. In particular, there is a general tendency towards falling mortality risks and rising wages among jobs providing health coverage. Hence, we observe a negative estimated VSL among those who never change jobs. The wage of non job changers at jobs without health coverage apparently responds positively to increased fatality risks such that we observe a positive VSL in Column 4 of Table 2.10. Interestingly, the implied VSL of the uninsured switchers—i.e. non-job changers without health insurance—is slightly lower than that of uninsured with full sample in Column 4 of Table 2.8. A possible explanation to this is that job switchers who lose health insurance are also those who are more likely to accept lower wages, and consequently, receive lower wage compensation for risk than do the average uninsured workers.[26] Although it is also plausible, it is less likely that job switchers who never have health coverage tend to move to riskier jobs while accepting lower risk premium.[27]

The Sample of Married Men

Previously I showed that married men tend to receive a higher risk premium than do single men. In the model with the interaction term between the fatal risk and health insurance, I find that the VSL of married men without health insurance is

[25] Several papers also use job changers—i.e. displaced workers—to solve endogeneity of health coverage and then estimate the health insurance-wage tradeoff (Simon, 2001; Lehrer and Pereira, 2007).

[26] My estimate does not separate job switchers by those who never have health insurance and those who lose health insurance due to changing job.

[27] This could happen when the unemployment rate is high. Thus, workers are willing to take riskier jobs with lower risk premium.

the major contributor to high VSL among the uninsured. Part of the explanation on this is high risk aversion to non-injury risks among married men—e.g. risk to financial loss. Splitting the sample between married men and single men also allows me to minimize the issue created by health insurance coverage information—that is, I cannot distinguish between policy holder and dependent. Despite splitting the sample and estimating the model separately, I find that the coefficient on health insurance status qualitatively similar. A larger magnitude on the coefficient on health insurance of single men tell us that mismeasurement in EHI status plausibly bias the coefficient, although the bias seems to be small. However, we could argue that single men have different characteristics than married men and they may systematically choose different types of job that are correlated with health coverage and wages. In that situation, this approach may not yield a better estimate of EHI parameter.

In this section, I use a similar approach but I focus only on married men and divide the sample into married men with a working spouse and those with a non-working spouse. The observed EHI coverage among married men with a non-working spouse implies that they are policy holder. Table 2.11 shows the results with fixed effects. We see that the implied VSL of married with working spouse is \$ 8.3 million which is lower than the one whose spouses are not working (i.e. \$ 28 million). The finding is consistent with the risk aversion story where the single earner is more risk averse than dual earners such that he requires higher wage premium for fatal risk. In the model with the interaction between the fatal risk and health insurance status, we find that the VSL of the uninsured men whose spouses are not working is the largest among other groups. This may suggest that this group—i.e. the insured with non-working spouses—faces greater risk to, among others, financial loss stemming from the cost of illness and being a single earner. Risk aversion among the group then induces them to ask very high risk premium.

Moreover, we observe that the coefficient on EHI among both samples are qualitatively similar. The point estimate of the health insurance coefficient is positive although it is not statistically significant in all samples. The coefficient on EHI is higher among the sample of married men whose spouses are not at work. As the observed EHI coverage with this sample reflects the coverage of policy holder, this seems to suggest that measurement error in health insurance variable brings the coefficient to zero—that is, measurement error may be classical. However, given that the coefficient on EHI from both samples are not statistically significant, I cautiously conclude that classical measurement error is the only issue for the health insurance variable. Overall, using the samples of single men and married men with non-working spouses does not change our conclusion.

2.5.5 Some Alternative Hypotheses

In this part, I consider two alternative hypotheses to the findings. In general, the empirical strategy addresses issues raised by these alternatives. While some plausible explanations are complementary to facts in this paper, the empirical observation and findings substantiate our framework.

The first alternative explanation to our findings is that health insurance picks the effect of workers' compensation on VSL. Many studies find that inclusion of workers' compensation in the hedonic wage model raises estimates of compensating differentials for risk and thus, VSL (Arnould and Nichols, 1983; Viscusi and Moore, 1987). The reason is that workers' compensation essentially put employers as the party that assumes the liability for job-related injuries. Thus, workers' compensation is expected to shrink wage-risk premiums. In the absence of workers' compensation, risk premiums will be higher while increasing the level of workers' compensation benefits reduces wage levels. Different but related issue is about job selection. If workers' compensation covers medical expenses as does EHI, the uninsured workers tend to go to jobs in which the likelihood of getting approval on workers' compensation claims is high. Therefore, one may expect that the observed effect of EHI on the rate of wage-risk tradeoff picks up the influence of workers' compensation on the hedonic wage model.

As discussed previously, however, the above hedonic wage models exploit the capabilities of panel data in controlling for person-specific heterogeneity that may influence people job decisions involving job risks, EHI coverage, and wages. I do not specifically control for workers' compensation in our econometric models for the reason that the workers' compensation variable exhibits little variation over time. By 2010, more than half the states have the replacement rate is at 66.66 % (Sengupta et al., 2011), and it has not changed substantially over years (Kniesner et al., 2012). Furthermore, the extent to which workers' compensation vary across states can be controlled by state and year fixed effects of our models. In addition, many studies do not find strong evidence that the uninsured use workers' compensation to get medical benefits (Card and McCall, 1996; Biddle and Roberts, 2003; Lakdawalla et al., 2007). In summary, it is less likely that the effect of EHI on wage-risk premiums is affected by workers' compensation.

The second plausible explanation is that health insurance is simply a device to manage multiple risks. Individuals face multiple risks, and, their willingness to reduce some risks may depend on the presence of and characteristics of other risks. For example, a worker in a hazardous working condition could be exposed to pollutants that has a harmful effect on his health. If he falls ill, he could lose working days, potential income, and spend dollars for unexpected medical expenses. Thus, facing risk of reduction in wealth lead him to adjust his behavior at work. For example, he regularly wear protective measures such as, safety gears at worksite and that action reduces both risk of illness and financial risk. Eeckhoudt and Hammitt (2001) explore the effects of competing mortality risks and of financial risks, and predict that under a certain condition, a positive correlation between the mortality and financial risks increases VSL. We also see a similar role of health insurance in reducing the risk of catastrophic financial shocks from unexpected medical expenditures. As discussed in Section 5.2.1, aversion to financial risk among the uninsured married men leads to high implied VSL. Therefore, health insurance is simply a device to handle competing risks and thus, it does not have a productive impact on health.

This explanation is complement the fact that workers trade risk premiums for health insurance. But it cannot explain overall empirical findings in this paper. If health insurance is simply a mechanism to reduce financial risk from falling ill, we should observe a positive relationship between the fatal risk variable and employer-provided health coverage. Specifically, workers in dangerous jobs are more exposed to hazardous environments that put them at greater risk of illness. All else constant, these workers should have more incentive to demand for health insurance. The empirical observation and evidence suggest otherwise, that is, workers in dangerous jobs are less likely to have employment-based health insurance.

2.5.6 Wage premiums for health investment

A salient feature of the framework is labor market frictions that induce firms' incentive to pay for employees' health investment. The framework differs from the equalizing differences theory, and consequently, has different implications to the wage-health insurance tradeoff.[28] The canonical model of compensating differentials presume a perfect labor market. Hence, holding other things constant, jobs providing health insurance should offer lower than average wages: It implies a negative relationship between health insurance and wages.

[28]This paper is not the first one that sees the productivity impact of health insurance. Several researchers also view that health insurance, or medical expenditures, increases productivity (Fang and Gavazza, 2011; Dey and Flinn, 2005)

When labor market is imperfect, the negative relationship between health insurance and wages is not always warranted. For example, under the framework of the efficiency wage theory, firms may provide greater fringe benefits, including health insurance, while keeping wages the same to induce employees' performance. Nevertheless, it is important to highlight that the model is not completely in the opposite side of the canonical model of compensating differentials. In fact, I argue that the association between health insurance and wages is conditional on the level of risks. Beyond some levels of mortality risk, the model shows that I can recover the prediction of the compensating wage theory.

From Table 2.8, fixed effects estimator suggests that the annual wage premium for health insurance is 4.8%. This premiums is similar to findings in studies using arguably exogenous variation from displaced workers (Simon, 2001; Lehrer and Pereira, 2007). I also find that failure to control for person-specific heterogeneity results in a potentially upward bias in the estimated wage premium for health insurance. For example, with POLS, the insured workers earn 16.6 % higher in hourly wage rate than do the uninsured workers. It is important to note, however, that wage premiums for health coverage are the premiums for workers in very safe jobs (i.e. $Z_{jk} = 0$).

The model predicts that the wage premium for health insurance declines as the mortality risk increases. To show a declining wage premium for health insurance as the risk of death at work elevates, I calculate the premiums for health insurance for workers in the bottom 10 percent and the top 10 percent fatality risk. I use the mean of fatality risk in each group to estimate the premiums. The results are then presented in Table 2.12. With fixed-effects model reported in column 4 of Table 2.12, I observe a negative wage premium for health insurance among the top 10 percent although the point estimate is not statistically significant at 95% confidence level. Despite being insignificant, this suggests a tradeoff between health insurance and wages, and this finding confirms the prediction of the equalizing differences theory.

2.6 Conclusion

In this paper I investigate the implications of health insurance provision on wage premiums for mortality risk at workplace. The model shows that the elevated risk of death at work reduces the level of health investment made by employers. The reason is that productivity gains from health decline as working conditions become hazardous. Accordingly, the insured in risky jobs have to contribute more to the associated costs of health investment in the form of lower wages: they trade the risk premium for health insurance. The model shows that compensating wage differential for the insured will be lower than that of the uninsured.

I find that an increase in the mortality risk is associated with a lower probability of EHI coverage. The effect of risk on EHI coverage is statistically significant but small—i.e. employer-provided health coverage is less sensitive to the elevated mortality risk. On the estimates of VSLs, I find that controlling for unobserved heterogeneity leads to a reduction in the estimated VSLs by more than 53 %. With the baseline model accounting of individual heterogeneity, the estimated VSL is $ 7.68 million. Inclusion of health insurance in the baseline model leads to a slightly increase in the estimated VSLs by 2.5-7.2 %. The increase in the implied VSLs in the model with health insurance suggests that the VSL is likely to be biased downward when we omit health insurance status from the standard model. However, the bias seems to be small due to the low responsiveness of EHI to mortality risk at work. Salient evidence is heterogeneity in the estimated VSLs stemming from EHI coverage status. I find a reduction in the estimated VSL of those with health coverage by 26-37 %, depending on econometric specifications. From the model accounting of person-specific heterogeneity, I find that the implied VSL of the insured is $ 4.87 million while it is $ 20.87 million for the uninsured. As I investigate further, the high VSL of the uninsured is driven by uninsured married men who probably exhibit greater aversion to financial risk, and, require a higher wage premium to attract them to risky jobs. Finally, I observe the wage-health insurance tradeoff only for workers in risky jobs. This is consistent with the idea that workers in high risk jobs trade risk premiums for health coverage.

Moreover, the proposed framework shows that heterogeneity in VSL is driven by the employer's incentive to invest—that is correlated by fatal risk—in the employee's human capital. However, the employer could induce employee's productivity through various means, for example, other fringe benefits such as life insurance or pension.[29] Thus, they plausibly have an effect on VSL too and excluding them from the standard hedonic wage model may bias the estimated VSL. However, our regression results shows that the bias in VSL from omitting EHI status in the model is small, and, we may find similar evidence with other fringe benefits—that is, the bias may be small from omitting other fringe benefits. Despite little bias on VSL, omitting fringe benefits may bias the coefficient on health insurance status. In particular, if the employer induce productivity through *all* types of compensation (both wage and

[29] In the framework of the efficient wage hypothesis, the employer could raise wage above average wages or provide fringe benefits to influence workers' performance.

non-wage compensation such as health insurance and pension), the coefficient on EHI status would be upward bias. On the other hand, if the employer trades off types of fringe benefits, for example, providing generous health insurance coverage at cost of lower pension fund, we should expect downward bias in the coefficient on health insurance coverage. This conjecture, however, departs from an assumption that fringe benefits are used to induce worker productivity, leading to higher wages—that is, fringe benefits are positively correlated with wages. When we depart from the standard theory of equalizing differences, the opposite prediction would occur.

Figure 2.1: Sequence of the Events

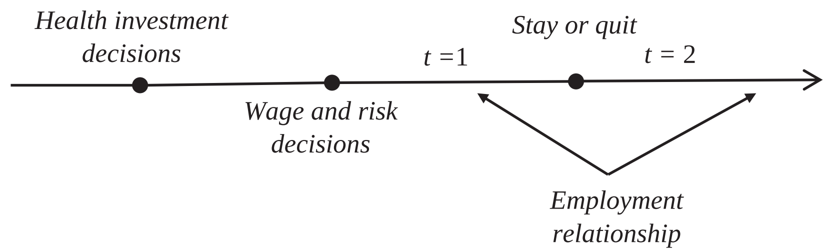

Figure 2.2: Compensating Wage Differential Loci

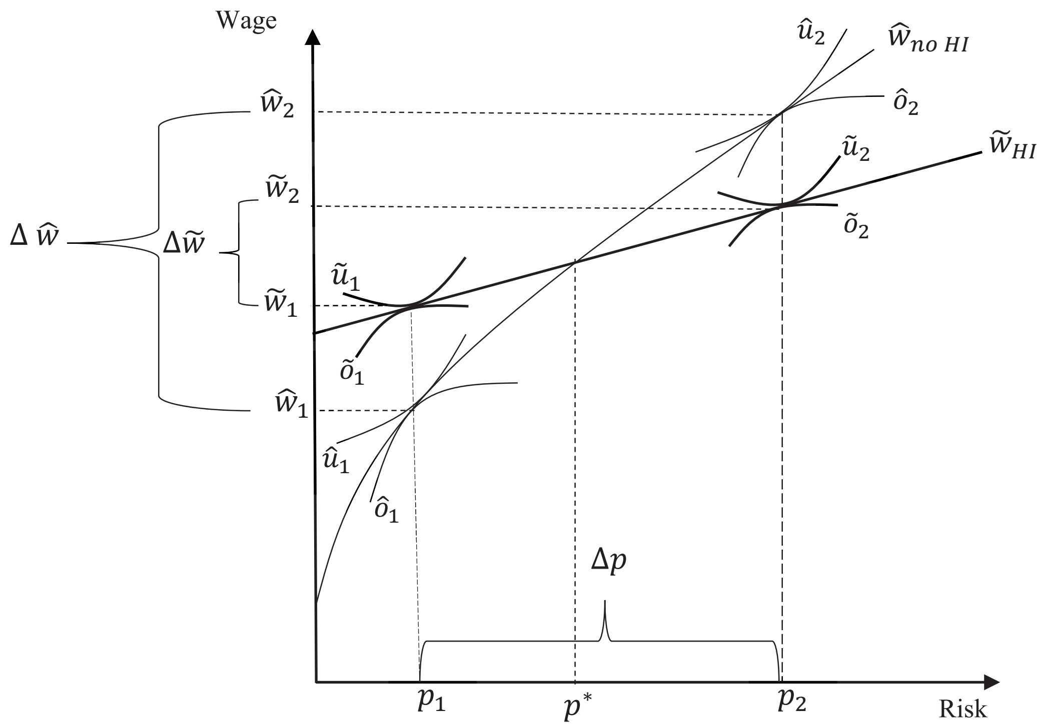

Table 2.1: Summary Statistics

Variables	**Mean**	**Standard Deviation**
Real hourly wage	23.44	14.92
Log real hourly wage	2.99	0.57
Fatality rate	4.23	6.63
EHI(1=take-up)	0.82	0.39
Years of schooling	13.64	2.20
Marital status (1 =married)	0.76	0.43
Union (1=member)	0.17	0.38
Race(1=white)	0.91	0.29
EHI(1=take-up)	0.82	0.39
Age	39.78	10.48
Occupation groups, the 1997/99 period		
Executive & Managerial	0.21	0.41
Professional	0.17	0.37
Technicians	0.04	0.20
Sales	0.05	0.21
Administrative Support	0.06	0.24
Services	0.09	0.28
Precision Production Craft	0.20	0.40
Machine Operators	0.08	0.28
Transportation	0.06	0.24
Handlers and Laborers	0.04	0.20
Occupation groups, the 2003/07 period		
Management, business, and financial	0.18	0.38
Professional	0.20	0.40
Services	0.10	0.31
Sales	0.07	0.25
Administrative Support	0.07	0.25
Construction & Extraction	0.11	0.31
Installation & Maintenance	0.09	0.29
Production	0.10	0.31
Transportation	0.08	0.27
Number of observations	10,254	

Source: PSID.

Table 2.2: Types of Coverage

Coverage	Frequency	Percent
No Insurance	1,265	12.34
Employer provided health insurance	8,373	81.66
Private health insurance purchased directly	310	3.02
Medicare	11	0.11
Medi-Gap	78	0.76
Medicaid/Medical Asst./ Medi- Cal	40	0.39
Military health care	63	0.61
Champus/Tricare/Champ-VA	7	0.07
Indian Health Insurance	26	0.25
State-sponsored health plan	10	0.10
Other	69	0.67
Unknown	2	0.02
	10,254	100.00

Source: PSID

Table 2.3: Between- and Within-Group Variation for Industry by Occupation Fatality rates

Sample	Overall variance	Within-group variance	Between-group variance
All sample	42.88	13.28	29.60
Never-change job	42.26	6.53	35.73
Ever-change job	43.06	15.90	27.16

Source: PSID

Table 2.4: Between- and Within-Group Variation for Industry by Occupation EHI coverage

Sample	Overall variance	Within-group variance	Between-group variance
All sample	0.145	0.047	0.098
Never-change job	0.211	0.037	0.174
Ever-change job	0.111	0.051	0.059

Source: PSID

Table 2.5: Marginal Effects of Risk of Fatal Injury on EHI Coverage

Variable	**LPM**	**Probit**	**CRE Probit**
Fatality rate	-0.0016*	-0.0018**	-0.0009
	(0.0009)	(0.0008)	(0.0008)
Mean of fatality rate			-0.0021**
			(0.0011)
Observations	10,254	10,254	10,254
R-squared	0.0146		
Log-likelihood		-4299	-3941

Note: Dependent variable is a binary variable indicating employer health insurance coverage (EHI). Each model controls for union status, marital status, a dummy for spouse working status, age, age squared, and 1 digit industries and occupations. For Probit additional control variables are years of schooling and race (i.e. white). Variables in CRE Probit are the same as in Probit, but I control for the mean of fatality rate, the mean of age, and the mean of age squared. Standard errors are in parentheses *** significant at 1%, **5%,* 10% Source: PSID

Table 2.6: Estimates of Wage Premium for Risk: the Baseline Specification

Variables	**POLS**	**Random Effects**	**Between Effects**	**Fixed Effects**
Fatality rate	0.00482***	0.00224***	0.00495***	0.00164*
	(0.000820)	(0.000731)	(0.00170)	(0.000949)
Observations	10,254	10,254	10,254	10,254
R-squared	0.472	0.3642	0.522	0.233
Implied VSL (millions)	22.60	10.52	23.23	7.68
	(3.85)	(3.43)	(7.97)	(4.45)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. Pooled OLS and Fixed effects estimators are robust to heteroscedasticity. Random effects, Fixed effects, and between effects model control for union status, marital status, a dummy for spouse working status, age, age squared, 1 digit industries and occupations, states of residence and year dummy . For pooled OLS additional independent variables are years of education and race (i.e white is 1 and 0 otherwise). *** significant at 1%, **5%,* 10%. Source PSID.

Table 2.7: Estimates of Wage Premium for Risk with Health Insurance

Variables	POLS	Random Effects	Between Effects	Fixed Effects
Fatality rate	0.00506***	0.00236***	0.00531***	0.00166*
	(0.0008)	(0.0007)	(0.0017)	(0.0009)
EHI	0.134***	0.0644***	0.147***	0.0309**
	(0.012)	(0.0094)	(0.018)	(0.012)
Observations	10,254	10,254	10,254	10,254
R-squared	0.479	0.4552	0.530	0.234
Implied VSL (millions)	23.74	11.08	24.90	7.87
	(3.83)	(3.42)	(7.9)	(4.44)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. Pooled OLS and Fixed effects estimators are robust to heteroscedasticity. Random effects, Fixed effects, and between effects model control for union status, marital status, a dummy for spouse working status, age, age squared, 1 digit industries and occupations, states of residence and year dummy . For pooled OLS additional independent variables are years of education and race (i.e white is 1 and 0 otherwise). *** significant at 1%, **5%,* 10%. Source PSID.

Table 2.8: Estimates of Wage Premium for Risk with the Interaction between Health Insurance and Risk

Variables	**POLS**	**Random Effects**	**Between Effects**	**Fixed Effects**
Fatality rate	0.00986***	0.00567***	0.00911***	0.00445***
	(0.00151)	(0.00120)	(0.00237)	(0.00164)
EHI	0.166***	0.0860***	0.178***	0.0483***
	(0.0157)	(0.0113)	(0.0227)	(0.0152)
Fatality rate X EHI	-0.00611***	-0.00420***	-0.00576**	-0.00341**
	(0.00153)	(0.00121)	(0.00253)	(0.00164)
Observations	10,254	10,254	10,254	10,254
R-squared	0.480	0.3648	0.531	0.235
Implied VSL without EHI (million)	44.70	26.60	42.72	20.87
	(7.10)	(5.64)	(11.12)	(7.71)
Implied VSL with EHI (million)	17.55	6.91	15.71	4.87
	(4.02)	(3.63)	(8.87)	(4.66)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. Pooled OLS and Fixed effects estimators are robust to heteroscedasticity. Random effects, Fixed effects, and between effects model control for union status, marital status, a dummy for spouse working status, age, age squared, 1 digit industries and occupations, states of residence and year dummy. For pooled OLS additional independent variables are years of education and race (i.e white is 1 and 0 otherwise). *** significant at 1%, **5%,* 10% Source PSID.

Table 2.9: Estimates of Wage Premium for Risk by Marital Status

Variables	**Baseline**		**Interaction**	
	Married	**Single**	**Married**	**Single**
Fatality rate	0.00182	0.00166	0.00575**	0.00218
	(0.00130)	(0.00161)	(0.00251)	(0.00238)
EHI			0.0304	0.0469*
			(0.0206)	(0.0251)
Fatality rate X EHI			-0.00437*	-0.000701
			(0.00243)	(0.00237)
Observations	7,746	2,508	7,746	2,508
R-squared	0.210	0.322	0.211	0.325
Implied VSL (million)	9.26	5.91		
	(6.56)	(5.76)		
Implied VSL without EHI (million)			29.17	7.76
			(12.69)	(8.49)
Implied VSL with EHI (million)			7.02	5.15
			(6.67)	(6.06)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. The reported coefficients are fixed effects estimators that are robust to heteroscedasticity. I control for union status, a dummy for spouse working status if married, age, age squared, 1 digit industries and occupations, states of residence and year dummy. *** significant at 1%, **5%,* 10% Source PSID.

Table 2.10: Estimates of Wage Premium for Risk By Job Change Status

Variables	**Baseline**		**Interaction**	
	Ever Change Job	**Never Change Job**	**Ever Change Job**	**Never Change Job**
Fatality rate	0.00231**	-0.00145	0.00411**	0.00227
	(0.000947)	(0.00260)	(0.00202)	(0.00344)
EHI			0.0506***	0.0387
			(0.0184)	(0.0261)
Fatality rate X EHI			-0.00218	-0.00433
			(0.00212)	(0.00280)
Observations	5,604	4,650	5,604	4,650
R-squared	0.231	0.283	0.233	0.284
Implied VSL (million)	10.81	-6.79		
	(4.44)	(12.21)		
Implied VSL without EHI (million)			19.26	10.66
			(9.44)	(16.14)
Implied VSL with EHI (million)			9.04	-9.68
			(4.72)	(12.28)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. The reported coefficients are fixed effects estimators that are robust to heteroscedasticity. I control for union status, a dummy for spouse working status if married, age, age squared, 1 digit industries and occupations, states of residence and year dummy. *** significant at 1%, **5%,* 10% Source PSID.

Table 2.11: Estimates of Wage Premium for Risk by Spouse Working Status

Variables	**Working Wife**	**Non-Working Wife**	**Working Wife**	**Non-Working Wife**
Fatality rate	0.00167	0.00523**	0.00552*	0.0141**
	(0.00160)	(0.00261)	(0.00311)	(0.00596)
EHI	0.00870	0.0109	0.0291	0.0664
	(0.0186)	(0.0358)	(0.0244)	(0.0436)
Fatality rate X EHI			-0.00425	-0.0101
			(0.00291)	(0.00625)
Constant	0.420	1.979	0.434	2.044
	(0.838)	(1.552)	(0.833)	(1.569)
Observations	5,943	1,803	5,943	1,803
R-squared	0.210	0.264	0.210	0.272
Implied VSL	8.30	28.00		
	(8.0)	(13.9)		
Implied VSL without EHI			27.4	75.2
			(15.4)	(31.9)
Implied VSL with EHI			6.30	21.37
			(7.97)	(15.77)

Note: Dependent variable is natural log of real hourly wage. Standard errors are in parentheses. The reported coefficients are fixed effects estimators that are robust to heteroscedasticity. I control for union status, age, age squared, 1 digit industries and occupations, states of residence and year dummy. *** significant at 1%, **5%,* 10% Source PSID.

Table 2.12: Annual wage premium for health insurance ($)

Mean	**POLS**	**Random Effects**	**Between Effect Effects**	**Fixed Effect Effects**
The bottom 10 % of fatality rate	7795.20 (735.89)	4033.99 (529.42)	8330.70 (1065.52)	2262.56 (712.17)
The top 10 % of fatality rate	2235.85 (1079.69)	217.49 (921.16)	3093.55 (1872.10)	-839.61 (1210.33)

Note: Wage premiums are calculated from equation 2.12. I use the mean of the bottom and top 10 % of fatality rate. Standard errors are in parentheses. Source: PSID

Chapter 3 Mortality Risk Premiums and Employer-Provided Health Insurance in Universal Health Care: Evidence from the UK

3.1 Introduction

Over the last three decades, a vast body of research has documented evidence that individuals are rewarded for taking work-specific risks, such as injury and fatality. Viscusi and Aldy (2003) review studies suggesting that individuals are voluntary willing to take risks at workplace in return for monetary reward. That is, they received a wage premium for higher risk of fatality they encounter at workplace. This evidence has become the bedrock for various job-safety policies in the US. This is, in part, because the wage premium essentially reflects a society's valuation of risk, and, consequently, the benefit of job safety policies. Economists have developed the value of a statistical life (VSL) to quantify individuals' willingness to pay for risk reduction and used VSL to assess the benefits of environmental regulations and workplace safety.

It is obvious that a society's valuation of risk depends on its characteristics. Higher income countries tend to have higher VSL that do poor countries (Viscusi and Aldy, 2003). Relatively older population are more likely to have lower VSL than are middle aged population (Aldy and Viscusi, 2008). These differences in VSL across the population would have policy implications. In particular, as improving safety is costly and may be valued differently across different populations, safety policies should take into account heterogeneity in VSL. In the US, the US Department of Transportation takes into income differences and makes adjustment VSL amount in accordance to individual incomes (Viscusi, 2010).

Heterogeneity in VSL may stem from workplace characteristics or other policies as well. In places where workers receive generous workers' compensation, they accept relatively lower wage premium for risk (Viscusi and Moore, 1987). This is conceptually can be explained as employers may compensate workers for risks they are taking either with additional wage payments (i.e. ex ante compensation) or workers' compensation benefits (i.e. ex post compensation). However, employers may provide non cash compensation in order to attract workers to work in unpleasant jobs such as health insurance or other fringe benefits (Dorsey, 1983).

Thus so far the literature has no extensive discussion yet on the effect of desirable job packages, such as employer-sponsored health insurance, on the estimated VSL.[1]

[1] I am only aware one paper that discusses the role of fringe benefits, including health insurance

The importance of employer-provided health insurance in the analyses of money-risk tradeoff is not whether health coverage directly improves job safety or compensates injured employees, like what workers' compensation does in the US. As workplace safety in most developed countries has improved substantially over decades, the rate of fatal accident at work has declined to an unprecedented level. Overall, occupational mortality rates in developed countries are much lower than they were in previous decades.[2] But at the same time, risks of illness and the associated costs increase substantially. Thus, individuals may accept a lower risk premium for health insurance.

Furthermore, the wage-health insurance tradeoff would have impact on the estimated VSL when workers' valuations on health insurance differ along different levels of job riskiness. For example, if safety is normal good, more productive workers would seek safer occupations. However, more productive workers that tend to earn higher incomes may value more health insurance than are less productive workers. On the other hand, workers who go to riskier occupations reveal that they are more tolerant to risks, including risk of death or illness, and, may value less the benefits of health insurance. At the same time, working environments where risks to human health are high make the costs of health insurance are high too. Thus, both employers and workers in risky occupations are less willing to invest in employees' health through health insurance. As a result, the rate of tradeoff between wages and health insurance is higher for workers in risky jobs than safe jobs. Now, as workers in riskier occupations prefer full wage compensation, we may expect that workers with health insurance that are mostly located in safe jobs would accept lower wage premium than do workers in risky jobs.

Using the US data, I find evidence that workers trade risk premium for health insurance. In particular, workers with health coverage receive lower wage premium for the elevated mortality risk at work than do workers without health insurance. It implies that the VSL of the former is lower than that of the latter. In the context of the US, we may expect that the tradeoff between the mortality risk premium and health insurance exists given that the US is a country with a strong link between health insurance and labor market outcomes—i.e. the majority of the US employees rely on employment-based health coverage. Thus, the adjustment in the estimated VSL that takes into account the tradeoff between 'value of life' and the value of health benefits is relevant to policy analyses.

I extend the framework from the US into the context of the United Kingdom (the

on the wage premium for risk, that is, the paper of Dorsey (1983).

[2]In the US, the overall fatality rate is 3.4 per 100,000 workers (BLS 2014). It is 1.2 in the United Kingdom (UK HSE 2014).

UK) labor market. Different from the US, the UK has universal health care system in which all eligible individuals (almost all the UK citizens) are covered by publicly-provided health care. Despite the low coverage of private medical insurance including employer-provided health benefits, investigating the effect of employer-provided health insurance on VSL is warranted for several reasons. First of all, the extent to which employer-provided health insurance (henceforth EHI) has impacts on labor market outcomes is less known in countries with a universal health care system. This paper provides evidence that private medical insurance in the universal health care system affects the risk premium. Second, private medical insurance in the UK continues to grow, and, corporate health insurance market—i.e. employer-sponsored health insurance—has been growing relatively fast in recent years (Foubister et al., 2006). Most of the empirical research on private medical insurance in the UK have been devoted to exploring determinants affecting demand for health benefits, and little attention is paid to understand the implication of health benefits to workers wages.

This paper contributes to the literature in three ways. Firstly, this paper is among the first research that systematically elaborates the effect of employer-sponsored health insurance on the wage-risk tradeoff under the universal health care. Secondly, the paper also contributes to the literature of health economics in general as it provides evidence that employer-paid health insurance, even in universal health care, has implications to labor market. The third contribution is that my paper reevaluates findings in the estimated VSL for the UK labor markets. Previous papers find very high estimated VSLs compared to other developed countries. As argued by Viscusi and Aldy (2003), such high VSL based from the UK labor market could not be attributed to income effect as the UK income level was not substantially higher than that of other developed countries. In this paper, I show that the implied VSL based from the UK data is actually within the range of the estimated VSLs found from the US labor data. Hence, the considerable high VSL seems to be driven by failure to control individual heterogeneity that affects both wage levels and job riskiness.

Using data from the British Household Panel Survey (BHPS), I find that workers in risky jobs are less likely to receive employer-provided health insurance. The negative effect of mortality risk on the likelihood of being covered by EHI is small but statistically significant. An increase in the fatality rate by 1 per 100,000 leads to a reduction of approximately 2.1 % in employer-provided health coverage. This implies that that employer-provided health coverage is less responsive to changes in the mortality risk.

Perusal of compensating wage differentials for risk suggests that failing to control for unobserved individual heterogeneity leads to an upward biased of VSL. Models accounting of individual heterogeneity reduce estimates of compensating differentials for risk—relative to cross-section estimator—by 68-89 %. In particular, the estimated VSL with fixed-effects model is £7.73 million. In the US $, this value is approximately equal to $ 11.6 million (2010 $). The estimate puts the estimated VSL based on the UK data within the range of estimated VSLs in the US (Kniesner et al., 2012).

Inclusion of health insurance in the baseline model leads to a slightly increase in the estimated VSLs by 7.3 %. The increase in VSLs in the model with health insurance suggests that the VSL is likely to be biased downward when we omit health insurance status from the standard model. However, the bias seems to be small due to the low responsiveness of EHI to mortality risk at work.

Furthermore, there is evidence of heterogeneity in the estimated VSL stemming from EHI coverage status. I find that workers without employer-sponsored health insurance receive a higher wage premium for mortality risk, implying a higher VSL for this group.[3] Specifically, interacting employer health insurance status with fatal risk increases the coefficient of risk by 63.25 %. This evidence is qualitatively similar to what I find in the US.

I find that the risk premium for workers with health insurance is negative, resulting in a negative VSL. This is inconsistent with the standard hedonic theory. I propose several explanations. First, this may be caused by universal health care system. Private medical insurance, including employer-purchased health insurance, offers access to health services that are also provided under the National Health Service (the NHS)—i.e the UK main public health care provider. Thus, providing additional health coverage while publicly-provided health care is available at no cost at service point would add costs to employers, particularly employers in industries with high levels of fatal risk.[4] Consequently, employers pass full costs of health benefits to workers. At the same time, workers who value the benefits of private medical insurance are willing to pay for it. Second, there are non classical measurement errors that are correlated with risks and other covariates. Several papers have attributed distinct results of VSL estimates from the UK data, including the negative risk premium to measurement error (see Viscusi and Aldy (2003) and Hintermann et al. (2010)).

[3]Despite not having employer-provided health insurance, under the universal health care all workers are eligible to publicly-provided healthcare.

[4]There is no cost at the service point. However the UK public healthcare is funded through general taxation.

In a comparative perspective, findings from the UK are qualitatively similar to those prevailing in the US labor market. That is, employer-provided health insurance reduces risk-premium. The effect of health coverage on the valuation of mortality risk at workplace is less well known in VSL literature. This suggests that employer-sponsored medical benefits have impacts on wage levels and the risk premium, a somewhat surprising result given that the UK does not have a strong link between health insurance and employment like in the US.

The rest of the paper is organized as follows. Section 2 discusses related literature while section 3 discusses the institutional setting of health insurance in the UK. Analytical framework is discussed in Section 4. Section 5 describes econometric implications derived from the framework. Section 6 covers the estimation results and conclusion is in section 7.

3.2 Related Literature

In general, variation in VSL estimates derived from labor market data can be attributed to both unobserved and observed variables. Much work has been done in order to deal with unobservables that could be correlated with injury risks but are not easily to capture from data. Moreover, workers are not randomly assigned to jobs. The theory of compensating differentials for risks implies that workers would sort to jobs that fit with their taste for risk. When the unobserved characteristics of workers systematically affect worker productivity and earnings, they influence workers' job decision. For example, a cool-headed worker who is able to work more productively in dangerous jobs would go to jobs with high risk levels (Garen, 1988). As a result, failing to handle unobserved characteristics results in biased estimates of premiums for risk. Using an instrumental variables approach in order to address this concern, Garen (1988) finds twofold increase in a mortality risk premium from the standard hedonic model with OLS.

The increase in wage premiums when taking into account unobserved productivity is also supported by subsequent theoretical findings in Hwang et al. (1992). They show that failing to account for unobserved heterogeneity may underestimate premiums of mortality risk, and potentially result in a negative coefficient of risk variable. Among studies focused on the US labor market, few studies confirm the conjecture of Hwang et al. (1992). There are, however, some exceptions with studies using data from the UK labor markets.

Contrary to Hwang et al. (1992), Shogren and Stamland (2002) argue that unobserved productivity may lead to the opposite conclusion. They posit that workers in risky jobs reveal themselves to have the ability to avoid injury, while those who are less able to avoid injury choose less risky jobs. As a result, failing to handle unobservables leads to overestimated wage premiums for risk. Recent studies employing longitudinal data confirm the theoretical findings in Shogren and Stamland (2002). Kniesner et al. (2012) use Panel Study of Income Dynamics (PSID) and find a significant reduction in the risk premiums associated with a method accounting for unobservables. Hintermann et al. (2010) employing British panel data also find qualitatively similar results as in Shogren and Stamland (2002).

Regarding the VSL research in the UK, Marin and Psacharopoulos (1982) are among the first researchers using labor market data in the UK to estimate mortality risk premiums. They find the estimated VSL for the UK workers about £0.6 million in 1975. Using relatively new data, Arabsheibani and Marin (2000) observe that the magnitude of VSL is far larger, and, nearly triple compared to their earlier study in Marin and Psacharopoulos (1982). It is unclear, however, whether higher VSL from a recent estimate reflects the rising value of longevity or some other problems related to endogeneity of risk measures. In this study, Arabsheibani and Marin (2000) estimate wage premiums using cross-section data and, thus, the ability to control for latent variables that could be correlated with the risk variable may be limited.

Because of data limitation, earlier studies on mortality risk premiums in the UK employ cross-sectional data. Recent research use panel data and come up with conclusions that the high estimated of VSL from cross-section estimators may be due to failure to control unobserved heterogeneity (Kniesner et al., 2012). Using the British Household Panel Survey (BHPS), Hintermann et al. (2010) employ various econometric techniques to address problems typically associated with the hedonic wage model. They find evidence of compensating wage differentials under restrictive assumptions, that is, no unobserved heterogeneity and strict exogeneity in the risk variable. Utilizing models that allow for heterogeneity, however, there is no evidence of the risk premium. It is important to note that low within-variation in the risk variable in their study (Hintermann et al., 2010) may contribute to the absence of wage premiums from panel data.

In addition to unobserved heterogeneity, some studies also reveal that mortality risk premiums vary depending on observed worker characteristics such as gender (Hersch, 1998) and age (Aldy and Viscusi, 2008). Theoretically speaking, it is possible that the wage premiums differ for different types of workers as individuals may encounter different wage offers. A wage offer curve also depends on demand side. Thus, the characteristics of workplace influence the wage-risk tradeoffs as well. Union is a striking example. Many studies document that union jobs earn a higher wage premium for risk they face than do similar workers in non-union jobs (Thaler and Rosen, 1976; Viscusi and Moore, 1987; Dorsey and Walzer, 1983; Smith, 1983; Biddle and Zarkin, 1988; Garen, 1988). An explanation to this is that unionized workers are more able to bargain for better safety workplace and wages.

In a comparative perspective, risk premium estimates in the UK are generally higher than that of other developed countries (Viscusi and Aldy, 2003). This is even after considering the levels of income per capita. While the level of risk in the UK is the lowest among developed countries, high returns to risks would require very high income effects. That is, high-income workers would demand considerable amounts of wage premium to take an additional risk. Yet the per capita income in the UK is not substantially higher than incomes of other developed countries.

This paper takes into account health insurance status into the canonical hedonic wage model. Similar to union status, inclusion of health coverage status in the hedonic wage model departs from the notion that there are differences in characteristics between jobs that provide health insurance and those without it. Importantly, the differences systematically affect wage levels. Lehrer and Pereira (2007) show that returns to schooling are substantially larger in jobs with health insurance. In fact, they show that health insurance provision has affected wage inequality (Lehrer and Pereira, 2007). Meanwhile the extensive literature in health economics has shown strong links between health insurance and employment (Currie and Madrian, 1999; Gruber, 2000). The literature of health economics in the UK has not much explored this area. Most of the empirical research on private medical insurance has been devoted to exploring the demand for private health insurance and its determinants. Many studies point out that the growth of private health insurance market in the UK is triggered by relatively lower quality of public health services, such as the long waiting lists of major health treatments in public health providers (Besley et al., 1999; Propper et al., 2001; Wallis, 2004).

3.3 Private Health Insurance in the UK

The UK operates a mixed system of health care that combines public and private participation on both the financing and delivery of health care. Public health care providers are managed under the National Health Service (NHS). The NHS purchases health services from both publicly owned and private health care providers (Foubister et al., 2006). As is under the system of universal health coverage, a large share of health care expenditures are from public funds. In addition, there are also private funds that come from private health insurance (PHI) and out-of-pocket spending.

Although there are two types of financing, the government regulates a separation between public and private finance streams. Public funds are allowed to flow to both public and private health care providers. That is, in some situations the NHS purchases health services from privately-owned providers. Despite receiving public funds through the NHS, private institutions providing services to the NHS cannot mix private revenue and public revenue for the same NHS-contracted service.[5] On the other hand, private funds cannot flow to public providers. In other words, private funds are limited only to private providers, such as independent hospitals or hospitals that are part of private hospital groups. From this context, we see that private health insurance (PHI) essentially gives individuals access to private hospitals and thus adds more options to health care services.

Despite the dominant role of public funds, the UK has witnessed growing private health expenditures since the 1990s. Private health spending account for almost 20% of all expenditures on health care and part of the increase in the spending is from PHI (Foubister et al., 2006; Wallis, 2004). Interestingly, PHI continues to grow although privately-provided health care services generally duplicates many of the services provided by the NHS. Many address the increase in PHI to quality gap or, at least perception about it, between public and private providers. For example, the length of waiting lists for treatment in public providers is considered the major factor of PHI growth (Besley et al., 1999; Propper et al., 2001; Wallis, 2004). Compared to the NHS, PHI is more attractive because the privately insured can get faster access to treatment and has a wider choice of specialists, treatment facilities and timing of treatment (Foubister et al., 2006; Wallis, 2004).

Regarding health insurance markets, individuals purchase private medical insurance in two health insurance markets, namely, the corporate market and the individual market. In the corporate market, employers purchase health insurance on behalf of their employees and, thus, health insurance is provided as part of a non-pecuniary benefit. While the majority of employers providing medical benefits bear the costs associated with health insurance premium, only about 7 % of company schemes require the contribution of employees to the premium (AON Hewitt, 2013). In the corporate health insurance market, there is typically no medical underwriting, and, the health

[5]For example, a general practitioner serves a patient under NHS contract. The general practitioner is not allowed to provide similar services for the same patient with private funds.

insurance premium is generally experience-rated. Different from the corporate market, in the individual market and the market for small companies, health insurance is underwritten. That is, the insurer companies assess health risks of enrollees, decide risks for which they are responsible, and typically exclude all pre-existing conditions from coverage. The difference between corporate and individual markets is more related to the size of risk pools. As we also see in the US, corporates generally could provide relatively low cost of health coverage due to bigger risk pools.

In spite of having private medical coverage, individuals still have access to the NHS services that are mostly free at service points. Subscribers to PHI essentially have "dual health coverage". It is intriguing to observe why the majority of employers providing medical benefits pay the costs while the alternative health care at no cost to them is available. A plausible explanation is that private medical insurance may benefit not only employees but also employers. A survey of corporates regarding reasons for providing medical benefits to employees shed light as to why employers are willing to pay full amount of health insurance premiums. As we can see from Table 4.1, productivity-related reasons are the major motivation.[6] If productivity from health is conditional on job riskiness, it is then natural to ask whether the incentive of employer to pay the costs of health insurance is affected by risk levels as well.

Employment-based health insurance in the UK is provided as a fringe benefit. Different from the US, however, employer-provided health insurance in the UK is taxable benefit (Foubister et al., 2006). There are two schemes of health insurance provision: 1) partially paid health insurance coverage and 2) fully paid coverage. Besley et al. (1999) note that jobs providing higher wages are more likely to provide health insurance, particularly jobs that require the sort of specialized professional worker. That is, the advantages of private medical insurance that plausibly minimize disruption to work schedules due to faster and better care may incentivize certain employers with specialized workers. Table 3.2 displays sectoral patterns of health insurance coverage in our sample, with employment-based coverage prevalent in mining and quarrying, and financial services.

3.4 Conceptual framework

In this paper, I extend the model of my second chapter into the universal health care environment. The main premise of the framework is that health is a form of

[6]We can include the following motivations as the productivity-related reason, that is, 1) getting staff back to work quickly, 2) increasing productivity and 3) reducing sickness-absence costs.

general human capital. Similar to other forms of human capital, health increases labor productivity.[7] Healthy individuals experience shorter sick days (Pinheiro and Dizioli, 2012), and, abler to avoid occupational injuries. In this view, health can be seen as an input for production and health insurance, or medical expenditures in general, is health investment.

Current health investments affects the productivity surpluses of future employment relationship. That is, both workers and employers would enjoy productivity gains from health when they stay together. When the labor market is perfect, a worker could move to another firm at no cost, taking all the return to health investments.[8] Thus, the current employer cannot recover the costs of the investments. In the perfect labor market, therefore, employers are not willing to invest in employees' health. However, when outside opportunities for the worker are worse than the wage offer of the current firm following the health investments, the worker is less willing to move to the alternative firm. The gap between the wage offer of the current firm and the outside opportunities reflects an imperfect labor market.[9] Hence, employers can capture the surpluses and recoup the associated costs of health investment only when the labor market is imperfect. That is, frictions provide firms with incentives to invest in their workers' health (Fang and Gavazza, 2011). As shown in Acemoglu and Pischke (1999), the more distorted labor markets, the more incentives firms have to provide health investments.[10]

Despite inducing worker productivity, the extent to which health insurance improves productivity is constrained by firms' underlying technology that is tied to occupational hazards. Hazardous working environments have negative impacts on human health. Workers who have constant exposures to carcinogens or dangerous chemical substances have higher likelihood of getting ill and their health would deteriorate over time. Thus, health as human capital may be far less productive when the rate of occupational hazard is increasing. Another implication is that health care costs for workers in dangerous jobs would be high as the workers are more likely to get sick. Consequently, firms are less likely to pay for health investment when the probability of death is high. This model implies that the extent to which employers are willing to provide private medical insurance depends largely on 1) labor market frictions and 2) the levels of job riskiness.

[7] This idea is similar to Fang and Gavazza (2011) and Tompa (2002).

[8] In a perfectly labor market, the worker is the residual claimant of health investments

[9] Recall that under a competitive labor market, wage offers are the same across all firms.

[10] Acemoglu and Pischke (1999) also provide various mechanisms that leads to the gap between the wage offer of the current firm and alternative offers.

This framework, however, departs from the context of the US labor market in which the majority of workers rely on employment-based health coverage. In the UK, all eligible workers are covered by publicly provided health care. Thus, there are differences in the relationship between health insurance and employment between the US and the UK. However, the context of health care institution in the UK does not alter substantially the implications of the model. The availability of publicly provided health care would reduce employers' incentives to provide health benefits to their employees. The universal health care may also reduce frictions arising from health investment, and thus, we return to the situation of a perfect labor market in which workers pay for their own health investments.

In summary, the model generates two predictions that can be tested empirically. First, firms with high rates of fatal injury are less likely to provide health insurance. The second prediction is that, as the provision of health coverage is conditional on risk levels, workers receiving health coverage would trade risk premium for health benefits. It implies that the VSL of workers with employer-provided medical insurance is lower than that of their counterpart without the insurance.

3.5 Data and Econometric specifications

3.5.1 Data

I use data from the British Household Panel Survey (BPHS). The BHPS collected information on a sample of the UK households annually from 1991 to 2008 (i.e. 18 waves). Employment data in the BHPS covered information on occupations, earning, education, tenure with the present employer, private health insurance coverage, and marital status. In this paper, I use the BHPS data from wave 12 to wave 17, which corresponds to the years of 2002-2007. Moreover, the BHPS also provided detailed information on health insurance coverage. I am able to identify respondents who are policy holders or dependents. We are also able to get information on the payment sources of private health insurance coverage. Specifically, there are three payment sources in BHPS data: 1 workers pay the coverage directly, 2 employers pay the coverage by deducting wages, and 3 employers fully pay the coverage. I define that a worker is covered by employer-sponsored health insurance if the coverage payment is in condition 2 or 3. I include condition 2 into the category of workers with EHI because the wage reduction compensating for EHI may not be one-for-one, that is, one pound sterling cash compensation does not necessarily compensate for one pound sterling value of health insurance. However, I use only condition 3 in robustness checks to see whether the estimation is sensitive to the definition of EHI.

Regarding the fatality variable, I employ fatality data from the UK Health and Safety Executive (HSE) that collects fatal injury rates at two-digit major industries annually. However, I use a two year average fatality rate in order to avoid large swings in fatality rates. For example, for the fatality rate in 2005, I use the average fatality rates of 2004 and 2005. The use of average fatality rates is common in many studies on VSL (Kniesner et al., 2012; Hintermann et al., 2010).

To make empirical results comparable with previous studies(Arabsheibani and Marin, 2000; Hintermann et al., 2010), furthermore, I pursue the same approach in constructing the sample. I focus on full-time male workers aged 20-65 living in England, Scotland, and Wales. I exclude Northern Ireland because UK HSE data do not cover the region. Similar to the US, I exclude self-employment. I also exclude farmers, agriculture sector, firefighters, police officers, persons in the Armed Forces and security personnel from the sample. Following a norm in the literature of VSL in the UK, moreover, I use annual labor income per year instead of hourly wage (Hintermann et al., 2010).

Table 4.2 presents the summary statistics of the UK sample. Real annual labor income in the UK sample is £27,480 at the 2010 price level. The fatality rate in the UK is substantially lower than the one in the US, that is, 1.15 per 100,000 workers. As we may expect, there is a striking difference between the US and the UK in regard to employer-sponsored health insurance. In the UK where the health care system is universal and all individuals are covered by National Health Service (NHS), the percentage of workers with employer-sponsored health insurance is small. In our sample, 17.5 % of the UK workers are covered by employer provided health coverage while it is around 82% from the US sample.

3.5.2 Econometric specifications

In this section, I present econometric specifications aimed at testing the main implications of the framework. I begin with the first implication of the framework, namely, jobs with high risk of fatal injury are less likely to provide health insurance. Ideally, one would use premium costs borne by firms. However, the BHPS does not provide such costs and we only observe health coverage status. With these data at my disposal, I estimate the following regression to test the first hypothesis.

$$H_{ijt} = c_i + \delta Z_{jt} + X_{ijt}\beta + \varepsilon_{ijt} \tag{3.1}$$

H_{ijt} is health insurance take-up for worker i (i = 1,. . . , N) in industry j (j =1,. . . ,J) at time t (t = 1,. . . , T). ; X_{ijt} refers to a vector consisting demographic variables: education, age, age squared, race, union status, marital status, occupations and states of residence. The error term is denoted by ε_{ijt}. Z_{jt} is the industry specific fatality rate. The fatality rate is the variable of interest.

A challenge to the identification of model 4.1 is that workers are not randomly assigned to jobs. Worker characteristics could induce workers' decision on the choices of job riskiness and of desirable fringe benefits, such as private health insurance. For instance, workers with relatively high ability would go to low-risk jobs that provide health insurance as well. If these characteristics are unobserved as is in ability the estimated δ will be biased.

To address this problem, I formulate the model as a linear probability model with fixed effects, and estimate it using the within estimator. This approach, however, imposes an assumption that health insurance status has a linear relationship with all explanatory variables. Another estimation strategy is the Chamberlain-Mundlak device (i.e. Correlated Random Effects or CRE), which can be used with non-linear models like probit. The CRE technique allows us to control for individual specific heterogeneity while it preserves a non-linear relationship between health insurance coverage status and covariates (Wooldridge 2010). Finally, to understand the magnitude of the bias stemming from not controlling heterogeneity, I also estimate model 4.1 with probit model.

The interest is to estimate wage premium for mortality risk at work and calculate value of statistical life. I begin with the standard hedonic model that is as follows.

$$lnw_{ijt} = c_i + \alpha Z_{jt} + X_{ijt}\beta + \varepsilon_{ijt} \tag{3.2}$$

$\ln w_{ijt}$ denotes the natural log of annual income and, the same as before, c_i is individual latent variable. The focal coefficient in our analysis is the coefficient of risk variable, α. It reflects the wage premium for risk and is a basis for calculating VSL.

The main implication of the framework is that the provision of health insurance affects the wage-risk tradeoff. In particular, If health insurance is negatively associated with risk but positively correlated with wage, as what we may observe empirically from model 4.1, omitting health insurance status from the standard model will lead to a downward bias in the risk coefficient. Consequently, the inclusion of health insurance increases the wage premium for mortality risk. In the following model, I include employer-provided health insurance status into the standard model.

$$\ln w_{ijkt} = c_i + \alpha_1 Z_{jkt} \ + \alpha_2 H_{ijkt} + X_{ijkt}\beta + \varepsilon_{ijkt} \tag{3.3}$$

In model 4.3, I assume that the slope of wage offer curve of the insured is the same as that of the uninsured, though they may have different levels of wages. However, the proposed framework in this paper suggests that workers with and without health insurance encounter different wage offers. Specifically, workers are willing to pay for the associated cost of health benefits in the form of lower risk premium such that risk affects the wage structure of the insured. That is, workers contribution to health insurance is now conditional on the level of job riskiness where workers in very dangerous jobs pay more than do workers in safe jobs to the costs of health insurance. To capture the impact of health insurance on the structure of wages, I interact the variable of risk of fatal injury and the indicator of health insurance coverage. Thus the specification 4.3 becomes

$$\ln w_{ijt} = c_i + \alpha_1 Z_{jt} \ + \alpha_2 H_{ijt} + \alpha_3 Z_{jt} * H_{ijt} + X_{ijt}\beta + \varepsilon_{ijkt} \tag{3.4}$$

In the above expression, α_1 now has a different interpretation. α_1 measures the wage premium for risk of workers without health insurance (i.e $H_{ijt} = 0$). The new feature of this specification is the interaction between risk and EHI status (i.e. $Z_{jt} \times H_{ijt}$). The coefficient of the interaction, α_3 , is aimed at capturing the effect of EHI on VSL. Thus, $\alpha_1 + \alpha_3$ is the risk premium of workers with health insurance.

Similar to the health insurance and risk relationship, there is a major issue pertaining to the identification of the hedonic wage models in equations 3.2, 4.3 and 4.4, namely, selection problem. That is, workers are not randomly allocated to jobs. Thus, unobserved heterogeneity, such as ability or unobserved productivity associated with risk is correlated with fatal injury and the health insurance coverage in jobs they choose. Failure to control for unobservables implies that the estimated coefficients of interest (i.e. α_1, α_2, and α_3) will be biased.

To better understand the magnitude of the bias due to unobservables, I use several econometric methods. First, I use models accounting for heterogeneity. In particular, I use panel fixed effects estimator—the most preferred specification—and panel random effects. Despite controlling for unobserved heterogeneity, in random effects model I impose an assumption that the unobserved individual heterogeneity is not correlated with the risk variable. I compare the models with a cross-section estimator: Pooled OLS (POLS). Here I assume individual heterogeneity is independent of the fatality risk variable.

The preferred specification, fixed-effects model, permits us to control for person-specific heterogeneity by employing within-transformation of data. However, within-transformation of data plausibly leave little variation in the fatality rate and as such, we may not be able to identify credibly the fatality parameter. Table 3.4 shows that between-group variation exceeds within-group variation. However, for all sample, the within-variation in the fatality rate is sufficiently large—i.e. it is about 39.6 % of the between variation. Thus, using fixed effects model is feasible to estimate VSL. Furthermore, the decomposition of variation by job switch status suggests that job switchers are the one that contributes substantially to within-group variation—, that is, the within variation of job switcher is 94.7 % of the between variation. Table 3.5 displays variation in employer health insurance coverage. We see that within-group variation in EHI status in the total sample is sufficient to identify the health insurance parameter (about 34.7 % of the between variation). Similar to fatality risk, a large fraction of within-group variation in EHI status is driven by job switching. I exploit this evidence to address potential endogeneity in risk and health insurance by estimating the fixed-effects model with the sample of job changers.

The implied value of a statistical life at the level of wages, $\bar{w}$, can be calculated as follows

$$\text{VSL} = [(\frac{\partial w}{\partial Z} = \alpha_1 \times \bar{w}) \times 100,000] \tag{3.5}$$

3.6 Results

3.6.1 Employer-provided Health Insurance and Fatality Rate

I begin with empirical results aimed at investigating the likelihood of health insurance coverage conditional on risk (i.e. equation 4.1). The specification is estimated by three econometric methods: Linear Probability model (LPM) with fixed effects, Probit and Probit with Correlated Random Effects (CRE). The results are then presented in table 4.3. The column 1 of the table exhibits the result of LPM while the column 2 and 3 report Probit CRE and Probit respectively. It is important to note that health insurance take-up reflects the equilibrium condition between health insurance offer from the firm side and the worker decision. Thus, in general, we can interpret the coefficient of risk in Table 4.3 as the equilibrium condition.

I find that workers in risky job injury are less likely to received employer-provided health insurance. In column 1, a one unit increase in fatality rate per 100,000 workers leads to a reduction in probability of receiving employer-provided health coverage by 0.35 percent. The coefficient of risk is significant at the confidence level of 95 percent. Compared to the employment-based health insurance rate of 16.6 %, this estimate represents a reduction of approximately 2.1 % in employer-provided health insurance coverage. We also see a similar effect of risk on the health insurance coverage with CRE probit in column 2, although it is not statistically significant at the five percent significance level.

It is also evident that failure to control for unobserved heterogeneity results in biased estimate of the risk coefficient. The marginal effect of fatality rate under probit model is positive although it is statistically insignificant. The difference in marginal effects of fatality rate between probit and linear model is clearly not driven by the difference in functional forms. The result of CRE probit, which is similar to linear model, confirms that latent heterogeneity is correlated with the fatal risk variable.

3.6.2 Health insurance and Wage Premium for Fatal Injury

In this section, I discuss my estimates on the wage-risk relationship, beginning with the baseline hedonic wage models. Table 4.4 presents the results of various model specifications, namely, pooled OLS (POLS), random effects model, and fixed effects model. Comparisons between panel fixed effects and other estimates inform us the magnitude of the bias in estimates of wage-risk premiums. Furthermore, I also calculate the implied value of a statistical life based on equation 4.11.

With the model controlling for person-specific heterogeneity—i.e. fixed effects model, the estimated risk premium for an increase in deaths per 100,000 workers is 0.28 %, and accordingly, the implied VSL is £7.73 million (2010 £). The estimate is statistically significant at the ten percent significance level. We see here an incorrect assumption regarding the relationship between latent variable and the fatality rate leads to biased estimate of the risk coefficient. The estimate from random effects specification assuming that latent variable is independent of fatal risk yield a high estimate of risk premium, and the implied VSL is around £23.21 million.[11] We also notice that failing to account for latent heterogeneity yields high VSL. With POLS model, the implied VSL is around £72.76 million.

For comparison with previous studies, the estimated VSL with fixed-effect estimator in this paper falls in the lower bound of estimated VSL relative to other papers that use cross-section estimators. Arabsheibani and Marin (2000) use cross-section

[11]Random effects assumes that heterogeneity is distributed normally and independent of the variable of interest. If the assumption is violated, the estimate will be biased.

estimators and find that the implied VSL is around £16.4 million (2010 £). For the sample of manual workers, Siebert and Wei (1994) find the implied VSL around £8.1-9.90 million, and Sandy and Elliott (1996) £5.05-68.07 million.[12] From Table 4.4, it is clear that an inability to control for individual-specific heterogeneity results in an upward biased in the estimated VSL. This explains why earlier studies that use cross-section estimators yield high VSL. Hintermann et al. (2010) using the BHPS data find lower VSL than what I find, and the risk coefficient in their estimate is not statistically significant. A plausible explanation to the insignificant coefficient of risk in their finding may be related to the sample size. In particular, they exclude the sample of Scotland from the estimation.[13]

Compared to recent findings from the US labor market data, the estimated VSL in this paper is within the range of estimated VSLs in the US. The exchange rate in 2010 was $1.5 per £, the implied VSL from this study is $ 11.6 million. From recent research in the US, Kniesner et al. (2012) find the range VSLs around $ 1.1 -15.1 million ($ 2010). Viscusi and Aldy (2003) review VSL studies on the UK and find that the implied VSLs from the UK are generally far higher than the implied VSLs from most developed countries. Different from previous studies on the UK, the finding from this paper suggests that the VSL from the UK is essentially comparable to those estimated from most developed countries.

It is also instructive to note that the substantial difference in estimates of VSL with heterogeneity versus without heterogeneity confirms the theoretical conjecture of Shogren and Stamland (2002) that failing to control for unobserved skill will overestimate the VSL. In particular, the reduction in the estimated VSLs after controlling for individual-specific heterogeneity suggests that heterogeneity reflects more safety-related productivity and risk preferences than general unobserved productivity in the context of Hwang et al. (1992).

In the next discussion, I present the result of VSL with health insurance as an additional control in the hedonic wage equation (Table 4.5). I find that with fixed-effects estimator, the estimated VSL including health insurance status is a half million higher than the VSL ignoring health insurance—i.e it is £8.3 for model with health insurance. This is consistent with the notion that health insurance is positively correlated with wages but is negatively related with risk, leading to the underestimated

[12]As Siebert and Wei (1994), and, Sandy and Elliott (1996) use the sample of manual workers. Thus, the implied VSL presented here is more comparable to the VSL based on Arabsheibani and Marin (2000)

[13]Hintermann et al. (2010) also use the same source of fatality data, that is, the UK Health and Safety Executive (HSE).

VSL in models ignoring EHI as a control variable. However, we also notice that EHI coverage is not sensitive to risk changes—i.e. this is a suggestive of small bias. Thus, the bias from omitting health insurance in the hedonic models seems to be small. Additionally, I still observe a consistent pattern that models accounting of person-specific heterogeneity yield lower VSLs.

The result of Table 4.5 departs from the model assuming that both workers with and without employer-supported health insurance face the same slope of wage offer curves. The framework in this paper, however, predicts that the provision of health insurance is conditional on the level of job riskiness. In particular, the contribution of employers to employees health benefits depends on risk levels: workers in risky jobs have to pay more than do workers in safe jobs to health insurance in the form of lower wages. Consequently, we expect that there is heterogeneity in VSL stemming from health coverage status: workers with employer-provided health benefits would have lower VSL than do workers with health coverage.

Model 4.4 is intended to test empirically the prediction, and, the empirical results are presented in Table 4.6. In general, models with an interaction between EHI and fatality risk increase wage-risk premiums relative to the standard model. Particularly, the coefficient on risk increases by 11-68 %, depending on the specifications, relative to models without health insurance. Given that the coefficient on risk in these specifications actually measures the rate of the wage-risk tradeoff for the uninsured workers (i.e. $H_{ijkt} = 0$), this evidence suggests that workers without employer-provided health insurance receive higher wage premium for risk of death at work than do the average workers (i.e. the wage-risk premium for all sample).

Columns 2 and 3 of Table 4.6 report estimates from the panel random-effects and the fixed-effects estimators respectively. The fixed-effects estimator produces the implied VSL of workers without employer-provided health insurance at £13.55 million, which is almost double the estimated VSL in the hedonic model without health insurance. The finding from the US, I find the VSL of uninsured workers is around \$ 23.2 million (\$ 2010). If we convert the implied VSL of the UK workers without health insurance, it is \$ 20.3 million (i.e. £13.55 $\times$ \$ 1.5 per £). So the VSL of workers without employment-based health insurance is quite comparable to that of the uninsured workers in the US. Moreover, columns 1 of Table 4.5 presents the result of the cross-sections estimator. In contrast to specifications controlling for person-specific heterogeneity, these specifications produce considerably high wage premiums for risk—about 2.86 %, and the implied VSL is £78.7 million.

I estimate the risk premium for workers with health insurance from the the sum of the risk coefficient and the coefficient of the interaction term between the risk and health insurance (i.e. $\alpha_1+\alpha_3$). I find that workers with health insurance receive a negative risk premium, implying negative VSLs in both fixed-effects and random-effects estimators. The negative risk premium is inconsistent with the standard compensating differential theory. But, it suggests that workers may be willing to trade their value of life for health benefits that cost greater than their risk premium. To be more specific, a worker without health insurance accepts risk premium at £136 annually for an increase in fatality rate by 1 per 100,000 workers (i.e the risk coefficient times the average annual earning, that is, 0.0049 times £27,480). Now, a worker who wants health coverage has to give up the risk premium, which is £136 annually, and, he is willing to pay additional £409 annually (i.e. 0.0198 times £27,480) for the coverage in the form of lower wages. That is, the cost of health insurance that workers are willing to pay for an additional increase in fatality rate, on average, is £545 annually. Therefore, as the cost of health insurance for an increase in one unit fatality rate is greater than the risk premium, we observe the negative risk premium for workers with health insurance.

It is instructive to note that the cost of health insurance discussed above is not necessarily equal to the market price of health insurance. Instead, it reflects more the rate of tradeoff between risk premium and health insurance that workers are willing to make. However, this finding from the UK is intriguing, particularly as we compare the finding with that of from the US. In the US, I find the positive risk premium for the insured, suggesting that the health insurance cost less than the risk premium for an increase in one unit fatality rate per 100,000 workers. A plausible explanation to this rests on the UK healthcare system that universally covers all eligible individuals. Under universal health care system, all workers essentially get necessary health care at free cost. Additional provision of health care through private medical insurance can be viewed as luxurious for employers and workers in jobs with high risk of death. Therefore, the employer-provided health coverage must be compensated by a substantial wage reduction, and, the extent of wage reduction depends on risk levels.

Another plausible explanation to the negative coefficient on the interaction between health insurance and risk is because spurious negative correlation between wage and risk for the sample of workers with health insurance. This may happen when other covariates such as time dummies do not control a trend that workers may move to jobs offering health insurance, higher wages and less risky jobs. To check this possibility, I separate estimations by the sample of those who stayed and changed their jobs (I discuss this in the robustness checks section). However, the findings from the split samples do not confirm this. The negative risk premium for workers with health insurance may be attributed to non classical measurement error. Black and Kniesner (2003) find that non classical measurement error contribute to inconsistent estimate of VSL. The same argument is also proposed by Viscusi and Aldy (2003) in explaining high estimated VSL from the UK, or Hintermann et al. (2010) that also find the negative VSL.

Furthermore, it is useful to put the findings presented in Table 4.6 into the context of theoretical predictions in Hwang et al. (1992) and Shogren and Stamland (2002). The substantial difference in estimated VSL with individual-specific heterogeneity versus without individual-specific heterogeneity in the model reaffirms the theoretical emphasis of Shogren and Stamland (2002). That is, latent individual heterogeneity is likely to represent unobserved skill related to personal ability to avoid injury, and risk preferences. Accordingly, failure to control for unobserved skill leads to a potentially substantial upward bias in the estimates of compensating differentials for fatal risk. However, job characteristics inducing labor productivity are also important to control in the hedonic wage function, and particularly, if these characteristics vary with the level of mortality risk (i.e. health insurance). We see that employment-based health insurance induce, indirectly, worker productivity and omitting health insurance status from the hedonic wage model leads to a potentially substantial downward bias in the estimated VSL. This evidence lends support to the theoretical conjecture in Hwang et al. (1992).

3.6.3 Robustness Checks

In this section I undertake several robustness checks. First, I consider the importance of job change status in the estimated VSL. Here I focus on the VSL estimated by fixed effects estimator. Second, for the model with the interaction between health insurance and the fatality risk, I define workers with employer-provided health insurance as those whose health insurance is fully paid for by their employers.[14]

Fixed Effects Estimator Specification Checks

The fixed-effects model permits us to control for person-specific heterogeneity by employing a within-transformation of data. However, it comes at the cost of eliminating

[14]Recall, previously I define those with health insurance as workers whose health insurance are 1) paid through wage deduction and 2) fully paid for by employers.

cross-sectional variation that provides important information on wage differentials across industry groups—i.e. variation that reflects true differences in job riskiness. Under the fixed-effects model, the main source of identification relies on within-group variation that arises from 1) changes in fatality risk in a given industry group and 2) job changes resulting in the changes of fatality risk—i.e. workers move to different industry cells over the sample periods. Variation coming from changes in the industry specific fatality risk could confound estimates of risk premiums if these changes are not systematically reflected in wage levels. That is, over time workplace safety tends to improve (i.e. fatality risks fall), and, at the same time, for other reasons real wages are more likely to increase. Another possible confounding factor for the fixed-effects model is that individuals may learn about risks on the job over some periods and switch if wage compensation for the risk is inadequate.[15]

On health insurance, workers generally stay in jobs that provide health coverage, and, the effect of health coverage on real wages could also be confounded by the general trend of increased wage levels. Moreover as we observe the same individuals over time, the source identification of the effect of EHI on wages comes mainly from changes in health insurance status—i.e. workers who gain or lose health coverage. Thus, it is likely that health insurance gainers/losers are also those who change jobs.

This implies that the fixed effects model—despite controlling for heterogeneity—potentially underestimates the VSL. In this part, I investigate the importance of job changing status for the wage-risk premium estimates in Tables 4.5 and 4.6. Particularly, first I estimate risk premiums for job changers while I still control for unobserved heterogeneity (Schaffner and Spengler, 2010; Kniesner et al., 2012).[16] I then compare the estimated VSLs for job changers with that of workers who never change jobs. The results are presented in Table 4.7.

Columns 1 and 2 of Table 4.7 exhibit estimates of VSLs by job change status. In addition, Columns 3 and 4 present VSLs for workers with and without health insurance by job change status as well. Overall, the main identification of compensating differential for fatality risk comes from workers who switch industry groups. the variation of fatal risk for job stayers, however, does not reveal much compensating differentials for fatality risk. I find that VSL with the sample of job changers is around £1 million higher than the estimated VSL with the whole sample presented in

[15]Another possibility is that over time workers may accumulate skills that enable them to cope with risk of injury.

[16]Several papers also use job changers—i.e. displaced workers—to solve endogeneity of health coverage and then estimate the health insurance-wage tradeoff (Simon, 2001; Lehrer and Pereira, 2007).

Table 4.5. The job stayers, however, receive lower wage premium than do the overall workers. The low VSL of job stayers suggests that wages do not fully respond to an industry-specific fatality risk, leading to underestimate the VSL.

In the model with the interaction between health insurance and fatality risk, we also see that much variation producing a compensating differential comes from job changers. The job changers accept far lower and negative risk premium in exchange for health insurance than do their counterpart who never change jobs. Here, we do not see that the negative risk premium for workers with health insurance can simply be explained by spurious relationship between wage and risk. This finding supports the argument in Hintermann et al. (2010) that the risk measurement errors may be correlated with other covariates, and that, the direction of bias is unknown.

Changing the Definition of Employer-Provided Health Benefits

Above estimates of VSL that include health insurance in the model define employer-health insurance as health insurance that 1) is paid for by workers in the form of reduced wages (I call this as Group 1), and, 2) is fully paid for by employers (Group 2). This definition may not truly fit with the criteria of 'employer-provided health insurance' as workers of Group 1 pay their own health insurance through deducted wages. These two groups have different constraints with respect to their ability to trade wage compensation for health insurance. Specifically, workers of Group 1 have more flexibility to trade health benefits for cash compensation. Suppose a worker of Group 1 finds that it is not optimal to have health insurance, he could drop the health coverage and receive full wage compensation instead. On the other hand, the worker of Group 2 accepts a job package consisting of 'fully-paid' employer-sponsored health insurance and wage. Here, he cannot trade his health insurance coverage for cash compensation. As a result, both groups may behave differently with respect to health coverage as fatal risk increases. In particular, the demand for health coverage among Group 1 —i.e. those who pay for it in the form of lower wages—tends to be more responsive to the increased risk. This is in contrast to workers of Group 2 that might be less sensitive to changes in fatal risk as they have limited ability to adjust their job packages. Although workers in Group 2 report that their health coverage is fully paid by employers, holding other things the same, their relative wages may be, after all, similar to wages of workers in Group 1—i.e. employers tacitly reduce Group 2's wages to compensate health benefits.

Different constraints that these two groups face bring several implications to the estimates of VSL. First, we should expect that the bias in VSL due to omitting health insurance would be lower when we only use Group 2's health coverage status in the estimation. That is, since health insurance coverage for Group 2 is less responsive to fatal risk, health insurance status would be weakly correlated with both risk and wage levels. The second implication is that the rate of tradeoff between risk premium and health coverage would be larger, in the absolute term, among workers of Group 2. This is because the workers of Group 2 cannot exchange health coverage for cash compensation although they may have low value on health coverage. As a result, they accept substantial lower risk premium than it would have been if they could trade health benefits for cash compensation.

In this part, I perform additional tests in which employer-provided health insurance is defined as health coverage that is fully paid for by employers (i.e. Group 2 only). Table 4.8 exhibits the result of VSL where health coverage status used in the model refers to only Group 2' health insurance status. Compared to Table 4.5, the implied VSL with fixed-effects estimator is slightly lower. It suggests that the bias of not including health insurance in VSL is more likely to arise due to omitting the health insurance status of workers who pay for it. Moreover, Table 4.9 shows that the VSL of workers without fully-paid employer-provided health insurance is £1 million lower than the VSL of workers without any employer-sponsored health insurance presented in Table 4.6. The coefficient of the interaction term between health insurance of Group 2 and fatality rate is also lower than the same interaction term but using the health insurance status of both groups. It suggests that the Group 2's rate of tradeoff between risk premium and health insurance is higher, in the absolute term, than that of overall sample of workers with any employer-provided health insurance.

Although we observe changes in VSL when we use only the health insurance status of Group 2, overall the changes are small. This additional analysis suggests that previous findings are quite robust with changes in the definition of employer-sponsored health insurance.

3.7 Conclusion

In this paper, I investigate whether non-pecuniary benefits have an impact on wage premiums for risk of death. The link between health insurance and compensating differentials for risk rests on the incentive of employers to provide health insurance and the workers' valuation of the coverage. Health benefits can be profitable to employers if employers can capture productivity gains from better health. Yet, improving workplace safety and providing health benefits at the same time are costly to employers. It is even more costly when the costs of health benefits are increasing with respect to the level of job hazards. Employers with high level of hazards, therefore, are less likely to provide health benefits. It also implies that workers have to trade risk premium for health benefits.

Using data from the British Household Panel Survey (BHPS), I find that workers in risky jobs are less likely to receive employer-provided health insurance. The negative effect of mortality risk on the likelihood of being covered by EHI is small but statistically significant. Perusal of compensating wage differentials for risk suggests that failing to control for unobserved individual heterogeneity leads to an upward biased of VSL. Models accounting of individual heterogeneity reduce estimates of compensating differentials for risk—relative to cross-section estimator—by 68-89 %. In particular, the estimated VSL with fixed-effects model is £7.73 million. Inclusion of health insurance in the baseline model leads to a slightly increase in the estimated VSLs by 7.3 %. The increase in VSLs in the model with health insurance suggests that the VSL is likely to be biased downward when we omit health insurance status from the standard model. However, the bias seems to be small due to the low responsiveness of EHI to mortality risk at work.

There is evidence of heterogeneity in the estimated VSLs stemming from EHI coverage status. I find that workers without employer-sponsored health insurance receive higher wage premium for mortality risk, implying a higher VSL for this group. Specifically, interacting employer health insurance status with fatal risk increase the coefficient of risk by 63.25 %. Workers with employer-provided health insurance, however, receive, a negative wage premium for fatality risk. It is less clear why workers with health insurance receive a negative risk premium. One explanation is that it may be related to the UKs universal health care system. Private medical insurance, including employer-purchased health insurance, offers health services that are similar to those provided under the NHS. Hence, providing additional health coverage while publicly-provided health care is available at no cost at service point would be costly to employers, particularly employers in industries with high levels of fatal risk. So employers pass the full associated costs of health benefits to workers. At the same time, workers who value the benefits of private medical insurance are willing to pay for it. Another possible explanation is that the risk measurement errors that are correlated with other covariates in the hedonic wage model.

Table 3.1: Motives for purchasing private health insurance (percentage of employers)

Motives	**1998**	**1999-2000**	**2001**
To get staff back to work quickly	33.0	35.0	25.3
As a "perk" for employees	13.0	13.4	18.3
To keep the benefit package competitive	17.0	12.9	16.5
To ensure staff are well cared for during illness	20.0	22.7	17.0
To increase productivity	7.0	6.2	10.8
To reduce sickness-absence costs	10.0	9.8	10.1

Source: AON Health Solutions (2002) cited from Foubister et al. (2006)

Table 3.2: Coverage of Employer-Provided Health Insurance by Industry Group

Industrial Grouping	Covered by EHI	Sample Size
Mining And Quarrying	37.80	164
Manufacturing	17.36	4066
Electricity, Gas And Water Supply	17.22	209
Construction	9.99	1422
Trade, Repair of Motor Vehicles and Personal and Household Goods	10.61	1980
Hotels And Restaurants	6.65	406
Transport, Storage And Communication	10.01	1438
Financial Activities	41.67	732
Property, Business And Research Activities	22.52	1856
Public sector	1.58	1074
Education	1.18	763
Health and Social Work	1.16	689
Other Social Services	8.13	578
Total	17.52	15377

Source:BHPS

Table 3.3: Summary Statistics

Variables	Mean	Standard deviation
Real annual income	27,480	16,991
Natural log of real annual income	10.06	0.616
Fatality rate	1.154	1.886
Employer health insurance	0.175	0.380
Age	39.61	11.36
Years of schooling	13.79	3.689
White	0.904	0.295
Married	0.568	0.495
Union	0.279	0.449
Natural log of tenure	1.441	0.884
Occupations		
Managers and Senior Officials	0.209	0.406
Professional	0.102	0.303
Associate professional and Technical	0.123	0.328
Administrative and Secretarial	0.096	0.295
Skilled trade	0.181	0.385
Personal Service	0.033	0.178
Sales and Customer Service	0.045	0.207
Process, Plant and Machine Operatives	0.144	0.351
Elementary Occupations	0.068	0.251
Employment Size		
< 9	0.155	0.362
10-49	0.273	0.446
50-99	0.119	0.324
100-199	0.114	0.318
200-499	0.150	0.357
500-999	0.077	0.267
> 1000	0.111	0.314
Observation	15377	

Source: BHPS

Table 3.4: Between- and Within-Group Variation for Industry Fatality Rates

Sample	Overall variance	Within-group variance	Between-group variance
All sample	3.52	1.00	2.52
Never-change industry	3.12	0.43	2.69
Ever-change industry	4.24	2.06	2.18

Source: BHPS

Table 3.5: Between- and Within-Group Variation for Industry EHI coverage

Sample	Overall variance	Within-group variance	Between-group variance
All sample	0.11	0.03	0.08
Never-change industry	0.11	0.02	0.09
Ever-change industry	0.10	0.04	0.07

Source: BHPS

Table 3.6: Marginal Effects of Fatality Rate on EHI coverage

VARIABLES	FE	CRE Probit	Probit
Fatality rate	-0.0035**	-0.0027	0.0024
	(0.0016)	(0.0061)	(0.0070)
Mean fatality rate		0.0076**	
		(0.0036)	
Observations	15,377	15,377	15,377
R-squared	0.0149		
Log-likelihood		-6204.58	-6211.84

Note: Dependent variable is employer-sponsored health insurance coverage (EHI). Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For probit and CRE Probit, additional control variables are years of schooling and race (i.e. white). CRE Probit also control the mean of fatality, the mean of age, the mean of age squared, and the mean of log tenure. Standard errors are in parentheses. Standard errors for Probit and the fixed-effects estimator are clustered by industry and robust to heteroskedasticity. *** significant at 1%, **5%,* 10%.

Table 3.7: Estimates of Wage Premium for fatal risk: Baseline Specification

Variables	**POLS**	**Random Effects**	**Fixed Effects**
Fatality rate	0.0265**	0.0084*	0.0028*
	(0.0102)	(0.0044)	(0.0015)
Observations	15,377	15,377	15,377
R-squared	0.3454	0.2905	0.1100
Implied VSL (millions)	72.76	23.21	7.73
	(27.91)	(12.13)	(4.18)

Note: Dependent variable is natural log of real annual labor income. Standard errors are in parentheses. Standard errors for the Pooled OLS and Fixed effect estimators are clustered by industry and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For Pooled OLS and random effects estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source BHPS.

Table 3.8: Estimates of Wage Premium for Fatal Risk: Models with Health Insurance

Variables	POLS	Random Effects	Fixed Effects
Fatality rate	0.0256**	0.0090**	0.0029*
	(0.0088)	(0.0042)	(0.0015)
EHI	0.277***	0.144***	0.062***
	(0.0415)	(0.0211)	(0.0160)
Observations	15,377	15,377	15,377
R-squared	0.3711	0.3176	0.1103
Implied VSL (millions)	70.43	24.73	8.29
	(24.27)	(11.48)	(4.22)

Dependent variable is natural log of real annual labor income. Standard errors are in parentheses. Standard errors for the Pooled OLS and Fixed effect estimators are clustered by industry and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For Pooled OLS and random effects estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source BHPS.

Table 3.9: Estimates of Wage Premium for Fatal Risk: Models with the Interaction between Health Insurance and Fatal Risk

Variables	POLS	Random Effects	Fixed Effects
Fatality rate	0.0286**	0.0109**	0.0049**
	(0.0094)	(0.0043)	(0.0019)
EHI	0.3028***	0.1635***	0.0803***
	(0.0466)	(0.0234)	(0.0134)
Fatality rate X EHI	-0.0261	-0.0190*	-0.0198***
	(0.0202)	(0.0106)	(0.0037)
Observations	15,377	15,377	15,377
R-squared	0.3717	0.3181	0.1122
Implied VSL without EHI (million)	78.72	29.93	13.55
	(25.80)	(11.80)	(5.26)
Implied VSL with EHI (million)	6.98	-22.19	-40.91
	(58.53)	(32.83)	(6.65)

Note: Dependent variable is natural log of real annual labor income. Standard errors are in parentheses. Standard errors for the Pooled OLS and Fixed effect estimators are clustered by industry and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For Pooled OLS and random effects estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source BHPS.

Table 3.10: Estimates of Wage Premium for Fatal Risk by Job Change Status

Variables	**Baseline**		**Interaction**	
	Ever Change Job	**Never Change Job**	**Ever Change Job**	**Never Change Job**
Fatality rate	0.0035*	0.0009	0.0065**	0.0014
	(0.0019)	(0.0025)	(0.0024)	(0.0024)
EHI			0.0847**	0.0709**
			(0.0287)	(0.0309)
Fatality rate X EHI			-0.0284***	-0.0063
			(0.0067)	(0.0073)
Observations	6,817	8,560	6,817	8,560
R-squared	0.1238	0.1119	0.1266	0.1140
Implied VSL (million)	9.31	2.41		
	(5.14)	(6.99)		
Implied VSL without EHI (million)			17.30	3.94
			(6.28)	(6.81)
Implied VSL with EHI (million)			-57.75	-13.81
			(14.74)	(20.63)

Note: Dependent variable is natural log of real annual labor income. Standard errors are in parentheses. Standard errors for the fixed effect estimators are clustered by industry and robust to heteroscedasticity. The model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. *** significant at 1%, **5%,* 10% Source BHPS. significant at 1%, **5%,* 10% Source BHPS.

Table 3.11: Estimates of Wage Premium for Fatal Risk with Fully-Paid EHI

Variables	POLS	Random Effects	Fixed Effects
Fatality rate	0.0252**	0.0088**	0.0029*
	(0.0089)	(0.0042)	(0.0015)
EHI	0.3005***	0.1446***	0.0555***
	(0.0384)	(0.0178)	(0.0136)
Observations	15,377	15,377	15,377
R-squared	0.3707	0.316	0.1112
Implied VSL (millions)	69.34	24.10	8.00
	(24.52)	(11.51)	(4.16)

Note: Dependent variable is natural log of real annual labor income. EHI is fully-paid employer-provided health insurance. Standard errors are in parentheses. Standard errors for the Pooled OLS and Fixed effect estimators are clustered by industry and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For Pooled OLS and random effects estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source BHPS.

Table 3.12: Estimates of Wage Premium for Fatal Risk with the Interaction between Risk and Fully-Paid EHI

Variables	POLS	Random Effects	Fixed Effects
Fatality rate	0.0274**	0.0103**	0.0045**
	(0.0092)	(0.0042)	(0.0018)
EHI	0.3232***	0.1638***	0.0767***
	(0.0439)	(0.0206)	(0.0112)
Fatality rate X EHI	-0.0225	-0.0186*	-0.0205***
	(0.0176)	(0.0105)	(0.0032)
Observations	15,377	15,377	15,377
R-squared	0.3711	0.3163	0.1118
Implied VSL without EHI (million)	75.16	28.30	12.49
	(25.37)	(11.48)	(5.08)
Implied VSL with EHI (million)	13.43	-22.87	-43.95
	(53.99)	(33.75)	(4.93)

Note: Dependent variable is natural log of real annual labor income. Standard errors are in parentheses. Standard errors for the Pooled OLS and Fixed effect estimators are clustered by industry and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, log tenure, the size of employees, 1 digit occupations, regions of residence and year dummy. For Pooled OLS and random effects estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source BHPS.

Chapter 4 Personality Traits and the Choice of Job Riskiness

4.1 Introduction

Different occupations exhibit vastly different job-related likelihood of death and injury. Certain occupations expose workers to high probabilities of injury, such as construction laborers or truck drivers. Despite these risks, some people are voluntarily willing to bear the risks for higher wages in return, holding other things constant. Meanwhile others are less disposed to tradeoff wages and risk. This observed behavior in the labor market is the key prediction of the compensating differential theory that heterogeneous people would sort into jobs based on their preferences to exchange wages for risk.

The extent of worker sorting by risk preferences has implications for labor market policies. Researchers and policy makers have long used observational labor market data to estimate wage premium for risk. The estimated wage premium reflects workers' valuation of risk, and thus, the benefits of job safety improvement (Viscusi and Aldy, 2003). The sorting of worker in the labor market based on preferences for risk suggests that job assignment is not random. Thus, failure to account for heterogeneity in risk preferences will bias the estimated wage premium, implying that the benefits of job safety could be overestimated (or underestimated).

However, Shogren and Stamland (2002) note that an individual who chooses to work in a riskier occupation reveals that "he is more tolerant to risk or has personal ability to reduce risk of death or both". This implies that the sorting of workers in regard to job riskiness is not only driven by risk preferences but also skills—i.e. personal ability to reduce personal risk of injury. Meanwhile previous research focuses more on the sorting of workers based on risk preferences (Garen, 1988; DeLeire and Levy, 2004). The extent of sorting in the labor market based on the personal skill has not been adequately tested. The reason may be due to the difficulty of measuring workers' personal skill as it cannot be observed directly using observational labor market data. Yet, there is practical importance of taking into account the job-safety related skill, particularly, for the estimated wage premium for risk. Kniesner et al. (2012) estimate workers' valuation of fatal risk using modified hedonic wage models accounting for two forms of latent variables—i.e. unobserved general productivity and job safety-related productivity/skill. They find that controlling for the latent variable reduces the estimated wage premium for risk: this lends support to the prediction of

Shogren and Stamland (2002) and suggests that workers in dangerous jobs are more likely to have, at least, the personal skill to avoid risk of fatal injury.

This paper investigates worker sorting based on safety-related skills. Recent research has suggested that skills consist of multiple dimensions (Borghans et al., 2008). Using a common term in the literature, economists and psychologists distinguish two skills into cognitive and non-cognitive skill. Cognitive skill is well known as a strong predictor for socio-economic outcomes. Recent studies suggest that non-cognitive skill or *personality trait* (i.e. perseverance, extraversion, self-control) play as equally important role as cognitive skill. Undoubtedly, cognition is essential in forming safety-related skills. This is obvious as cognition is critical in learning, processing information and decision making that are helpful for one to avoid accidents at workplace. However, occupations that intensely employ cognition are more likely to be safe jobs. Thus, individuals with high level of cognitive skill tend to be employed in safer occupations. Different from cognitive skill, personality traits consist of a wide array of elements and the importance of each element at workplace can vary substantially across occupations.

In this paper, I focus on the role of personality traits in safety-related skill and their influence on worker sorting based on job risk. I pursue a pragmatic approach by which I use measures of personality traits that have been developed by personality psychologists and, recently, widely used by economists. Specifically I use Five-Factor Model of personality or also known as the Big Five personality traits (Borghans et al., 2008). The big 5 personality traits are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. In our framework, these personality traits are inputs and the technology of skill formation transforms the traits into safety-related skill. This notion is similar to that of Heckman et al. (2006). Yet I use a simpler approach in which I directly employ measures of personality traits to observe worker sorting.

Individual with different personality traits would sort into different occupations as each occupation may demand and value more particular traits. For instance, a construction job requires workers to do a thorough and organized work. Hence, dutifulness (or not careless) would be an essential facet that workers must have to avoid accidents. This facet may not be essential for workers in sales job that require more social skill or gregariousness. Some personality facets under this big 5 personality inventory encompass individual's qualities that are important for one to survive in riskier occupations.

The sorting of workers occurs because individuals are differentiated to the extent of their personality traits. Everyone could develop ability to be careful and more organized at work. But an individual with a strong trait of dutifulness tends to develop the ability more quickly at lower cost than other who have no strong dutiful trait.[1] As individuals have different degrees of traits, we may expect that they have different skill levels. Under the big 5 personality traits, dutifulness is part of conscientiousness. Therefore, high conscientious individuals are expected to have higher safety-related skill.[2]

The framework of this paper is related but conceptually different from the literature on "grit" (Duckworth et al., 2007). In this paper, worker sorting occurs because some traits tend to be more crucial than others for specific vocations. As discussed previously, gregariousness is more relevant to sales job than construction. Grit, on the other hand, seems to be essential to success regardless the domain. (Duckworth et al., 2007) note that grit includes continuous working toward challenges, maintaining effort and interest over some long periods despite failure and adversity.[3] Hence, grit is the key to high achievement in many fields. Despite this, grit might overlap with some facets of the Big 5 personality traits—that is, grit overlaps with achievement aspects of conscientiousness, such as achievement striving, self-discipline, and self-control. But different from conscientiousness, grit emphasizes more on long-term stamina rather than short-term intensity (Duckworth et al., 2007). This is the key distinction between the Big 5 traits that I use in this paper and grit. It is plausible, however, that grit is the underlying factor behind worker sorting too. That is, harsh jobs typically do not require persistence effort over some long periods. For instance, someone who works continuously in music would finally achieve a prominent career in the music industry, which is, obviously, safer occupation while there might no need persistent effort for one choosing career as a carpenter. However, data at my disposal do not provide me with relevant grit measures such as consistency and perseverance of effort. Despite these limitations, for our purpose the Big 5 personality traits provide enough measures to assess worker sorting based on traits.

In this vein, moreover, I view that personality traits have a productive dimension (i.e. productive traits) and they emerge into safety-related personal skills. However, different from the standard human capital theory in which skill is typically valuable in all occupations, individual traits are rewarded differently across occupations. Some aspects of conscientiousness, as in the previous example, could be valued more in

[1]The cost can be in the form of time needed to develop this skill.

[2]We can think of safety-related skill as specific skill that is valued more in riskier occupations.

[3]In the words of Duckworth et al. (2007) , the gritty individual approaches achievement as a marathon.

riskier jobs compared to safer jobs. Consequently, conscientious individuals choose to work in riskier occupations. My approach to personality traits as productive traits is part of growing research focusing the role of non cognitive skills in the labor market. There is a large body of studies that view personality traits as skills or a set of productive traits, and, find that personality traits play as equally important role as cognitive ability in many socio-economic outcomes (see Bowles et al. (2001); Nyhus and Pons (2005); Heckman et al. (2006); Mueller and Plug (2006); Borghans et al. (2008); Fortin (2008); Heineck and Anger (2010); Almlund et al. (2011)).

Using data from the United Kingdom Household Longitudinal Study (the UKHLS), I find evidence of worker sorting based on personality traits. I particularly find that conscientious and extravert individuals tend to be employed in riskier jobs (i.e. jobs with high rate of fatal and nonfatal injury). In regard to conscientiousness, personality facets covered in this category describe qualities that are clearly important for someone to handle a harsh working environment. On the other hand, I also find that agreeableness, openness, and neuroticism are negatively associated with risk of injury—i.e. individuals with these traits are inclined to choose safer jobs. Neuroticism in particular includes dimensions such as anxiety, nervous (vs relaxed) and impulsiveness. These traits do not render the necessary skill to reduce risk of injury and are less valued in riskier occupations.

There is concern about the reliability of personality measures (i.e measurement error). To quantify the extent of measurement error, I calculate reliability coefficients for personality trait measures by calculating Cronbach's alpha coefficients. While the estimated coefficients are close to the ones from previous studies, a considerable fraction of the variability in the measured traits is because of measurement error. Another concern is the direction of the relationship, that is, *current* environments (e.g. occupations, age) influence individuals' responses to personality trait questions in the survey. Heckman et al. (2006) show that scores of personality test are affected by the levels of schooling at the time of test. Meanwhile some studies on personality suggest that personality traits are relatively stable and insulated from environment (Costa Jr and McCrae, 1994; McCrae and Costa, 2003). Despite finding from personality literature, I conduct several sensitivity analyses. First, I use 'adjusted' personality traits. The adjusted personality traits are residuals from the regression of personality traits on age and occupations. Hence, the adjusted traits are expected to be independent from the effects of age and occupations. Using this approach, I still find a consistent pattern on job sorting—i.e. agreeableness, openness, and neuroticism are associated negatively with risk of injury while conscientiousness and extraversion have a positive relationship with risk. Second, I use lagged measurers of traits. In particular, I regress current risk on past five year personality measures. Under the full specification, four traits (agreeableness, conscientiousness, extraversion and neuroticism) have the same sign as the previous estimates although they are not statistically significant.[4] It is only openness that changes the sign from negative in the previous estimates to positive in the estimate using the lagged score of personality traits. However, it is also not statistically significant. Overall there is evidence suggesting that sorting of workers and jobs based on personality traits and risk of injury occur.

In addition, I test whether inclusion of personality traits into the hedonic wage model reduces the wage premium for risk. That is, if the sorting of worker takes place and personality traits are inputs for safety-related skill, failure to control them results in upward bias on the coefficient of risk. Empirical results confirm the notion that personality traits can serve as a proxy for safety-related skill. In particular, OLS model controlling for personality traits yields lower estimated wage premium for risk than that of OLS model without traits. This informs us that inability to control the traits results in the upward bias of the risk coefficient. However, the OLS model with personality traits does not perform better relative to panel data estimators such as fixed effects and random effects. This is not surprising as job sorting is not only driven by heterogeneity in personality traits. Preferences on risks and other unobservables are clearly correlated with the decision of job riskiness and wage levels. Thus, they are important to be controlled as well in the hedonic wage equation.

This paper contributes to the literature in several ways. It provides new evidence about the relationship between personality traits and decision to work in risky jobs. The results complement DeLeire and Levy (2004) that show the role of family structure as risk preferences (or measures of risk aversion). Yet this paper conceptually differs from theirs where I treat personality traits as inputs for skill. In regard to this, this paper provides indirect evidence to the conjecture of Shogren and Stamland (2002) that workers who choose risky occupations suggest that they may possess skill to reduce personal risk of death at workplace. The paper may also provide additional insight on the observed earning differences by personality traits from previous studies. The relationship between personality traits and earnings are mediated through job sorting, and the sorting based on skills and job riskiness is among the one that could trigger differentials in earnings.[5]

I proceed as follows. In section 2, I discuss extensively the related literature. I also

[4]When I do not control for occupations, it is only neuroticism that is statistically significant.

[5]There is ample evidence of the positive relationship between wages and occupation-specific risks (Viscusi and Aldy, 2003).

propose a simple conceptual framework in section 3 to understand the relationship between personality traits and the choice of job riskiness. In this section, I discuss how personality traits can be used as inputs for skills. Section 4 data and econometric specifications. In regard to data, I elaborate measurements of risks and personality traits. The results are discussed in section 5 and provide sensitivity analyses. Section 6 concludes.

4.2 Related Literature

This paper is closely related to studies that job sorting based on the preferences of workers (Bonin et al., 2007; Krueger and Schkade, 2008). Bonin et al. (2007) show that workers sort into occupations based on risk preferences. In particular, individuals that show strong willingness to take risks are more likely to go to jobs with high earning variability—i.e. interpreted as high earning risk. They also show that attitudes toward risk affect wages, suggesting that, in addition to human capital such as education, individual attributes have an impact on incomes. Krueger and Schkade (2008) provide evidence that gregarious individuals are more likely to go to jobs that involve frequent social interaction. Specifically, workers who spent much time interacting with others (e.g. friends) tend to work in jobs that require high frequency of job-related interaction. In addition, they also show that these workers (i.e. workers in jobs with high frequent interaction) exhibit higher levels of job satisfaction. Their finding also suggest that working conditions, such as time pressure, close supervision, and perceived risk of job loss, determine work satisfaction. My paper elaborates further the evidence from Krueger and Schkade (2008). That is, I investigate how some individuals with particular personality traits enabling them to work under unpleasant working conditions tend to take such dangerous jobs.

In the literature of job-related risk, we also observe that individuals with particular attributes are sorted to occupations with different levels of risk of injury (Garen, 1988; DeLeire and Levy, 2004). Garen (1988) uses family structure, such as marital status and the number of children, to address the potential endogeneity of job riskiness in the hedonic wage model used to estimate the valuation of risk reduction (i.e. the value of a statistical life). The basic assumption here is that the family structure influences workers' willingness to accept risk and thus, job decision. DeLeire and Levy (2004) undertake a direct test on occupational sorting based on job riskiness. They show that individuals in the role of primary care givers are less willing to trade risk for wages and as a result, they choose to work in relatively safer jobs. Single moms and single dads are among the group of primary care givers who tend to work in occupations with low risk of death. They also find that among a group of married workers, the presence of children increases risk aversion more for women than for men (DeLeire and Levy, 2004). These papers are suggestive of family structure serving as a good proxy for worker preferences toward risk of injury at workplace.

This paper is also part of emerging research exploring the role of non-cognitive ability (i.e. personality traits) in the labor market (Bowles et al., 2001; Nyhus and Pons, 2005; Mueller and Plug, 2006; Heckman et al., 2006; Borghans et al., 2008; Cunha and Heckman, 2008; Fortin, 2008; Heineck and Anger, 2010; Cobb-Clark and Tan, 2011; Heineck, 2011; Bollinger et al., 2012; Nandi and Nicoletti, 2014). Heckman et al. (2006) provide evidence that cognitive and non-cognitive abilities affect social and economic outcomes. Consistent with previous research, they find evidence of cognitive abilities explaining much variation in wages. However, they also find that the effects of cognitive abilities are equally strong to the effects of non-cognitive abilities on the wage variation (Heckman et al., 2006). In some cases, the effects of non-cognitive abilities are stronger than cognitive abilities. For example, they find that non-cognitive abilities determine schooling decision (i.e. acquisition of skills) and earnings conditional on schooling levels. Both cognitive and non-cognitive also explain risky behaviors such as smoking, marijuana use, and teenage pregnancy and marriage. Cunha and Heckman (2008) argue that cognitive and noncognitive abilities affect labor market outcome through skill formation that is important in labor markets. In this paper, I pursue the basic idea in Cunha and Heckman (2008) that personality traits are essentially inputs for the skill formation that is required in risky jobs.

My paper is complementary to papers by Mueller and Plug (2006), Heineck and Anger (2010), and Heineck (2011) that use big 5 personality traits to predict labor market outcomes. Mueller and Plug (2006) suggest that personality matters in labor market and its effect on earning is comparable to that of cognitive ability. They propose the idea that big 5 personality traits (i.e extroversion, agreeableness, conscientiousness, neuroticism, and openness to experience) have productivity dimension—i.e. the idea views personality traits as human capital. Mueller and Plug (2006) show evidence that individuals possess higher levels of particular traits are observed of having higher earnings. Interestingly, returns to personality traits differ across gender. Men receive premium for being antagonistic (i.e. low level of agreeableness) and emotionally stable (i.e. low level of neuroticism). Being more conscientious (i.e. high level of conscientiousness) and open (i.e. high level of openness) are associated with higher earnings for women.

Using data from Germany, Heineck and Anger (2010) also provides evidence that lower level of agreeableness is associated with higher level of wages for men. However, he also finds that antagonistic females (i.e. low level of agreeableness) are also associated with higher wages. Thus, it suggests that agreeableness in general has a negative effect on wages. Heineck (2011) use data from the British Household Paney Survey (BHPS) and show evidence that higher agreeableness and neuroticism are associated with lower wages and they are particularly strong for female workers. Meanwhile being open to new ideas and conscientious are associated positively with wages.

Meanwhile these papers examine a direct impact of personality traits on earning. My paper focuses on the intermediary channel of personality traits. That is, personality traits affect wages through their influences on individual occupational choices. Cobb-Clark and Tan (2011) show that personality traits influence occupation segregation contributing to the disparity in relative wages between men and women. In this paper, I examine job sorting based on the risk of job-related injury and how personality traits determine this sorting process.

4.3 Conceptual framework

The framework of this paper is built upon the theory of equalizing differences (Rosen, 1986; Krueger and Schkade, 2008). The basic idea of the framework is that workers are differentiated by the extent to which they possess skills that make them more productive in dangerous jobs.[6] The skill is produced through the technology of skill formation that uses personality traits as inputs (Heckman et al., 2006). For example, a worker with personality of being organized tends to be more vigilant at work, and, this personality increases awareness toward his working environment. Thus, that worker has more ability to avoid injury. This notion is also related to the paper of Shogren and Stamland (2002) in which they argue that workers who take dangerous occupations reveal themselves that they are risk tolerant or they possess personal job-safety skills. The implication is that high skill workers would go to risky jobs and low skill workers go to relatively safe jobs. Hence, job sorting occur because workers differ in their skills driven by variation in personality traits.

To be more concrete, let D represent the level of job riskiness (i.e. both fatal and non-fatal injury). Let us assume D takes two value where $D = 1$ is the risky job and $D = 0$ is the safe job. The distribution of jobs depends on the technology of firms. However, I assume that it is too costly for a firm to change the level of riskiness given

[6] Skills here are individual abilities to reduce risk of injury at workplace (Shogren and Stamland, 2002).

the current technology. For instance, it would take an expensive technology for a construction job to reduce the rate of injury to the same level as that of a retail job. Hence I take the distribution of firms along D as given and focus matching on the side of workers.

The preference of a worker is represented by the wage rate and the job risk, that is, $U(W, D)$. The utility of all workers increases with wage. In regard to risk of injury, workers generally dislike the risk. Hence for some workers, D creates disutility and thus, $U(W, 1) < U(W, 0)$. However, some workers may find themselves more productive when working at risky job such that $U(W, 1) > U(W, 0)$. Shogren and Stamland (2002) posit that some workers may be more tolerant to risk or possess ability to reduce risk of injury and thus, they choose to work in risky jobs. Coolheaded workers, for example, probably are more productive working in risky occupations than safe jobs (Garen, 1988). Here I focus on the sorting of workers based on 'skill', and, pursue other studies that view personality traits as a set of productive traits that may be valued in particular occupations (i.e. riskier occupations)

Moreover, the skill enabling workers to reduce personal mortality risk at workplace is developed from the personality traits of a worker. Specifically, there is a technology of skill formation that transforms personality traits (e.g. self-consciousness, self-discipline, gregariousness) into skill. Hence, personality traits are five inputs to the skill formation. They are Openness (denoted by t_O), Conscientiousness (i.e. t_C), Extraversion (t_E), Agreeableness (t_A), and Neuroticism (t_N). Let s denotes skill and the technology of skill formation is governed by the following function.

$$s = k(t_O, t_C, t_E, t_A, t_N) \tag{4.1}$$

$k(.,.,.,.,.)$ is the technology of skill formation that I assume to be continuous and the same across all workers. A challenge for equation (4.1) is to predict the effects of personality traits on the personal skill reducing the personal likelihood of being injured. Regarding this, I rely on the description of personality facets and findings from previous psychological studies.

- *Openness to experience* encompasses the preference for ideas and imagination. Individuals with high openness show interest in artistic activities and occupations. Costa et al. (1984) find that open individuals are interested in occupations such as author, anthropologist, journalist, playwright, and independent research scientist. They are also generally curious and highly value knowledge (McCrae and Costa, 2003). These adjectives of openness are somewhat different from circumstances in risky jobs that are clearly not too artistic. Hence, I expect that open individuals are less able to develop the skill necessary for riskier jobs. As a result, I expect that $\partial k/\partial t_O < 0$,

- *Conscientiousness* indicates individual differences in dimensions of organization and achievement. It includes an individual preferences for self-disciplined and organized. Highly conscientious individuals tend to be dutiful and do a thorough job. These characteristics would enhance the skill relevant to deal with circumstances in risky occupations that often require order and vigilance. Therefore I expect that conscientiousness has a positive effect on the skill (i.e. $\partial k/\partial t_O > 0$).

- *Extraversion* incorporates the preference for social interaction. The personality facets include gregariousness, assertiveness and adventurous. Despite these adjectives, it is less clear whether extravert individuals are risk loving. In many instances, gregarious individuals would go to occupations with high social interactions with coworkers or customers such as sales or teachers. These occupations typically are low-risk jobs. Vestewig (1977), however, find the evidence that extroverts prefer gamble more than do introverts. Therefore, the effect of extraversion on the skill is ambiguous (i.e. $\partial k/\partial t_E \gtreqless 0$).

- *Agreeableness* encompasses individual dimensions of trusting and generous sentiments. Agreeable people show strong tendency to act in accordance with other people's interests. Antagonism (i.e. the opposite of agreeableness) is associated with tough minded and hardheaded. Some risky occupations require aggressiveness that means low agreeableness. Thus, agreeableness has a negative effect on the skill (i.e. $\partial k/\partial t_A < 0$)

- *Neuroticism* is a dimension of individual differences in anxiety (i.e. nervous versus relaxed), impulsive (i.e. emotional vs. calm) and mental stability. High neurotic individuals tend to worry a lot and get nervous easily. They are also not able to handle stress well. Lauriola and Levin (2001) find that high neuroticism is associated with less risky decision-making. Hence, I expect that the neuroticism has a negative effect on the skill required to reduce risk of injury (i.e. $\partial k/\partial t_N < 0$)

I assume that personality traits (i.e. t_p where $p = O, C, E, A, N$) are distributed normally across member of workforce (i.e $t_p \sim N[\mu_t, \sigma_t^2]$). This may be a strong assumption but Figure 4.1 shows that the distribution of personality traits resemble normal distribution. The skill technology is assumed to additive and linear in personality traits, so the distribution of s will be normal as well $s \sim N[\mu_s, \sigma_s^2]$, where μ_s and σ_s are the unconditional mean and standard deviation of s respectively.

The skill makes workers more productive and firms value the skill. Let denote r the unit price of the skill. Thus, total reward that the worker receives for the skill level s at price r is z (i.e. $z = rs$). That is, z is the total monetary value of the skill that is equivalent to the wage-payment.[7] As a result, the skill enters into the utility function through its monetary values generated by its productive use. Hence, the monetary value of skill is additional wage payments as workers possess the skill that is productive in risky jobs. Alternatively, in this setting we can think of z as compensating variation.

Now, there is z such that a worker is indifferent between accepting a risky job and a safe job i.e. $U(W_1 + z, 0) = U(W_1, 1)$. The safe job and the risky job pay differently and thus the wage differential between the two can be denoted as $\Delta W = W_0 - W_1$ where W_0 and W_1 are the safe job and the risky wages respectively. The job sorting process among workers depends on the relationship between z and ΔW for a worker. If $\Delta W < z$ for a worker then the worker would go to the risky job ($D = 1$). On the other hand, if $\Delta W > z$, thus the worker would go to the safe job ($D = 0$).

This framework shows a mechanism in which personality traits affect the choice of job riskiness through the skill formation. As workers are differentiated by the extent of personality traits, they would have different levels of the ability, s, and as a result, they receive different compensation, z. For instance, holding other traits constant, a worker with high level of neuroticism tends to have lower ability to handle stress. That is, that worker would have lower s and then, lower z. When z is low enough such that $\Delta W > z$, the worker chooses a safe occupation. Meanwhile a worker who is vigilant tends to be more protective and able to work carefully (i.e. high level of conscientiousness). This worker accumulates the skill reducing the likelihood of getting injured (i.e. high level of s). As the reward to the skill is linear on the level of the skill, higher s results in higher z. Consequently, the worker would choose a riskier job.

In the equilibrium, the assignment of workers to firms is determined by the number of job types (i.e. risky and safe jobs) and the distribution of workers' skill. On the demand side, the number of job types depends on the distribution of firm technology.

[7] This framework is similar to Almlund et al. (2011).

More specifically, job riskiness is tied to the firm technology.[8] Given the nature of technology, in the short run, firms find that reducing risks is too costly and they cannot switch from offering risky jobs to safe jobs. Thus, the technology of firms and types of jobs offered will be fixed. Further, holding the demand side (i.e. the firm side) and the skill price (i.e. r) constant, the supply of workers to risky jobs would depend on the distribution of z, which is also determined by the distribution of s. In particular, if the skill reward follow distribution $F(z)$ with smooth density function of z as $f(z)$ and normalize total labor force to 1, the fraction of workers going to safe jobs (i.e $D = 0$) is $\int_0^{\Delta W} f(z)\,\mathrm{d}z$ and the fraction to the risky job is $1 - F(\Delta W)$.

This simple framework suggests that workers would go to jobs where their skill is valued more. Workers whose personality traits improve the skill to reduce the probability of getting injured will seek riskier jobs, and, similarly, employers producing high levels of risk will seek such workers—that is, the job safety-related skill is valued more in riskier jobs. On the other hand, workers with traits that produce less the ability would go to safer jobs. This implies that job assignment is nonrandom. Thus, one can investigate further the sorting by examining the selection bias that occurs due to heterogeneity in the skill reward, z—i.e. this is also an implications of heterogeneity in the skill of workers, s. The selection bias is expressed as the gap between the conditional and unconditional expectation of z given D. Also, recall that the safety-related skill s is normally distributed, thus $f(\bullet)$ is also normally distributed. Therefore, the conditional expectation of z given that the job is risky (i.e. $D = 1$) can be written as

$$\mathbb{E}(z|D = 1) = \mu_z + \sigma_z \phi(\alpha)/(1 - \phi(\alpha)) \tag{4.2}$$

Where $\alpha = (\Delta W - \mu_z)/\sigma_z$. The unconditional mean of skill reward is μ_z and the standard deviation of z is denoted by σ_z. $\phi(.)$ and $\Phi(.)$ are the standard normal probability density function and cumulative distribution respectively. With data at my disposal, I am not able to observe directly skill s. However, as the skill technology is assumed to be linear and additive in personality traits, I parameterize skill as the first order approximation (I will discuss this more detail in the econometric section.).

[8]This conceptually follows Thaler and Rosen (1976) that job-related injury is by-product of production. The basic idea here is that the firm produces not only output sold to the consumer market but also risk of accidents sold to the labor market.

4.4 Data and Econometric specifications

4.4.1 Data

For the analysis, I use the United Kingdom Household Longitudinal Study (UKHLS or Understanding Society). The UKHLS is one of the largest longitudinal datasets. It collects the sample of 40,000 households with 100,000 individuals. Currently, there are three waves from the plan of 18 waves. The first three waves are the year of 2009, 2010, and 2011. The information of the UKHLS consists of hours worked, earning, workers' occupation, education, health condition and family status. Starting in the wave 2, the UKHLS includes sample from another longitudinal survey that took place before, namely, the British Household Panel Survey (BHPS). The BHPS is conducted annually from 1991 to 2009. In this regard, the UKHLS can be seen as the continuation of the BHPS, although the UKHLS collected additional non-BHPS respondents. Furthermore, the UKHLS collected more diverse socio-economic questions than did the BHPS. However, regarding data on employment and wages, the BHPS had more detailed information.

In the wave 3 (2011), the UKHLS collected information on the big 5 personality traits (i.e. personality module). The big 5 personality traits are collected through 15 personality related questions (in the following subsection I will explain more detailed on the big 5 personality trait questions). These questions are not asked in every wave. Given that, I merge the personality trait module with employment and individual information from three waves of the UKHLS. Moreover, I restrict the sample to respondents who were between the ages of 20 and 65 years, currently living in the UK, in full-time job and paid employment. The total person-year sample is 34,407 observations. Then, I merge the UKHLS data with data on job-related injury rates (i.e. both fatal and non fatal injury) the UK's Health and Safety Executive (HSE) from 2008-2012. The job-related injury dataset provides information on fatal and nonfatal accidents at the two digit Standard Industrial Classification code (SIC).

Risk Measures

I use two measures of job-related risk, namely, fatal and non-fatal risks. The risk variables are constructed from rates of fatal and nonfatal injury. The UK HSE provides a comprehensive inventory of all work-related injuries in a given year and it comes from reports by the Reporting of Injuries, Diseases and Dangerous Occurrences Regulations (RIDDOR).

In the UK, RIDDOR imposes a legal responsibility on employers to report workplace incidents to the enforcing authority, that is, Health and Executive Safety (HSE) and several local authorities. The workplace-safety regulations stipulate three categories of reportable injury to workers: 1) fatal, 2) major injuries and 3) over-3-day injuries. Some examples of major injuries are fractures and amputation. Over-3-day injuries are injuries that lead workers absence from work or inability to carry their usual job for over three days. Considering the severity of injuries, and, the purpose of this paper, I use fatal injury and major injuries as measures of risk of injury.

The use of reported injuries (i.e. fatal and major injuries) as the risk measure relies on a crucial assumption that the subjective risk assessments by workers and employers are aligned with the objective measures of the risk represented by the rates of injuries (Kniesner et al., 2012). Viscusi and Aldy (2003) reviewed studies suggesting that there is a strong correlation between workers' subjective risk assessments and reported injury rates. Here, we may think that the reported injury rates render workers and employers about the nature of the job, and thus, workers use this information to form risk beliefs. Therefore, we expect that the rates of injuries could serve as a proxy for the subjective risk beliefs.

Personality Trait Measures

Personality psychologists have constructed various measures for personality traits. The most prominent personality measure is Five-Factor Model or the big-five personality traits. The big 5 traits have long been used and widely acknowledged in the psychology literature as a way to summarize wide arrays of personality characteristics (see John and Srivastava (1999)). Many recent economic studies looking at the role of non-cognitive skills on labor market outcomes also utilize the measures. Thus, using the big five inventory is both practical and widely accepted in economics and psychology literatures. Here, I also use the big 5 personality trait measures to elicit individual personality characteristics.

As discussed above, the big 5 personality traits consist of the five basic psychological elements: 1) Openness to experience, 2) Conscientiousness, 3) Extraversion, 4) Agreeableness, and 5) Neuroticism. It is instructive to note that these five traits are not a mutually exclusive psychological classification i.e. individuals differ in the degrees of these traits. For example, an extrovert individual may tend to be lazy—i.e. high level of extraversion but low in conscientiousness. Researchers elicit personality traits through psychological surveys that typically consist of a long list of questions.

Individual responds to these questions are then classified into the five psychological arrays.

Information on personality traits in the UKHLS, however, is based on a short version personality questions. Despite of using concise-version personality questions, many studies support the reliability of this approach (see for example Benet-Martínez and John (1998) and Gosling et al. (2003)). Specifically, the UKHLS asks 15 questions containing claims, and, of which three each are intended to capture the associated personality trait. Respondents are then asked to rate these questions on how they see themselves on a 7-point scale (i.e. 1 "does not apply" to 7 "applies perfectly"). Similar to other studies, I construct each personality trait by averaging the score of three related questions. There is a concern that variation in personality measures stem from measurement error. To assess this problem, I compute Cronbach's alpha reliabilities.[9] For each personality trait , I find that Cronbach index as follows: Agreeableness 0.60, Conscientiousness 0.52, extraversion 0.65, neuroticism 0.71, and Openness 0.63. These coefficients are close to the ones found from Heineck (2011), Bollinger et al. (2012), and Nandi and Nicoletti (2014) that use the British Household Panel Survey (BHPS).

Table 4.1 shows the big five personality traits and the questions asked in the UKHLS to measure each trait. As was discussed previously, some personality traits could be thought as important inputs enabling workers to handle risk of injury at workplace. For instance, a worker with high score of neuroticism indicated by high level of anxiety and inability to handle stress is expected to choose a safer workplace as they will have low level of personal skill to reduce mortality risk at workplace. On the other hand, a worker with high level of extraversion who is more adventurous tend to be more skillful in reducing personal risk of injury and thus, they are more likely to go to a relatively dangerous occupation, holding other things constant. These various measures of personality traits could capture latent individual skill that determines job sorting based on risk of injury.

4.4.2 Econometric specifications

In order to test the effect of personality traits on the level of risk that workers are willing to bear, I use the following econometric model

$$Risk_{ijt} = s_i + X_{ijt}\beta + u_{ijt} \tag{4.3}$$

[9]Cronbach's alpha reliability index is the standard procedure used to assess the validity of personality measures.

$Risk_{ijt}$ is risk variable. I use two risk variables: the rates of fatal injury and non-fatal injury. s_i is the worker skill. X_ijt is the vector of individual characteristics. Some of the characteristics are time-invariant such as sex and education. The skill, s_i, is not observable through data. Yet as s_i is linear in personality traits, the first order approximation to the technology of skill formation can be written as

$$s_i = \sum \gamma t_i^p + \varepsilon_i \tag{4.4}$$

where $p = O, C, E, A, N$ (i.e. personality traits). The idiosyncratic aspect of skill is denoted by ε_i where ε_i is distributed normally. Substituting equation (2) to (1), we get the following econometric equation.

$$Risk_{ijt} = \sum \gamma t_i^p + X_{ijt}\beta + \varepsilon_i + u_{ijt} \tag{4.5}$$

The above model is estimated with OLS (or pooled cross-section time series to be precise) and tobit. Tobit model allows us to censor observation with zero value of injury rate. This is important as fatalities are rare event and thus we may observe a large number of 'zero' in fatality rate.

4.5 Results

4.5.1 Baseline Personality Traits and Risk

Table 3 exhibits estimates of OLS and Tobit models where the dependent variable is the rate of fatal injury[10]. As fatalities are rare events, RIDDOR does not report publicly fatality rates close to zero for some industries. Tobit model then may fit to address this issue as the model allows for censoring at zero. The variables of interest are personality traits: agreeableness, conscientiousness, extraversion, neuroticism and openness to experience. In addition to these variables, in some models I include a dummy variable indicating whether a respondent became smoker at age 16 years old. The decision to smoke at early age may indicate their tolerant attitudes toward risky behavior, including risk of fatal injury. Related to this, Viscusi and Hersch (2001) also find that smokers are more likely to choose riskier jobs. Column 1 of OLS and Tobit models in Table 4.3 report results in which I do not include control for occupations. As personality traits may be correlated with occupations, controlling for occupations in Column 2 of Table 4.3 is expected to reduce omitted variable bias.

[10]it is in per 100,000 workers.

The results confirm some of the model expectation in 4.1. I in particular find that Agreeableness, Neuroticism, and Openness are negatively related with fatality rate. From column 1 of OLS estimate, a one standard deviation increase in agreeableness, neuroticism and openness are associated with a decrease in fatality rates by 0.034, 0.029, and 0.041 per 100,000 workers respectively. This translates into a percentage reduction in fatality rate by 7.4% (agreeableness), 6.3 % (neuroticism), and 8.9 % (openness). This suggests that friendly, tense, and more open individuals tend to go to relatively safe jobs. On the other hand, conscientiousness and extraversion are associated positively with fatal rate. A one-standard deviation increase in conscientiousness and extraversion are associated with an increase in fatality rate by 0.03 and 0.016 per 100,000 workers respectively. That is, more organized and extrovert individuals tend to go to riskier jobs.

The result in the model with full specification still confirms the pattern. One-standard deviation increase in agreeableness, neuroticism and openness are still associated negatively with fatality rate at workplace and positively with conscientiousness and extraversion. In column 2, we see that smokers at 16 years old tend to go to riskier job. Yet, when I control for occupation dummies, the effect of smoking at early age becomes insignificant. This might be due to highly correlation between types of occupations and the smoking variable.

Tobit models with censoring at zero yield higher coefficients of personality traits and the results are the same as the ones with OLS. Column 1 of Tobit model shows that agreeableness, neuroticism and openness are associated with lower fatality rate. Furthermore, a one-standard deviation increase in these traits reduces fatality rate by 0.05, 0.056 and 0.09 per 100,000 workers respectively, suggesting a percentage reduction in fatality rate by 10.9 %, 12.2 %, and 19.6 % respectively. Meanwhile a one standard deviation increase in conscientiousness and Extraversion are associated with an increase in fatality rate by 0.054 and 0.027 per 100,000 workers or an increase proportionally by 11.7 % and 5.9 %. There is a tendency that the coefficients of personality traits are attenuated when I include control for occupations in tobit estimates. Comparing to the OLS estimates, the attenuation, moreover, seems to be larger in tobit. However, tobit models suggest a stronger tendency of job sorting due to personality traits.

Other variables in the regression reported in Table 4.3 also provide some insight on job sorting. Men are more likely to go to riskier jobs than are women. White tends to risky jobs and riskier jobs are mostly in private sector. Highly educated workers typically sort into safer jobs. Despite being insignificant, married workers tend to go to safer jobs. This is similar to previous findings on the marital status-risk relationship (Garen, 1988; DeLeire and Levy, 2004).

Furthermore there is ample evidence suggesting a close connection between risks of fatal injury and non-fatal injury. The literature on the risk-wage relationship suggests that both risks are positively correlated —i.e. jobs with high risk of fatal injury are typically also the ones with high risk of nonfatal injury. Thus, we may expect that personality traits play the same effect in regard to risk of non fatal injury as they do in risk of fatal injury. Table 4.4 reports the results for non-fatal injury, and the same as in Table 4.3, I report the results of both OLS and Tobit. The results from Table 4.4 shows that the coefficients of personality traits have the same sign as they are in the regression of fatal injury.

From column 1 of Table 4.4 we see that a one standard deviation increase in agreeableness, neuroticism, and openness leads to a reduction in nonfatal injury by -2.08, -2.18 and -4.34 per 100,000 workers respectively. It means a percentage reduction in the risk of nonfatal injury by 2.1 %, 2.2%, and 4.4% for agreeableness, neuroticism and openness respectively. Compare to sorting based on risk of fatal injury, the reduction of non-fatal risk is much smaller. This could be because almost many jobs have non zero nonfatal injury. Thus, workers may be indifferent about two jobs with small differences in the risk of nonfatal injury. Moreover, the majority of workers may be far more tolerant to risk of nonfatal accidents at workplace. Consequently, it results in a weaker job sorting process. This is different from the risk of fatal injury where workers encounter various jobs with substantial differences in the mortality risk.

Previously we observed that women tend sort to safer jobs. Table 4.5 provides the results of job sorting by gender. In general, I do not find evidence that personality traits are associated with the job sorting of women except for extraversion where extrovert women are more likely to choose riskier jobs. For men, we see a consistent pattern on the relationship between personality traits and risk. Concise men tend to go to riskier jobs—a one standard deviation increase in conscientiousness is associated with an increase in fatality rate by 0.042 per 100,000 workers (or an increase in fatality rate by 9%). Meanwhile, the association between conscientiousness and nonfatal injury rate among the sample of men is not statistically significant. It is important to note that the model specification of Table 4.5 is similar to the one in column 3 of Table 4.1 of OLS model. Hence, comparing both tables, we see that much of job sorting due to fatality rate is driven by men.

Table 4.6 exhibit the results by job sectors (i.e private vs public). Earlier we saw that public sector is associated with safer occupations. Here we observe that among public sector workers risk of fatal injury is less sensitive to agreeableness, conscientiousness and neuroticism. On the other hand, extrovert and less open individuals tend to go to riskier occupations in public sector. On the other hand, antagonistic, more organized and more stable mentally individuals in private sector would go to riskier jobs. Moreover, evidence that some personality traits are significantly associated with the risk in private sector while other traits and the risk are strongly correlated in public sector may suggest that some traits are awarded differently across sectors.

4.5.2 Robustness Checks

There is a concern that social and economic environments may influence personality, and thus, personality traits are endogenous. For example, Heckman et al. (2006) shows that the level of schooling at the date of the test may affect the score of personality tests among young individuals. This creates several problems. First, we encounter the problem of reverse causality and one is simply unable to draw the causal effect of personality traits on the choice of job riskiness based on the previous results. Second, I rely on an assumption that personality traits are latent and stable over time. Previous works in personality traits suggest that personality traits are relatively insulated from environment and fairly stable for individuals beyond 30 years old (i.e. this is known as the plaster hypothesis) (Costa Jr and McCrae, 1994; McCrae and Costa Jr, 1996, McCrae and Costa Jr; McCrae and Costa, 2003). Yet Srivastava et al. (2003) show that some traits evolve overtime. While Heckman et al. (2006) find the effect of schooling on the scores of personality measures among young individuals and personality traits evolve, this could raise the issue of spurious relationship between the choice of job riskiness and personality traits if the variable of schooling does not fully capture its effect on both personality traits and job riskiness.

Regarding the first problem, it is instructive to note that this paper does not attempt to make a causality claim. In spite of not making causality claim, I attempt to address the reverse direction between personality traits and risk by using the lagged measures of personality traits. In particularly I regress risk on the personality traits in the past. The main assumption here is that the current choice of job riskiness should have no effect on the measured of personality traits in the past. In this approach, I merge personality traits in the BHPS with the UKHLS.[11] On the second problem, I

[11] Starting the second wave, the UKHLS take the original respondents in the BHPS. So I am able to merge the personality traits from the BHPS to the UKHLS dataset.

undertake a common approach that is used in the literature (Nyhus and Pons, 2005; Heineck and Anger, 2010). Specifically, I regress each personality trait on age and age squared and take residuals from the regression to replace the variables of personality traits. The residuals are expected to be free from age effects. Although this may be imperfect, this approach is expected to handle the effect of environment and age on personality traits.

Residual Personality Traits

I begin to address the second problem where I use the residuals of the regressed personality traits on the characteristics of workers—i.e. I call them as adjusted personality traits—and use them to examine job sorting. To be specific, I estimate the following model

$$t_i^p = Z_i\alpha + \hat{t}_i^p \tag{4.6}$$

t_i^p is personality trait p of individual i. Z_i is the vector of individual characteristics. It contains age, age squared, a dummy for private sector, and 9 dummies of occupations at the time where the test of personality traits was conducted (i.e. it is in the third wave or 2011-2012) . $\hat{t}_i^p$ is the residuals that are expected to be uncorrelated with age and types of occupations. In some sense, they also reduce the effect of distaste (or taste) of occupations on personality traits. I then use $\hat{t}_i^p$ for the second stage of estimation. Thus equation 4.11 becomes

$$Risk_{ijt} = \sum \gamma\widehat{t_i^p} + X_{ijt}\beta + \varepsilon_i + u_{ijt} \tag{4.7}$$

Table 4.7 reports the result of adjusted personality trait measures. This table is similar to Table 4.3 where I provided the results of both OLS and Tobit model. Compared to the result of column 1 from both OLS and tobit models in Table 4.3 (i.e. where we use direct scores of personality traits), we do not observe that the adjusted personality traits (i.e. residuals of personality traits) alter qualitatively the main conclusion (Column 1 of Table 4.7). Agreeableness and neuroticism are still associated with lower choice of job riskiness. Openness is still negative but insignificant. In spite of not being insignificant, we still observe that conscientiousness and extraversion are associated positively with decision to work in risky jobs. This is qualitatively similar to the previous result. Yet the substantial decline in the estimated coefficients as we use the residuals of personality traits is suggestive evidence that types of occupations may influence personality traits.

In the model controlling for all the characteristics of workers (i.e. column 3 of Table 4.7), the coefficients of adjusted personality traits are very close to the ones in the previous model presented in column 2 of Table 4.3 which controls for occupations. This points out that occupations and workplace environments seem to have effects on personality traits. Thus, the adjusted personality traits are expected to minimize these effects.

The Lagged Measures of Personality Traits

The second approach that I use to minimize the interdependency between the rates of injury and personality traits is using lag personality trait measures. In this approach, I combine two datasets, namely, BHPS and UKHLS. In 2005, BHPS asked respondents about personality traits. The questions about personality traits in BHPS are the same as the questions in UKHLS. I then merge personality traits in BHPS 2005 with data UKHLS for survey year 2010 and 2011 (wave 2 and 3). The reason of using UKHLS waves 2 and 3 is because UKHLS wave 2 started including the sample of BHPS.

Using the long lag of personality trait measures is important in many ways. First of all, if the current personality trait measures are sensitive to the current working environment, implying that the measures are less valid in capturing latent individual variables, we expect that current occupations should not shape the lagged personality traits. Second, similar to all studies in the literature, I depart from an assumption that personality traits as latent variable (i.e constant overtime). If the assumption is hold, the effects of the current scores and of the lagged scores of personality traits on the choice of job risk should be, to some extent, the same. Lastly, I use five year lagged scores of personality traits, and thus, individuals may change jobs within this period. Hence I allow that individuals change jobs that really suit their preferences and, thus, we can capture the effects of personality traits on decision to work in risky jobs.

With the lagged scores of personality traits, I estimate the following regression

$$Risk_{ijt} = \sum \gamma t_i^{p,2005} + X_{ijt}\beta + \varepsilon_i + u_{ijt} \tag{4.8}$$

Equation 4.8 is similar to equation 4.11, except that I use the scores of personality traits in the year 2005. Table 4.9 exhibits the result of the effects of lag personality traits on the current rates of job injury. Interestingly, the pattern of the effects qualitatively similar to the previous two models. In some cases, the magnitude of the effects are the same as it is in Table 4.3. Conscientiousness has a positive correlation with the decision to work in risky occupations and the magnitude, remarkably, is similar to the result presented in Table 4.3. Neuroticism and Openness to new experience are associated negatively with the level of risk of injury and again, the magnitude of the coefficients is close to what we find with personality traits measures from UKHLS data. This suggests that the personality trait measures are able to capture the latent variables and, surprisingly, the effects of some measures are pretty stable in relatively long term. Moreover, Agreeableness is negative and significant for the case of non-fatal injury. Meanwhile Extraversion becomes negative when we use lag personality traits.

4.5.3 Hedonic Wage Model with Personality Traits

The evidence of worker sorting to risk-safe jobs based on personality traits suggests that people are not randomly assigned to jobs. Thus, differences in individual traits would affect both the choice of wage levels and job riskiness. This implies that failure to control for the traits would result in biased estimates of wage premium for risk based on OLS. If traits are similar to job-safety related skill, based on the prediction Shogren and Stamland (2002), we expect that the risk premium estimated through the OLS model without controlling for personality traits tends to be upward bias. In this section, I discuss the importance of controlling personality traits in the hedonic wage model. I also exploit the capabilities of panel data to control for unobserved heterogeneity. In particular, I use fixed effects and random effects estimators. Inclusion of these models will provide comparison between models accounting for unobservables (i.e. fixed effects and random effects) and those not controlling for unobservables (i.e OLS). I will start with panel data estimators controlling for unobservables. Specifically, I estimate the following model

$$\ln w_{ijt} = c_i + \alpha Risk_{ijt} + X_{ijt}\beta + \varepsilon_{ijt} \tag{4.9}$$

$\ln w_{ijt}$ natural log of real monthly labor income. The unobserved heterogeneity is denoted by c_i. X_{ijt} is other time-variant covariates that are similar to previous specifications. Under fixed effects model, c_i is parameter to be estimated while in random effects, c_i is assumed to be uncorrelated with observed covariates. The coefficient of interest is α that represents the risk premium.

I compare panel data estimators with pooled OLS. First, I run regression with OLS that does not control for personality traits.

$$\ln w_{ijt} = \alpha Risk_{ijt} + X_{ijt}\beta + \varepsilon_{ijt} \tag{4.10}$$

In the second OLS model, I include personality traits and estimate the following model.

$$\ln w_{ijt} = \alpha Risk_{ijt} + \sum \gamma t_i^p + X_{ijt}\beta + \varepsilon_{ijt} \tag{4.11}$$

α from these models provide information on the size of the bias. The fixed effects estimator provides us a consistent estimate of α. Thus, fixed effects model will be used as a benchmark for other models. Moreover, occupation or job sorting may also occur along gender basis. Hence, I estimate the risk premium for male workers and female separately.

Table 4.11 exhibits results for the mortality risk premium. With fixed effects estimator that controls for person-specific heterogeneity, the estimated risk premium for male workers due to an increase in one death per 100,000 workers is 0.69 %. Yet the point estimate is not statistically significant at the standard significance level. Random effects estimator that also controls for person-specific heterogeneity yields higher estimated mortality risk premium (i.e. the fatal risk premium is 1.6 %).

We compare these estimators with pooled OLS both with and without controlling for personality traits among men. The estimated mortality risk premium based on the standard pooled OLS is 2.15% for an increase in death per 100,000 workers. Controlling for the personality traits reduces the risk premium to 1.9%. This suggests that personality traits could serve as a proxy for the safety-related skill. This evidence also confirms the prediction of Shogren and Stamland (2002) that failure to control the safety-related skill would lead to upward bias in the risk premium. Comparing the OLS model controlling for traits (i.e. OLS-traits) with fixed effects estimators suggests that the former does not perform better than the latter. It is not surprising as there may be substantial unobserved heterogeneity that is not captured by personality traits but is correlated with the fatal risk—that is, unobserved heterogeneity can be preferences for risk.

We observe, in general, similar findings among women. In particular, the estimated mortality risk premium under models accounting for person-specific heterogeneity is lower than the ones with OLS. The estimated mortality risk premium under fixed effects is 1.04%. Meanwhile it is 1.59 % in the OLS model controlling for personality traits. Compared to estimators with the sample of men, the difference between fixed effects estimator and the OLS-Traits model among women is lower. This may suggest that personality traits capture part of unobervables in the sample of women. Moreover, the estimated risk premium of women is higher than that of men. This can be explained by risk-aversion among women by which women require higher compensating differential in order to take the same risky jobs.

In addition to risk variable, I also find there is association between personality traits and wages. Among the sample men, being conscience is associated positively with wages—i.e. a one standard deviation increase in conscientiousness is associated with 2.1 % higher wage and it is statistically significant. On the other hand, neuroticism and agreeableness are associated negatively with wages. Different from men, among women, extraversion and openness result in higher wages by 1.16% and 2.03% respectively. Similar to men, agreeableness and neuroticism have negative effects on wages in the sample of women. As women and men may enter different types of occupations, this suggests that personality traits are valued differently across occupation and, consequently, gender as well. Overall, the finding on the relationship between personality traits and wages is similar to previous studies.

Table 4.12 displays the results for non-fatal injury. Under fixed effects estimator, the wage premium for non fatal injury is 0.01 % due to an increase in one non-fatal injury per 100,000 workers. However, the estimated non-fatal risk premium under OLS models is biased and they yield an inconsistent sign as what compensating differential theory predict. Random effects estimator that accounts for person-specific heterogeneity also produces the inconsistent sign of non fatal injury variable. Furthermore, there is no substantial difference in the wage premium for non-fatal injury between men and women.

I investigate further on how distributions of personality traits affect the wage premium for risk. Table 4.13 exhibits the results of hedonic wage model where I interact the fatal risk with personality traits. We now observe that, in the model with the interaction, the difference in the coefficient on the risk measure with between the OLS and fixed effect estimator is not as large as in the previous models. It is important to note, however, the coefficient on risk suggests the risk premium for the average individuals. The results also suggest that there is heterogeneity in the risk premium due to personality traits. In particular, with the fixed effect estimator—our preferred specification—suggests that agreeable men are more likely to ask for a higher risk premium than do the average men.[12] This is consistent with the previous finding where we find that individuals with high level of agreeableness tend to avoid in risky jobs. Thus, as the risk increases, high agreeable workers demand higher premium to compensate the risk they are taking. The interaction term between the fatal risk and agreeableness in the OLS model is negative. While we expect that fixed effects estimator control for unobservables, the coefficient on agreeableness with

[12]Recall that I normalize the distribution of personality traits. Thus the average men should have traits around zero or negative.

the OLS estimator is downward bias. Furthermore, we do not observe substantial heterogeneity in the risk premium due to other types of personality traits.

4.6 Conclusion

As noted by Shogren and Stamland (2002), a worker who chooses to work in riskier occupation reveals himself about his risk preference or ability to reduce risk of death at workplace, or both. Thus far, the extent of sorting in the labor market based on ability to reduce personal risk of injury has not been adequately tested. In this paper, I use big 5 personality traits as a proxy for the skill to reduce risk of injury at workplace. The big 5 personality traits are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. Different from previous papers that study the sorting of workers based on risk preferences and risk of death, in this article I treat personality traits as inputs for skill.

Using data from the United Kingdom Household Longitudinal Study (the UKHLS), I find that personality traits determine job sorting. I particularly find that conscientious and extravert individuals tend to be employed in riskier jobs (jobs with high rate of fatal and nonfatal injury). In regard to conscientiousness, personality facets covered in this category describe qualities that are clearly important for someone to handle a harsh working environment. On the other hand, I also find that agreeableness, openness, and neuroticism are negatively associated with risk of injury—i.e. individuals with these traits are inclined to choose safer jobs. Neuroticism in particular includes dimensions such as anxiety, nervous (vs relaxed) and impulsiveness. These traits do not render the necessary skill to reduce risk of injury and are less valued in riskier occupations. I conduct several sensitivity analyses. Overall, I find evidence suggesting that sorting of workers and jobs based on personality traits and risk of injury occur.

Moreover, it is plausible that personality traits are developed through interaction between individuals and institutions, and they vary across geography. For example, Scotland has stronger labor union tradition than do England and it is also the strong base of Labour Party, which may suggest that Scotland and England have different institutions. Thus, the relationship between personality traits and job sorting is confounded by this unobserved factor. However, the extent to which this institution may influence the sorting is controlled by region fixed effects, and despite controlling for geography, we still observe the evidence of worker sorting.

As we discussed previously, another concern regarding personality traits is that they are changing during individual life stages. For instance, personality traits during adolescence may affect the school level and thus, it affects someone's future occupation, including the choice of job riskiness. Thus, the current job sorting is a result of the observed personality traits in the past—for example, Heckman et al. (2006) show the influence of traits on the levels of schooling and thus they have long-term consequences. Unfortunately, data at my disposal do not allow me to trace the effect of personality traits at every stage of individual life. A worthwhile direction for future research would be to measures personality traits over life stages and then test how they affect related outcomes at every stage.

Table 4.1: The Big Five personality traits: related facet-adjectives and the UKHLS questions

Big Five traits	**Personality facets**	**Respondents see themselves as someone who**
Openness	Ideas (curious)	O1. is original, comes up with ideas
	Fantasy (imaginative)	O2. values artistic, aesthetic experiences
	Aesthetics (artistic)	O3. Has an active imagination
	Actions (wide interests)	
	Feelings (excitable)	
Conscientiousness	Competence (efficient)	C1. does a thorough job
	Order (organized)	C2. tends to be lazy (reversed score)
	Dutifulness (not careless)	C3. Does things efficiently
	Achievement striving (thorough)	
	Self-discipline (not lazy)	
Extraversion	Gregariousness (sociable)	E1. Is talkative
	Assertiveness (Forceful)	E2. Is outgoing, sociable
	Activity (energetic)	E3. Is reserved (reversed score)
	Excitement seeking (adventurous)	
	Positive emotions (enthusiastic)	
Agreeableness	Trust (forgiving)	A1. Is sometimes rude to others (reversed score)
	Straightforwardness (not demanding)	A2. Has a forgiving nature
	Altruism (warm)	A3. Is considerate and kind
	Compliance (not stubborn)	
	Modesty (not show-off)	
Neuroticism	Anxiety (tense)	N1. Worries a lot
	Angry hostility (irritable)	N2. Gets nervous easily
	Depression (not contended)	N3. Is relaxed, handles stress well (reversed score)
	Self-consciousness (shy)	
	Impulsiveness (moody)	

Source: Cited from Nandi and Nicoletti (2009)

Figure 4.1: Distribution of Personality Traits

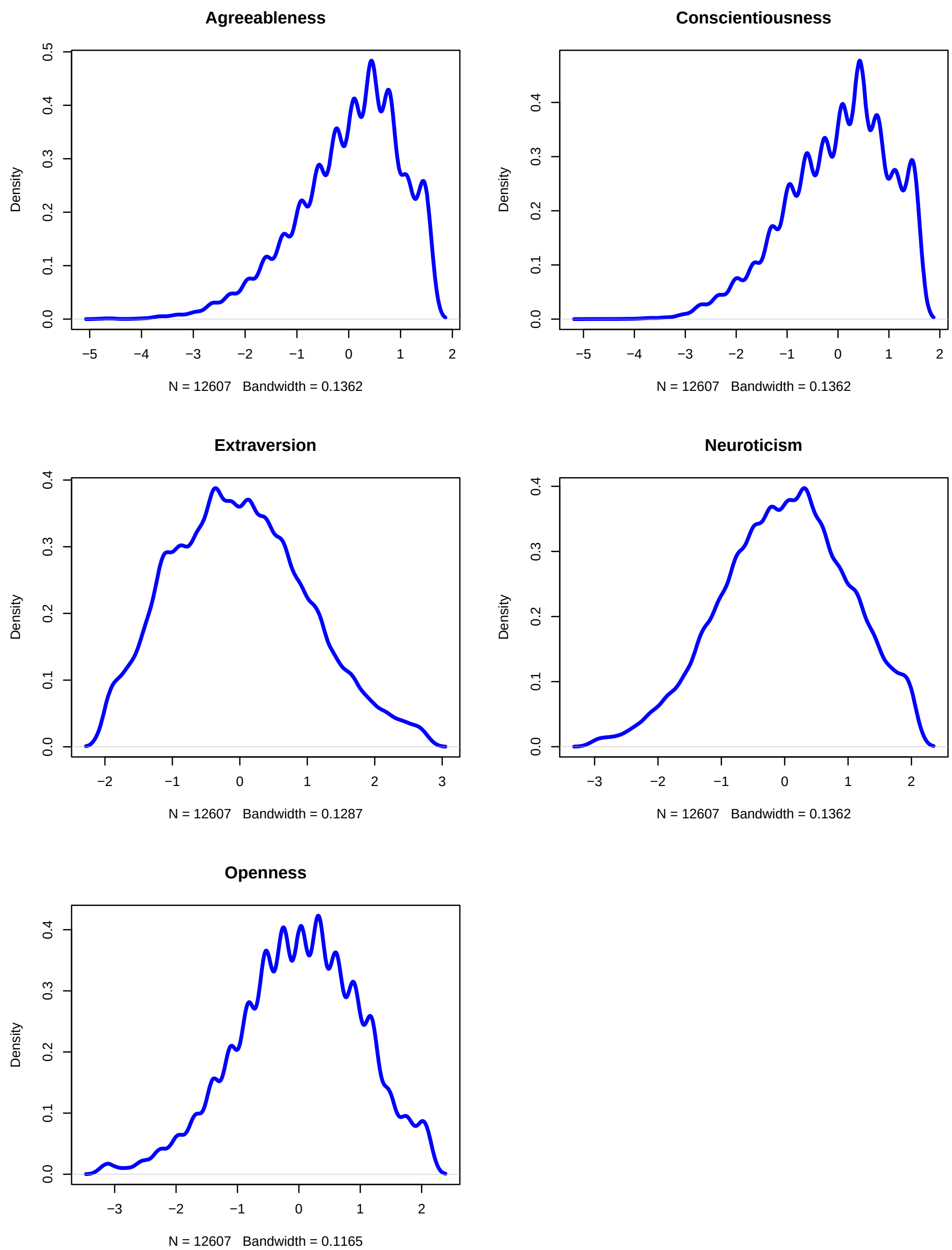

Table 4.2: Summary Statistics

Variable	Mean	Standard Deviation
Fatal rate	0.46	1.03
Non fatal rate	97.83	71.90
Personality traits		
Agreeableness	5.58	0.98
Conscientiousness	5.59	0.96
Extraversion	4.59	1.24
Neuroticism	3.50	1.32
Openness	4.63	1.17
Years of Schooling	14.35	3.41
Age	41.78	11.03
white	0.88	0.33
married	0.56	0.50
Male	0.53	0.50
Smoker at age 16	0.33	0.47
Private Job	0.61	0.49
Number of Employment		
< 9	0.13	0.34
10-49	0.28	0.45
50-99	0.12	0.33
100-199	0.11	0.32
200-499	0.13	0.34
500-999	0.07	0.26
> 1000	0.15	0.35
Occupations		
Managers and Senior Officials	0.18	0.39
Professional Occupations	0.16	0.37
Associate professional and Technical Occupations	0.18	0.39
Administrative and Secretarial Occupations	0.12	0.33
Skilled trade occupations	0.08	0.27
Personal Service Occupations	0.08	0.27
Sales and Customer Service Occupations	0.05	0.22
Process, Plant and Machine Operatives	0.07	0.26
Elementary Occupations	0.07	0.26

Note: UKHLS

Table 4.3: OLS and Tobit Models for risk of fatal injury

Variables	**OLS**		**Tobit**	
	(1)	**(2)**	**(1)**	**(2)**
Agreeableness	-0.0339***	-0.0270***	-0.0534***	-0.0393***
	(0.0097)	(0.0096)	(0.0137)	(0.0134)
Conscientiousness	0.0330***	0.0257***	0.0540***	0.0436***
	(0.0091)	(0.0089)	(0.0133)	(0.0130)
Extraversion	0.0161*	0.0167*	0.0272**	0.0234*
	(0.0094)	(0.0091)	(0.0137)	(0.0133)
Neuroticism	-0.0298***	-0.0217***	-0.0556***	-0.0398***
	(0.0082)	(0.0079)	(0.0125)	(0.0121)
Openness	-0.0409***	-0.0213**	-0.0909***	-0.0539***
	(0.0088)	(0.0088)	(0.0130)	(0.0128)
Smoker at age 16	0.0369**	0.0147	0.0467*	0.0098
	(0.0180)	(0.0176)	(0.0259)	(0.0252)
Male	0.3948***	0.2533***	0.6692***	0.4661***
	(0.0166)	(0.0158)	(0.0272)	(0.0257)
Age	0.0027	0.0001	0.0022	0.0024
	(0.0055)	(0.0053)	(0.0078)	(0.0076)
Age Squared	-0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Years of Schooling	-0.0220***	-0.0095***	-0.0507***	-0.0233***
	(0.0023)	(0.0023)	(0.0037)	(0.0037)
Married	-0.0162	-0.0056	-0.0374	-0.0113
	(0.0163)	(0.0159)	(0.0245)	(0.0239)
White	0.1009***	0.1018***	0.0889**	0.1033***
	(0.0220)	(0.0214)	(0.0371)	(0.0360)
Private Job	0.2875***	0.1917***	0.4860***	0.2718***
	(0.0156)	(0.0172)	(0.0246)	(0.0269)
Constant	0.5427***	0.4644***	0.4228**	0.1391
	(0.1356)	(0.1325)	(0.2007)	(0.1986)
Number of employment	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Occupation	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes
Observations	34,407	34,407	34,407	34,407
R-squared	0.1005	0.1491		
Log Pseudolikelihood			-44444.314	-42894.308

Note: Dependent variable is three-year average fatality rate at two digit industry level. For tobit models, observations are censored at 0. Column 2 controls for occupations. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.4: OLS and Tobit models for risk of nonfatal injury

Variables	**OLS**		**Tobit**	
	(1)	**(2)**	**(1)**	**(2)**
Agreeableness	-2.0816***	-1.8185***	-2.0816***	-1.8189***
	(0.6469)	(0.6089)	(0.6469)	(0.6088)
Conscientiousness	1.9641***	1.2805**	1.9558***	1.2742**
	(0.6386)	(0.5999)	(0.6384)	(0.5997)
Extraversion	1.8916***	1.8732***	1.8906***	1.8724***
	(0.6296)	(0.5911)	(0.6297)	(0.5912)
Neuroticism	-2.1890***	-1.5741***	-2.1801***	-1.5667***
	(0.5965)	(0.5656)	(0.5964)	(0.5655)
Openness	-4.3386***	-1.7945***	-4.3471***	-1.8041***
	(0.6193)	(0.5862)	(0.6195)	(0.5865)
Smoker at age 16	3.5181***	0.5017	3.5413***	0.5222
	(1.2577)	(1.1916)	(1.2575)	(1.1914)
Male	23.7699***	12.3450***	23.7560***	12.3372***
	(1.2295)	(1.1876)	(1.2293)	(1.1872)
Age	0.4083	0.5484	0.4058	0.5459
	(0.3792)	(0.3618)	(0.3791)	(0.3616)
Age Squared	-0.0028	-0.0055	-0.0027	-0.0054
	(0.0045)	(0.0043)	(0.0045)	(0.0043)
Years of Schooling	-2.9494***	-1.1413***	-2.9462***	-1.1400***
	(0.1749)	(0.1754)	(0.1749)	(0.1753)
Married	-3.3799***	-1.2807	-3.3934***	-1.2927
	(1.1905)	(1.1307)	(1.1902)	(1.1303)
White	-2.4397	0.3602	-2.4538	0.3455
	(1.8542)	(1.7116)	(1.8534)	(1.7108)
Private Job	4.1337***	-5.5667***	4.1160***	-5.5777***
	(1.1200)	(1.1882)	(1.1199)	(1.1878)
Constant	141.0618***	108.4133***	141.1743***	108.5519***
	(9.8979)	(9.7439)	(9.8967)	(9.7429)
Number of employment	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Occupation	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes
Observations	34,407	34,407	34,407	34,407
R-squared	0.0831	0.1733		
Log Pseudolikelihood			-194371	-192593

Note: Dependent variable is three-year average nonfatal injury rate at two digit industry level. For tobit models, observations are censored at 0. Column 2 controls for occupations. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.5: OLS models for fatal and nonfatal risk by gender

Variables	**Fatal Risk**		**Non Fatal Risk**	
	Male	**Female**	**Male**	**Female**
Agreeableness	-0.0436***	0.0040	-2.7469***	0.1160
	(0.0153)	(0.0082)	(0.9180)	(0.7137)
Conscientiousness	0.0422***	-0.0020	1.0848	1.2278*
	(0.0152)	(0.0070)	(0.9599)	(0.6448)
Extraversion	0.0108	0.0214***	2.2990**	1.0927*
	(0.0159)	(0.0073)	(0.9704)	(0.6277)
Neuroticism	-0.0372***	0.0031	-1.9248**	-0.9208
	(0.0142)	(0.0069)	(0.9238)	(0.6431)
Openness	-0.0272*	-0.0153*	-2.9229***	-0.6180
	(0.0150)	(0.0088)	(0.9795)	(0.6305)
Smoker at age 16	0.0377	-0.0178	1.4224	-0.8666
	(0.0287)	(0.0166)	(1.8424)	(1.3790)
Age	-0.0053	0.0131***	0.4787	0.9892**
	(0.0092)	(0.0044)	(0.5827)	(0.3860)
Age Squared	0.0001	-0.0002***	-0.0037	-0.0115**
	(0.0001)	(0.0001)	(0.0069)	(0.0046)
Years of Schooling	-0.0165***	-0.0021	-1.6056***	-0.6269***
	(0.0040)	(0.0023)	(0.2865)	(0.1946)
Married	-0.0211	0.0057	-2.6627	0.0819
	(0.0278)	(0.0147)	(1.9042)	(1.2227)
White	0.1577***	0.0352*	3.2162	-2.5243
	(0.0360)	(0.0201)	(2.6630)	(2.0226)
Private Job	0.1934***	0.2023***	-8.5821***	-0.8104
	(0.0307)	(0.0159)	(1.8986)	(1.4303)
Constant	1.0649***	-0.1233	138.7043***	75.9274***
	(0.2238)	(0.1217)	(15.2064)	(11.0532)
Observations	18,159	16,248	18,159	16,248
R-squared	0.1238	0.0758	0.1903	0.0671

Note: Each model is estimated by OLS. Dependent variables are three-year average fatal and nonfatal injury rate at two digit industry level. All models control for regions, year dummies, occupations and number of employment. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.6: OLS models for fatal and nonfatal risk by job sectors

Variables	**Fatal Risk**		**Non Fatal Risk**	
	Private	Public	Private	Public
Agreeableness	-0.0326**	-0.0149	-2.5700***	-0.2505
	(0.0133)	(0.0112)	(0.8479)	(0.6483)
Conscientiousness	0.0297**	0.0151	1.0597	1.1863*
	(0.0128)	(0.0099)	(0.8623)	(0.6411)
Extraversion	0.0109	0.0216**	1.9304**	1.7845***
	(0.0137)	(0.0089)	(0.8715)	(0.6186)
Neuroticism	-0.0271**	-0.0107	-1.4616*	-1.5576***
	(0.0117)	(0.0078)	(0.8234)	(0.5761)
Openness	-0.0209	-0.0174*	-1.3442	-2.0817***
	(0.0128)	(0.0089)	(0.8438)	(0.6144)
Smoker at age 16	0.0271	-0.0087	0.2399	0.1592
	(0.0246)	(0.0197)	(1.6687)	(1.2993)
Male	0.2934***	0.1831***	13.7483***	12.0631***
	(0.0233)	(0.0184)	(1.7811)	(1.2515)
Age	-0.0026	0.0002	0.2397	0.9913**
	(0.0073)	(0.0062)	(0.4947)	(0.4164)
Age Squared	0.0000	-0.0000	-0.0005	-0.0128**
	(0.0001)	(0.0001)	(0.0060)	(0.0050)
Years of Schooling	-0.0130***	-0.0028	-1.4757***	-0.7082***
	(0.0033)	(0.0030)	(0.2640)	(0.1807)
Married	0.0208	-0.0466***	0.5482	-3.6193***
	(0.0231)	(0.0180)	(1.6656)	(1.1752)
White	0.1451***	0.0328	1.9893	-1.4523
	(0.0300)	(0.0247)	(2.4163)	(1.9136)
Constant	0.7473***	0.3211**	113.7220***	83.5808***
	(0.1801)	(0.1454)	(13.4864)	(10.7708)
Observations	21,019	13,388	21,019	13,388
R-squared	0.1166	0.1298	0.1722	0.2094

Note: Each model is estimated by OLS. Dependent variables are three-year average fatal and nonfatal injury rate at two digit industry level. All models control for regions, year dummies, occupations and number of employment. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.7: OLS and Tobit models for risk of fatal injury using residual personality traits

Variables	**OLS**		**Tobit**	
	(1)	**(2)**	**(1)**	**(2)**
Agreeableness	-0.0211**	-0.0260***	-0.0329**	-0.0386***
	(0.0100)	(0.0097)	(0.0140)	(0.0136)
Conscientiousness	0.0355***	0.0267***	0.0579***	0.0458***
	(0.0097)	(0.0095)	(0.0142)	(0.0138)
Extraversion	0.0230**	0.0173*	0.0297**	0.0236*
	(0.0094)	(0.0092)	(0.0138)	(0.0134)
Neuroticism	-0.0071	-0.0201**	-0.0230*	-0.0387***
	(0.0083)	(0.0081)	(0.0127)	(0.0123)
Openness	-0.0283***	-0.0217**	-0.0638***	-0.0555***
	(0.0094)	(0.0092)	(0.0138)	(0.0135)
Smoker at age 16	0.0372**	0.0146	0.0485*	0.0097
	(0.0181)	(0.0176)	(0.0260)	(0.0252)
Male	0.4079***	0.2545***	0.6870***	0.4675***
	(0.0164)	(0.0158)	(0.0271)	(0.0257)
Age	0.0041	0.0009	0.0047	0.0040
	(0.0055)	(0.0053)	(0.0078)	(0.0076)
Age Squared	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Years of Schooling	-0.0228***	-0.0095***	-0.0526***	-0.0234***
	(0.0023)	(0.0023)	(0.0037)	(0.0037)
Married	-0.0150	-0.0055	-0.0351	-0.0112
	(0.0163)	(0.0159)	(0.0245)	(0.0239)
White	0.0980***	0.1019***	0.0860**	0.1037***
	(0.0220)	(0.0214)	(0.0371)	(0.0360)
Private Job	0.2961***	0.1954***	0.5027***	0.2796***
	(0.0155)	(0.0172)	(0.0247)	(0.0269)
Constant	0.3144***	0.3560***	-0.0477	-0.1190
	(0.1206)	(0.1194)	(0.1764)	(0.1776)
Number of employment	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Occupation	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes
Observations	34,407	34,407	34,407	34,407
R-squared	0.0987	0.1490		
Log Pseudolikelihood			-44508	-42897

Note: Dependent variable is three-year average fatal injury rate at two digit industry level. For tobit models, observations are censored at 0. Column 2 controls for occupations. Personality traits are derived from residuals taken from regression of personality traits on age, age squared, and occupations. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.8: OLS and Tobit models for risk of nonfatal injury using residual personality traits

Variables	OLS		Tobit	
	(1)	(2)	(1)	(2)
Agreeableness	-1.6442**	-1.8210***	-1.6435**	-1.8213***
	(0.6559)	(0.6143)	(0.6558)	(0.6142)
Conscientiousness	2.1478***	1.3569**	2.1386***	1.3505**
	(0.6777)	(0.6350)	(0.6776)	(0.6348)
Extraversion	2.0293***	1.8683***	2.0281***	1.8676***
	(0.6380)	(0.5978)	(0.6382)	(0.5979)
Neuroticism	-0.7624	-1.5531***	-0.7537	-1.5453***
	(0.6144)	(0.5786)	(0.6143)	(0.5786)
Openness	-2.2216***	-1.8195***	-2.2335***	-1.8299***
	(0.6515)	(0.6144)	(0.6518)	(0.6146)
Smoker at age 16	3.5207***	0.4968	3.5442***	0.5174
	(1.2607)	(1.1918)	(1.2605)	(1.1916)
Male	24.2234***	12.3753***	24.2094***	12.3676***
	(1.2133)	(1.1847)	(1.2130)	(1.1842)
Age	0.4847	0.5684	0.4819	0.5658
	(0.3781)	(0.3601)	(0.3779)	(0.3599)
Age Squared	-0.0031	-0.0054	-0.0030	-0.0054
	(0.0045)	(0.0043)	(0.0045)	(0.0043)
Years of Schooling	-3.0704***	-1.1445***	-3.0673***	-1.1431***
	(0.1737)	(0.1752)	(0.1737)	(0.1752)
Married	-3.1965***	-1.2737	-3.2104***	-1.2858
	(1.1947)	(1.1308)	(1.1944)	(1.1304)
White	-2.6747	0.3772	-2.6894	0.3623
	(1.8631)	(1.7118)	(1.8623)	(1.7110)
Private Job	4.9067***	-5.3169***	4.8894***	-5.3275***
	(1.1169)	(1.1871)	(1.1167)	(1.1868)
Constant	123.1019***	100.3865***	123.1623***	100.4662***
	(8.5271)	(8.5774)	(8.5241)	(8.5742)
Number of employment	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Occupation	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes
Observations	34,407	34,407	34,407	34,407
R-squared	0.0798	0.1732		
Log Pseudolikelihood			-194432.24	-192594.56

Note: Dependent variable is three-year average nonfatal injury rate at two digit industry level. For tobit models, observations are censored at 0. Column 2 controls for occupations. Personality traits are derived from residuals taken from regression of personality traits on age, age squared, and occupations. Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.9: OLS and Tobit models for risk of fatal injury using past scores of personality traits

Variables	**OLS**		**Tobit**	
	(1)	**(2)**	**(1)**	**(2)**
Agreeableness	-0.0099	-0.0028	-0.0307	-0.0096
	(0.0216)	(0.0208)	(0.0297)	(0.0285)
Conscientiousness	0.0137	0.0052	0.0417	0.0244
	(0.0203)	(0.0196)	(0.0284)	(0.0276)
Extraversion	-0.0123	-0.0059	-0.0108	-0.0064
	(0.0204)	(0.0198)	(0.0285)	(0.0276)
Neuroticism	-0.0357*	-0.0237	-0.0551**	-0.0332
	(0.0185)	(0.0181)	(0.0269)	(0.0262)
Openness	0.0231	0.0482	-0.0292	0.0205
	(0.0296)	(0.0303)	(0.0367)	(0.0382)
Smoker at age 16	0.0685	0.0402	0.0944*	0.0303
	(0.0426)	(0.0417)	(0.0572)	(0.0549)
Male	0.3739***	0.2261***	0.6294***	0.4287***
	(0.0395)	(0.0385)	(0.0618)	(0.0572)
Age	0.0062	0.0132	-0.0001	0.0119
	(0.0120)	(0.0118)	(0.0167)	(0.0164)
Age Squared	-0.0000	-0.0001	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Years of Schooling	-0.0226***	-0.0102*	-0.0430***	-0.0220***
	(0.0052)	(0.0054)	(0.0076)	(0.0075)
Married	-0.0131	0.0190	-0.0463	0.0014
	(0.0387)	(0.0374)	(0.0543)	(0.0524)
White	0.1396*	0.1323*	0.2119	0.1716
	(0.0742)	(0.0718)	(0.1361)	(0.1325)
Private Job	0.3338***	0.2080***	0.4574***	0.2174***
	(0.0399)	(0.0432)	(0.0555)	(0.0626)
Constant	0.2783	-0.0595	0.3688	-0.1045
	(0.3451)	(0.3327)	(0.4891)	(0.4796)
Number of employment	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Occupation	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes
Observations	5,621	5,621	5,621	5,621
R-squared	0.1070	0.1602		
Log Pseudolikelihood			-7397	-7125

Note: Dependent variable is three-year average fatal injury rate at two digit industry level. For tobit models, observations are censored at 0. Column 2 controls for occupations. Personality traits are from the 2005 scores of personality traits (i.e. from the 2005 BHPS dataset). Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.10: OLS models for risk of nonfatal injury using past scores of personality traits

Variables	**(1)**	**(2)**
Agreeableness	-2.2438	-1.8231
	(1.4446)	(1.3753)
Conscientiousness	1.6125	0.9094
	(1.4594)	(1.3969)
Extraversion	0.3569	0.7777
	(1.3224)	(1.2118)
Neuroticism	-2.3816*	-1.3108
	(1.3290)	(1.2519)
Openness	-1.5369	1.2818
	(1.5441)	(1.4725)
Smoker at age 16	1.4993	-1.9248
	(2.6407)	(2.5161)
Male	25.7802***	14.2043***
	(2.6653)	(2.6245)
Age	-0.1141	0.8617
	(0.8112)	(0.7745)
Age Squared	0.0008	-0.0113
	(0.0095)	(0.0091)
Years of Schooling	-2.6647***	-1.3124***
	(0.3255)	(0.3193)
Married	-3.5292	-0.1529
	(2.6157)	(2.4945)
White	3.8906	3.8450
	(6.8459)	(6.2221)
Private Job	8.2391***	-2.8906
	(2.4079)	(2.5716)
Constant	126.1884***	81.1325***
	(22.8557)	(22.2207)
Number of employment	Yes	Yes
Region	Yes	Yes
Occupation	No	Yes
Year dummy	Yes	Yes
Observations	5,621	5,621
R-squared	0.0964	0.1872

Note: Dependent variable is three-year average nonfatal injury rate at two digit industry level. Personality traits are from the 2005 scores of personality traits (i.e. from the 2005 BHPS dataset). Standard errors are robust to heteroscedasticity and clustered at the level of the individual. *** significant at 1%, **5%,* 10%.

Table 4.11: Hedonic Wage Estimations: Fatal Injury

Variables	Male				Female			
	Fixed Eff.	**Random Eff.**	**OLS**	**OLS-Traits**	**Fixed Eff.**	**Random Eff.**	**OLS**	**OLS-Traits**
Fatal	0.0069	0.0160***	0.0215***	0.0197***	0.0104	0.0123	0.0156*	0.0159*
	(0.0057)	(0.0033)	(0.0035)	(0.0035)	(0.0098)	(0.0077)	(0.0087)	(0.0085)
Agreeableness				-0.0177***				-0.0358***
				(0.0051)				(0.0052)
Conscientiousness				0.0210***				0.0051
				(0.0052)				(0.0057)
Extraversion				-0.0012				0.0116**
				(0.0054)				(0.0053)
Neuroticism				-0.0291***				-0.0211***
				(0.0053)				(0.0051)
Openness				-0.0049				0.0203***
				(0.0053)				(0.0054)
Constant	6.0395***	6.0227***	5.8799***	5.8732***	6.8915***	6.3851***	6.1622***	6.1742***
	(0.7655)	(0.0706)	(0.0761)	(0.0765)	(0.7961)	(0.0755)	(0.0790)	(0.0793)
Number of employment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,159	18,159	18,159	18,159	16,248	16,248	16,248	16,248
R-squared	0.0122	0.3204	0.3373	0.3415	0.0151	0.3443	0.3568	0.3624

Note: Dependent variable is natural log of real monthly labor income. Standard errors are in parentheses. Standard errors for OLS and OLS-Traits are clustered by individuals and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, private job, the size of employees, 1 digit occupations, regions of residence and year dummy. For OLS and OLS Traits estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source UKHLS.

Table 4.12: Hedonic Wage Estimations: Non Fatal Injury

Variables	**Male**				**Female**			
	Fixed Eff.	**Random Eff.**	**OLS**	**OLS-Traits**	**Fixed Eff.**	**Random Eff.**	**OLS**	**OLS-Traits**
Non Fatal	0.0001	-0.0001	-0.0000	-0.0001	0.0004***	-0.0000	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Agreeableness				-0.0188***				-0.0357***
				(0.0051)				(0.0052)
Conscientiousness				0.0219***				0.0053
				(0.0052)				(0.0057)
Extraversion				-0.0009				0.0121**
				(0.0054)				(0.0053)
Neuroticism				-0.0300***				-0.0212***
				(0.0053)				(0.0051)
Openness				-0.0057				0.0199***
				(0.0053)				(0.0054)
Constant	6.0100***	6.0367***	5.9051***	5.8990***	6.8676***	6.3842***	6.1731***	6.1859***
	(0.7668)	(0.0710)	(0.0764)	(0.0767)	(0.7966)	(0.0764)	(0.0798)	(0.0801)
Number of employment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,159	18,159	18,159	18,159	16,248	16,248	16,248	16,248
R-squared	0.0122	0.3267	0.3355	0.3400	0.0160	0.3441	0.3567	0.3623

Note: Dependent variable is natural log of real monthly labor income. Standard errors are in parentheses. Standard errors for OLS and OLS-Traits are clustered by individuals and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, private job, the size of employees, 1 digit occupations, regions of residence and year dummy. For OLS and OLS Traits estimators, additional control variables are years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source UKHLS.

Table 4.13: Hedonic Wage Estimations: Interacting Fatal Risk with Personality Traits

Variable	**Male**		**Female**	
	OLS	**FE**	**OLS**	**FE**
Fatal	0.0187***	0.0127*	0.0238***	0.0154
	(0.0029)	(0.0070)	(0.0087)	(0.0147)
Fatal × Agreeableness	-0.0044*	0.0123*	-0.0023	0.0040
	(0.0026)	(0.0067)	(0.0063)	(0.0095)
Fatal × Conscientiousness	-0.0015	-0.0007	-0.0117*	-0.0125
	(0.0028)	(0.0060)	(0.0070)	(0.0103)
Fatal × Extraversion	0.0044*	0.0003	0.0010	-0.0050
	(0.0024)	(0.0046)	(0.0065)	(0.0106)
Fatal × Neuroticism	-0.0006	0.0059	0.0002	-0.0142
	(0.0029)	(0.0070)	(0.0078)	(0.0109)
Fatal × Openness	0.0022	-0.0006	0.0169**	-0.0044
	(0.0030)	(0.0067)	(0.0081)	(0.0085)
Constant	5.8733***	6.0200***	6.1720***	6.9065***
	(0.0585)	(0.7669)	(0.0626)	(0.7959)
Observations	18,159	18,159	16,248	16,248
R-squared	0.3417	0.0126	0.3628	0.0153

Note: Dependent variable is natural log of real monthly labor income. Standard errors are in parentheses. Standard errors for OLS are clustered by individuals and robust to heteroscedasticity. Each model controls for age, age squared, union status, marital status, private job, the size of employees, 1 digit occupations, regions of residence and year dummy. For the OLS estimator, additional control variables are personality traits, years of schooling and race (i.e. white). *** significant at 1%, **5%,* 10% Source UKHLS.

Chapter 5 Conclusion

In this dissertation, I study heterogeneity in VSL stemming from health insurance coverage. The second chapter of this dissertation discusses the role of employer-provided health insurance on the VSL using the US labor market data. In this chapter I build a framework showing that the level of job risks influences the incentive of employers to provide EHI. Using Panel Study of Income Dynamics (PSID), I find evidence of heterogeneity in VSL due to health insurance status: the estimated VSL for workers with health insurance is lower than those without one. Chapter 3 extends the framework of the second chapter into the United Kingdom (the UK) labor market. The main contribution of this chapter is that it provides empirical evidence that private health insurance affects labor market outcomes—this is less known in countries with a universal health care system. Using the British Household Panel Survey (BHPS) I find evidence that the workers trade substantially wage-risk premium for private medical insurance. This is consistent with the finding from the US. Chapter 4 specifically discusses worker sorting and how it may affect the mortality risk premium. In this chapter, I focus on the role of personality traits in safety-related skill and their influence on worker sorting based on job risk. Using data from the United Kingdom Household Longitudinal Study (the UKHLS), I provide evidence of worker sorting based on personality traits.

Further research can be extended to explore the influence of other fringe benefits on VSL. One may consider the provision of life insurance and pension, and, their effects on the estimated VSL. In addition, findings from Chapter 4 suggest that personality traits do not fully capture unobservables that may be correlated safety-related skill. A plausible explanation is probably that the functional form or specifications that describe the relationship between personality traits and worker sorting are not entirely correct. Therefore, further research can explore better models that are able to recover parameters of personality traits that affect the choice of job riskiness.

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  - ECO 391: Economics and Business Statistics (2 sections)
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- Short-term Consultant, The World Bank, Jakarta Indonesia 2009
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Publications

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  - Recent Development in Higher Education in Indonesia (with D. Friawan) in S. Armstrong and B. Chapman (eds) in *Financing Higher Education and Economic Development in East Asia* EABER 2011.
  - Narrowing the Development Gap in ASEAN (with D. Narjoko and P. Kartika) in M. Plummer and C. S. Yue (eds) *Realizing the ASEAN Economic Community: A Comprehensive Assessment* Singapore: Institute of Southeast Asian Studies 2009.

- Papers
  - The Socio-Economic Impacts of Global Financial Crisis (with R. Atje) *Indonesian Quarterly*. 2009
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Scholarships and Awards

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- Gatton Teaching Assistantship 2013-2014, University of Kentucky.
- Fulbright Presidential Scholarship for PhD in the US 2010-2013, Fulbright.
- Australian Leadership Awards for PhD in Australia 2010, AUSAID (declined for Fulbright).
- Australian Leadership Awards-Fellowship for the Australian Institute of International Affairs Conference 2008, AUSAID.
- Australian Partnership Scholarship for Master's degree 2005-2007, AUSAID.