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Do You Think Your Risk Is Fair Paid? Evidence From Italian Labor Market

Leandro Elia
University of Calabria

Vincenzo Carrieri
University of Calabria

Edoardo Di Porto
University of Rome "La Sapienza" and Laboratorio R. Revelli, Centre for Employment Studies, Collegio Carlo Alberto

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Laboratorio R. Revelli, *Collegio Carlo Alberto*
Via Real Collegio, 30 - 10024 Moncalieri (TO)
Tel. +39 011 670.50.60 - Fax +39 011 670.50.61
www.laboratoriorevelli.it - labor@laboratoriorevelli.it

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Leandro Elia*
University of Calabria

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Abstract

Starting from Adam Smith's intuition, compensating wage differentials are one of the most widespread explanation to describe why agents should bear occupational risk of injury and death. For nearly thirty years, economists have attempted to find empirical evidence on such wage differentials mostly relying on estimation of a simple wage equation. This paper claims to put one step forward. Using the Survey of Household Income and Wealth (SHIW) 2004 we estimate for Italy the wage premium held by workers in risky occupations by means of the matching estimator. Such technique is desirable because it attempts to remove all the differences in wage coming from heterogeneity across individuals and not directly imputable to risk. Estimates suggest that net hourly wage premium is about 3% to manual workers and nearly null to non-manual workers. When we split the sample along the employer size, our findings show a heterogeneous treatment with respect to occupational status. Small firms tend to flatten out any risk premium to manual workers, while they recognize roughly 6% to non-manual workers; the opposite occurs when we look at medium-large firms wherein manual workers gain 1.5% to 5% more with respect their counterparts. Therefore, it seems that wage-risk tradeoff does not always emerge as hedonic wage theory would predict.

Keywords: wage differentials; risky jobs; value of a statistical life; propensity score matching.
JEL classification: C14; J31; J28; I19.

*Corresponding author: Department of Economics and Statistics, University of Calabria, 87036 Arcavacata di Rende (Cs), Italy. e-mail: lelia@unical.it

1 Introduction

In Italy, the political debate about job safety is particular widespread especially in recent years. Despite Italian legislation obliges employer to take measures to prevent dangerous happening to the workers and thereby to reduce the probability of being injured, Italy is experiencing a significant rate of injury and death in workplace, with an average of more than 3 deaths per day (Inail, 2007) and with a non negligible proportion of workers that experience at least one injury in workplace in a year (3.7% in 2007) (ISTAT, 2008). The highest figures concern workers aged 35-44, males, non-native workers and blue-collars, while, with regard to economic sector, constructions, manufacturing and transports are the riskiest.

Irrespective of the efficacy of italian legislation to reduce risk on the job place, it is interesting to inquire whether bearing the risk is at least compensated by a higher wage. This intuition is very old in economic theory and it is known as the hedonic wage theory. According to Adam Smith, differences in wages reflect differences in the labor characteristics, such as arduousness, honorableness, different quality components of the job and so forth, as well as workers' productivity. In that framework, a risky job position should be compensated by differences in wage rate. Labor market, then, can be viewed as providing a mechanism for implicit trading in risk, with the degree of risk varying from one job to another.

The idea that a risky job should be paid more is also present in the health economic literature which highlights the risk premium as a component, perhaps the main one, of the so-called *value of life*, that is, how much people care about their own safety (Viscusi 2003b; Rosen, 2004). In a sense, wage risk premium can be viewed as the market value of the risk and it has been the subject of many empirical investigations about the value of a statistical life (see the comprehensive review of Viscusi, 2003b).

Both labour economics and health economics approach to estimate such a risk premium has followed, in the last two decades, the hedonic wage framework. Finding empirical evidence of such wage differentials, however, it is problematic, given the difficulty to disentangle the pure wage risk premium, if any, from other factors that affect wages, as unobserved workers' ability, firm size and/or firm industry-specific differentials and so forth. Even if one controls for both workers' productivity and different quality components of the job, endogeneity and sample selection issues might affect the estimates. These pitfalls turn out to be noteworthy if one consider that the statistical approach mainly used so far has been the canonical mincerian equation, which is well recognized to release biased estimates, due to the existence of unobservable traits of the workers to the researcher. As a result, it has not been always straightforward to derive a clear-cut causal relationship between risky job and wage.

In this paper we attempt to cope with some of these difficulties, estimating wage differentials between risky and non-risky jobs by means of a matching estimators, never used in empirical literature on risk premium so far. Such a technique seems desirable because it enables us to infer causal relationship between the "treatment", holding a risky position, and the "outcome", hourly wage, if there exists selection on observables and, in this way, it allows us to overcome both the bias of OLS estimates and sample selection bias (Heckman *et al.*, 1998; Blundell *et al.*, 2002) .

Using data from Italy, drawing from the Survey of Household Income and Wealth (SHIW) 2004, we find that wage risk premium, is quite small and not always recognized compared to other countries (amongst others see Biddle and Zarkin, 1998, Hersch, 1983 for US, Lalive 2000 for Austria). Hourly wage premium is about 3% to manual workers and nearly null to non-manual workers. When we split the sample along the employer size, results suggest a heterogeneous treatment with respect to occupational status. Small firms tend to flatten out any risk premium to manual workers, while they recognize roughly 6% to non-manual workers; the opposite occurs when we look at medium-large firms wherein manual workers gain 1.5% to 5% more with respect their counterparts.

The structure of the paper is as follows. Section 2 provide a simple theoretical framework of compensating wage differentials. Section 3 highlights the econometric strategy. Section 4 describes the data and provides summary statistics of the variables that we used in the econometric analysis. The last section shows results and gives some final remarks.

2 Theoretical Framework

A good example to sketch the theoretical framework underlain our empirical investigation is the basic illustration provided by Viscusi (2003b). Consider that risk to be transacted in the market; the market price of a unit of risk is the wage premium an individual would be willing to forgo to engage in an occupation with a lower probability of death or severe injury. Firms and workers then exchange wage-job risk bundles (w, r) within an implicit labour market.

Consider that workers' decision about their supply of labour depends on both wage as well as the level of risk they are exposed. Let $U(w)$ represent the von Neumann-Morgenstern expected utility function of a healthy worker at wage w and $V(w)$ represent the von Neumann-Morgenstern expected utility function of a injured worker at wage w. Further, assume that workers prefer to be healthy than injured, i.e. $U(w) > V(w)$ and that the marginal utility of wage is positive, i.e. $U'(w) > 0, V'(w) > 0$. All wage-risk combinations that satisfy a constant level of

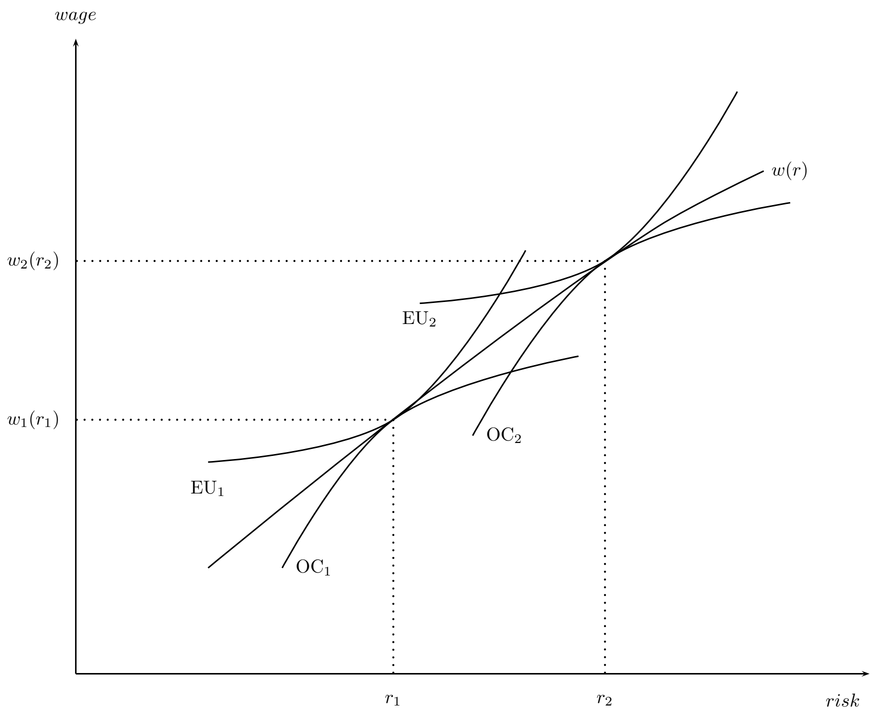

Figure 1: Long-run competitive equilibrium for compensating differentials.

expected utility are such that the following holds:

$$(1-r)U(w) + rV(w) = u \tag{1}$$

The above indifference curve is showed in figure (1) and labeled as EU_1 for worker 1 and EU_2 for worker 2 (worker 2 is unambiguously more prone to job risk).

Firms' demand for labor is decreasing with the total cost of employing a worker. Considering that the cost of a worker includes the costs of providing a safe working environment, the cost of employing a worker is thus increasing with the level of safety provided. As a result, for a given level of profit, firms must pay less workers with a safer working conditions. This is represented by an increasing offer curve in the wage-risk space. Fig. (1) displays two firms with wage-risk offer curves OC_1 and OC_2. The envelope of those offer curves detects then the market opportunities locus $w(r)$.

Workers maximize expected utility choosing the wage-risk combination along the market opportunities locus $w(r)$. As a result, worker 1's optimal job risk choice is the tangency between EU_1 and firm 1's offer curve OC_1; worker 2 maximizes expected utility at the tangency between EU_2 and OC_2.

Differentiating equation (1) with respect to w and r it can be shown that the wage rate is increasing in the risk level:

$$\frac{\mathrm{d}w}{\mathrm{d}r} = \frac{U(w) - V(w)}{(1-r)U'(w) + rV'(w)} > 0 \tag{2}$$

All these points of tangency reflect the joint influence of supply and demand of labour and thus the observed wage-risk tradeoff is only a local measure for marginal changes in risk. Non-marginal changes in risk must be made along the worker's expected utility locus and not the envelope $w(r)$. For instance, if individual 1 is exposed to risk r_2 the optimal wage choice must be detected on EU_1, thus worker 2 should be paid more than individual 2 at same risk r_2. It is worth pointing out that the only thing that we can observe and then estimate is the marginal changes in risk, which are expected to be positively associated with wage as showed above.

3 Econometric Strategy

The aim here is to show and explain our choice of using the method of matching in such a framework. In the discussion we strongly relate to the evaluation and selection literature (see Heckman *et al.*, 1999 amongst others). One might see the estimation problem in the risk wage differentials framework as synonymous with the construction of a counter-factual in the evaluation literature. Assuming that the treatment status is "working in a very risky job" we are interested to construct the counter-factual of interest "working in a non-risky job" for the same individuals, thus, according to some observable characteristics, we are able to recover the missing information on the outcomes of the treated had they not been treated and, by means of that, get an estimate of the wage risk premium.

To show the importance of constructing the counterfactual, consider the following model. Let T_i be the treatment index, $T_i = 1$ stands for worker employed in a very risky job and $T_i = 0$ worker employed in non-risky job. For any individuals i in the set of individuals that receives the treatment the earnings outcome is:

$$\ln \omega_i^1 = \alpha_i + \beta_i T_i + \epsilon_i \quad \text{for } i \in \{T_i = 1\}.$$

Whereas if the same individual were not to receive the treatment, that is, he is not employed in a risky job their earnings outcome would be:

$$\ln \omega_i^0 = \alpha_i + \epsilon_i \quad \text{for } i \in \{T_i = 0\}$$

the superscript 0 refers to the counter-factual earnings of an individual i for whom $T_i = 1$ in the observed data. If we could observe both outcomes for all individuals for whom $T_i = 1$ then the average

$$\sum_{i \in T_i = 1} \frac{\ln \omega_i^1 - \ln \omega_i^0}{n_1}$$

where n_1 is the number of individuals for whom $T_i = 1$ in a random sample of size n, would be a consistent estimate of the average treatment on the treated effect β_T, i. e., average wage risk premium of holding a very risky job. In a randomized experiment the control group is chosen independently of α_i, β_i and ϵ_i by design, as a result the average treatment effect can be measured straightforwardly from a comparison of the control group and the treatment group. As we use non-experimental data, and we do not observe both outcomes for all individuals for whom $T_i = 1$, we need to construct the control group. We do that through the method of matching. It attempts to mimic an experiment by choosing a comparison group from all the non-treated such that the selected group is as similar as possible to the treatment group in terms of their observable characteristics. Under the matching assumption[1] that all the outcome-relevant differences between any two individuals are captured in their observable characteristics, the only remaining difference between the two groups is "programme partecipation". Thus, it enables us to purge the relationship between "working in a very risky job" and wage of any observed heterogeneity that would lead to bias (Heckman *et al.*, 1999).

We carry out the matching procedure based on the results of Rosembaum ad Rubin (1983): rather than matching on each single characteristics a *balancing score* is implemented. More precisely, we make use of the *propensity score*, which gives us the propensity to be selected in a very risky job given the full set of observed characteristics of individuals (X_i): $p(X_i) \equiv P(T_i|X_i)$[2].

To construct the counterfactuals of interest, we estimate a propensity score (probit regression) of being selected into the treatment "filling a very risky position" using the set of covariates discussed in the following section. We perform several specification including and/or excluding some covariates and we achieve a satisfactory selection by using the covariates depicted in tab.(1). In doing so, we are able to pair to each treated

[1] The solution advanced by matching is based on the following assumptions:

i *Conditional independence assumption (CIA)*: conditional on the set of observables X_i, the non-treated outcomes are independent of the participation status: $\omega_i^0 \perp T_1 | X_i$.

ii All treated individuals have a counterpart on the non-treated population and anyone constitutes a possible partecipant: $0 < P(T_i = 1|X_i) < 1$

[2] Rosembaum and Rubin show that the CIA remains valid if controlling for $p(X)$ instead of X

individuals i some group of comparable non-treated individuals and then to associate to the outcome $\ln\omega$ of treated i, a matched outcome $\widehat{\ln\omega_i^0}$ given by the weighted outcomes of his neighbours in the comparison groups. The matching estimator for the average wage risk premium is then given by:

$$\widehat{\beta}_T = \sum_{i \in T_i=1} \left\{ \ln\omega_i^1 - \widehat{\ln\omega_i^0} \right\} \frac{1}{n_1}$$

where T represents the treatment group, n_1 the number of treated individuals and $\widehat{\ln\omega_i^0} = \sum_{i \in C} W_{ij} \ln\omega_i^0$. As it will be clear in the next section, we use three different matching estimators which differ in how they construct the matched outcome $\widehat{\ln\omega_i^0}$. More precisely, we make use of *nearest neighbour*, *stratification* (see Dehejia and Wahba, 1999), and *kernel-based matching* (see Heckman *et al.*, 1997; 1998). The rationale behind using three different approaches is simply to check that the estimates are not procedure-contingent. Uniformity of estimates' magnitude should allay concerns about imprecise matching between the treatment and comparison groups.

It is worth pointing out that what we are able to retrieve is only an estimate on how a particular worker must be compensated for marginal changes in risk. The wage-risk tradeoff estimated is thus a single point on the envelope in fig. (1) and this value varies according to the level of risk considered. Considering very risky jobs, as we do in this paper, implies that individuals working on such jobs have lower reservation supply prices of risk and as a result smaller demand prices for safety than the average worker. Rosen (2004) shows that using data on very risky jobs underestimates the average demand price for safety at the observed risk levels in the sample. Analogously, it has to be true that firms offering very risky jobs have a comparative disadvantage at producing safety, as a result, using data on very risky jobs overestimates the average supply price of safety (or demand price for risk) for most firms in the economy.

4 Dataset and Summary Statistics

We use a microdata sample from Survey of Household Income and Wealth 2004 (SHIW) of the Bank of Italy. The SHIW is based on a random sample of 8,012 households, 20,581 individuals. It contains information on both household and individuals. The leading purpose of this survey is to pick individual financial information, but it also contains a lot of individual characteristics such as the highest completed school degree, gender, age, years of working experience, weekly hours worked, gross yearly wages, region of residence, etc. Likewise, it includes information on parental education, sector and job position. Unfortunately, family background characteristics are available only for the heads of household. Indeed, we draw a subsample of 1544 heads of household, full time employed, aged 19 to 78.

Table 1: Summary statistics of the overall sample.

Variable	**Mean**	**s.d.**
log hourly wage	2.10	0.39
Age	43.09	9.38
Male	0.78	0.41
Married	0.70	0.46
Non-native	0.11	0.31
Education		
Primary school	0.11	0.32
Secondary school	0.38	0.48
Upper secondary school	0.43	0.49
College	0.06	0.25
Scientific college degree	0.046	0.21
Vocational	0.28	0.45
Degree score	0.33	0.40
Area of residence		
Urban	0.56	0.49
North-west	0.27	0.44
North-east	0.28	0.45
Middle	0.22	0.41
South	0.22	0.41
Family background		
Father's years of schooling	5.89	4.07
Father unemployed	0.01	0.12
Father blue-collar	0.52	0.49
Mother's years of schooling	5.23	3.80
Mother unemployed	0.56	0.49
Mother blue-collar	0.15	0.36
No. observations	1544	

To construct the propensity score of being selected into the treatment, we consider the following informational set:

- **Socio-demographic characteristics**: age, sex, status, nationality and area of residence. We make use of the canonical partitioning in 4 areas, that is, North-East, North-West, Middle and South. Whether individuals live in an urban area is also considered.

- **Educational background**: dummy variables for the educational level attained. As dataset miss information about precise years of schooling, we make use of educational degree attained, in particular we consider 4 educational levels: primary, secondary, upper secondary, college, which roughly correspond to $5, 8, 13, 18+$ years of schooling respectively . We also take into account whether individuals have followed a technical undergraduate route, whether have attained a scientific college degree and the score of the degree achieved.

- **Wage**: although hourly wage is not available in the SHIW dataset, thanks to information about hours worked we are able to build it as follows:

$$\frac{\text{yearly earning}}{\text{months worked} * \text{weekly hours worked} * 4}$$

  We use worker's after-tax wage because it is recorded benefits-free; in this way, we are certain that wage variable is comprised of only base-wage.

- **Family backgrounds**: We allow for both parental social class and educational level attained.

Lastly, to construct our risk measure we follow the standard approach in the literature. We use industry-specific risk measure provided by INAIL (Italian agency for the insurance against work-related injuries). It reflects an average of fatalities occurred in 2004. We consider risky jobs as those which lie above the 70% of the distribution of injury rate per sector. They belong to the conventional very risky sectors such as mining, manufacturing, construction and transports (see appendix 1 to see how we construct the treatment variable). Table 1 shows descriptive statistics of the above variables.

5 Results

Table 2 depicts the results obtained by matching estimator considering full sample and then both manual and non-manual workers[3]. We only show the estimates

[3] We perform the matching estimates thanks to PSMATCH2 Stata module v. 3.0.0 (Leuven and Sianesi, 2003) and atts.ado Stata module (Becker and Ichino, 2002)

that yield the better balancing between treatment and control groups. Full sample estimates suggest that there is no wage risk premium on average in the Italian labour market. A negligible wage premium appears from stratification method, that is bearing the risk is compensating by 0.6% more in terms of hourly wage. The result tends to be lower with respect to other empirical works carried out for other countries and with the same sample population (Biddle and Zarkin, 1998 find a point estimate of 1.6%; Duncan and Holmlund, 1983 find 2%; Lalive, 2000 obtains an estimate of 1.3%; Viscusi and Moore, 1987 finds 1.7% and 4.% depending on the type of specification). Unfortunately, there are no empirical works carried out for Italy in that topic and, at the same time, no one have used our econometric approach so far, then we lack for any appropriate comparison. Notwithstanding, we believe our low results, one one hand, might depend on an overall flat wage distribution typical of the Italian labour market (amongst others see Bertola and Ichino, 1995) and, on the other hand, they might be the consequence of more genuine estimate retrieved by the matching estimator, which is aimed at removing the amount of wage differentials not directly attributable to risk.

Table 2: Average treatment on the treated results (overall, manual and non-manual workers).

	ATT	s.e.†	obs.
overall sample			
Nearest Neighbour - all obs.	-0.004	0.034	1299
Kernel density - bwidth (0.06)	0.003	0.023	1299
Stratification	0.006	0.023	1299
manual workers			
Nearest Neighbour - cal. (0.0025)	0.028	0.043	666
Kernel density - bwidth (0.06)	0.035	0.031	753
Stratification	0.026	0.032	753
non-manual workers			
Nearest Neighbour - cal. (0.004)	0.002	0.064	525
Kernel density - bwidth (0.06)	0.010	0.040	546
Stratification	0.008	0.038	546

† Matching standard errors are bootstrapped (300 replications).

We cannot just limit the analysis on that estimates because the full sample may include a huge source of heterogeneity (e.g. workers ability, job positions, firm size, amongst others) and bounding the analysis on that leads surely to biased estimates. In order to cope with this heterogeneity and to allow for some labor market segregation effects we carry out our analysis separately for different sub-samples (e. g., Hersch 1998, Herzog and Schlottmann 1990, Sandy and Elliott 1996 carry out a similar strategy); in particular, we first investigate whether the magnitude of the wage risk premium is dissimilar with respect to manual and non-manual workers and further whether there might be some employer size-wage effect at work.

When we split the sample along the type of occupation such that non-manual workers are those which hold a managerial job, a positive premium emerges. Irrespective of the matching technique, manual workers in risky jobs gain about 3% compared to their counterparts in a non-risky position, whereas no or negligible compensating differential is detected when we look at non-manual workers, in line with Hersch (1998). The fact that every matching technique releases similar estimates further strengthens these findings.

It is recognized that part of wage differentials may be explained by firm and/or establishment size differentials, i.e., large firms generally pay higher wages than the small ones for several reasons (see Brown and Medoff, 1989; Oi and Idson, 1999). A component of the above risk premium might be likely associated to heterogeneity in firm size. Thus, to take into account this fact and to rule out some source of bias deriving from firm size, we perform a separate analysis for small and medium-large firms. A more detailed classification would require the orthodox partitioning in three groups (small, medium, large), unfortunately, owing to lack of observations in our sample, we are forced to use just those two groups. Nevertheless, such partitioning is not as bad as it could appear, because it is still able to capture the italian industrial organization that rely mostly on small firms (firms that employ less than 15 employees) and relatively little on large firms. We retrieve estimates for both manual and non-manual workers in small and medium-large firms as reported in table 3.

Empirical findings on wage differentials according to employer size-wage theory seems to be confirmed also for risk premium. As table 3 shows, small firms appear to pay less and likely to flatten out any wage premium, whereas medium-large firms only recognize about 1%. It is noteworthy that within these two groups manual and non-manual workers premium seems no to follow the path sketched above. In particular, non-manual workers' wage seems to be higher in small firms. It amounts to about 6% when one considers nearest neighbour and stratification matching. Unfortunately, we do not achieve the same correspondence in magnitude across the estimates as before: kernel matching detects a nearly null wage premium. This drawback may be the result of the small sample size which does not permit a satisfactory balancing of covariates between treatment and control groups.

On the other hand, when we consider medium-large firms the picture is wholly

Table 3: Average treatment on the treated results (small and medium-large firms).

	ATT	s.e.†	obs.
SMALL FIRMS			
overall workers			
Nearest Neighbour - all obs.	-0.003	0.054	519
Kernel density - bwidth (0.06)	-0.003	0.038	519
Stratification	-0.008	0.039	519
manual workers			
Nearest Neighbour - cal. (0.006)	-0.006	0.078	310
Kernel density - bwidth (0.06))	-0.003	0.055	354
Stratification⋆	0.006	0.062	354
non-manual workers			
Nearest Neighbour - cal. (0.0035)	0.058	0.180	141
Kernel density - bwidth (0.09)	0.007	0.104	162
Stratification	0.062	0.096	162
MEDIUM-LARGE FIRMS			
overall workers			
Nearest Neighbour - cal. (0.0025)	0.015	0.049	655
Kernel density - bwidth (0.06)	0.010	0.029	767
Stratification	0.004	0.031	780
manual workers			
Nearest Neighbour - cal. (0.0025)	0.015	0.066	262
Kernel density - bwidth (0.06)	0.030	0.045	371
Stratification	0.050	0.038	391
non-manual workers			
Nearest Neighbour - all obs.	-0.033	0.072	380
Kernel density - bwidth (0.06)	-0.001	0.044	380
Stratification	-0.014	0.481	380

† Matching standard errors are bootstrapped (300 replications).

⋆ *married* is not included in the estimation of the p-score to satisfy the balancing property.

reversed: manual workers gain on average a positive premium ranging 1.5% to 5%, whereas non-manual workers' estimates display a conter-intuitive negative risk premium. However, these negative values are informative of the presence of no compensating differentials. This figures might potentially be explained by the higher rate of unionization observed in the larger firms: as union tends to favor more the manual workers in the collective bargaining (and the collective contracts cover mostly manual jobs) it is likely that they succeed in obtaining a higher premium for this type of jobs.

6 Final Remarks

For nearly thirty years, labour and health economists were striving to find empirical evidence about the wage-risk tradeoff. The bulk of the literature seems to confirm Adam Smith's intuition about compensating differentials for occupational hazard across countries. The econometric approach mainly used so far has been the conventional wage equation, wherein a more or less sophisticated measure of risk on the job has been the principal concern on which drawing conclusions. This paper attempts to put one step forward by testing such old theoretical insight by means of a quite recent econometric methodology. We estimates wage differentials between risky and non-risky jobs in Italy, using a matching estimator. We believe that a semi-parametric technique is desirable whether inferring causal relationship between treatment, holding a risky position, and outcome, hourly wage, is the main concern.

One main limit of the paper is likely constituted by the fact of relying on an industry-specific risk measure which may lead to retrieve inter-industry rather than risk differentials. However, as Dorman and Hagstrom (1998) outlined, this is a common feature of any risk measure because the injury risk typically reflects industry-level risk. Moreover, many papers have shown that when one controls for both risk and industry variables, the magnitude of the risk premium is unaffected and still significant (for a comprehensive review see Viscusi, 2003).

Our main results can be summarized as follows: i) on average, risk premium is almost zero; ii) manual workers gain about 3% more, while non-manual workers do not receive any compensating differential; iii) small firms tend to recognize a risk premium only to non-manual workers, while medium-large firms recognize such a premium only to manual workers. To sum, the paper shows that in Italy wage risk premium is quite small compared to other countries and not always recognized as hedonic wage theory would predict. Notwithstanding, a positive premium is present for very risky positions as manual workers, that as ISTAT investigation depicts (2008) are those that experienced a significantly higher injury rate. In this case, the matching estimator seems to be more appropriate in detecting such a premium because it attempts to take off all the differences in wage coming from heterogeneity across individuals and not directly imputable to risk.

To answer to the question in the title, we might say that there is no a clear-cut trend. Although first results (manual workers risk premium is higher than non-manual one) are consistent with the theory, it seems that when a finer disaggregation of labour market aspects is carried out, this trend tends to be vanished (this is the case of the small firms). These mixed results lead us to wonder whether there exists something else at work. Safety-enhancing expenditure by firms explanation would seem unsatisfactory given the persistence of injuries and deaths in the workplace even in the small firms. Lower unionization rate in small firms might be a more reasonable explanation since a weaker workers' bargaining power should usually lead to lower wage differentials of any kind. If this is the case, besides the reduction of injury exposure, equalizing risk premium opportunities across workers should then be the main important policy intervention task.

References

[1] Ashenfelter, O. (2006). Measuring the value of a statistical life: problems and prospects, *The Economic Journal*, 116:14.

[2] Becker, O., S., and Ichino, A., (2002), Estimation of average treatment effects based on propensity scores, *Stata Journal*, vol. 2(4), pages 358-377.

[3] Bertola, G. and Ichino, A., (1995), Wage inequality and unemployment: US versus Europe, in Bernake, B. and Rotemberg, J., (editors), *NBER Macroeconomics Annual*, NBER.

[4] Biddle, J. E. and Zarkin, G. A. (1988), Worker preference and market compensation for job risk, *The Review of Economics and Statistics*, 70(4):660–667.

[5] Blundell, R. and Costa Dias, M. (2002), Alternative Approaches to Evaluation in Empirical Microeconomics, *Cemmap Working Paper*, 10(2).

[6] Brown, C. and Medoff, J. (1989), The Employer Size-Wage Effect, *Journal of Political Economy*, 97(5):1027-59.

[7] Dehejia, R. H and Whaba, S. (1999), Causal Effects in Non-experimental Studies: Re-Evaluating the Evaluation of Training Programmes, *Journal of American Statistical Association*, 94:1053–1062.

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

[9] Dorman, P. and Hagstrom, P. (1998), Wage compensation for dangerous work revisited, *Industrial and labor relations review*, 52(1):116-135.

[10] Heckman, J., Ichimura H., Todd P. (1997), Matching as an Econometric Evaluation Estimator: Evidence from evaluating a Job Training Programme, *Review of Economic Studies*, 64:605–654.

[11] Heckman, J., Ichimura H., Smith J., Todd P. (1998), Characterizing Selection Bias Using Experimental Data, *Econometrica*, 66(5):1017–1098.

[12] Heckman, J., Lalonde, R. and Smith, J. (1999), The Economics and Econometrics of Active Labor Market Programs, in Ashenfelter, O. and Card, D., (editors), *Handbook of Labor Economics*, vol. 3B, 2165-214, Amsterdam: North-Holland.

[13] Hersch, J. (1998), Compensating differential for gender-specific job injury risks *American Economic Review*, 88(3):598–607.

[14] Herzog, H. W. and Schlottmann, A. M. (1990), Valuing risk in the workplace: market price, willingness to pay, and the optimal provision of safety, *The review of economics and statistics*, 72(3):463–470.

[15] ISTAT (2008), Salute e Sicurezza sul Lavoro, Statistiche in Breve.

[16] Lalive, R. (2000). Did we overestimate the value of health?, *IEW Working Paper*, (60):23.

[17] Leuven, E. and Sianesi, B. (2003), "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing". http://ideas.repec.org/c/boc/bocode/s432001.html. This version 3.0.0.

[18] Oi, W. Y. and Idson, T. L. (1999), Firm Size and Wages, in Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, vol. 3B, 2165-214, Amsterdam: North-Holland.

[19] Olson, C. A. (1981), An analysis of wage differentials received by workers on dangerous jobs, *The Journal of Human Resources*, 16(2):167–185.

[20] Rosen, S.. (2004), *Market and Diversity*, Harvard University Press, Cambridge MA.

[21] Rosenbaum, P. R. and Rubin, D. B. (1985), The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika*, 70:41–55.

[22] Sandy, R. and Elliott, R. F. (1996), Unions and Risk: Their Impact on the Level of Compensation for Fatal Risk, *Economica*, 63(250):291–309.

[23] Thaler, R. and Rosen, S. (1996), The Value of Saving a Life: Evidence from the Labor Market, in Nestor E. Terleckyj, editor, *Household Production and Consumption*, New York, NBER.

[24] Viscusi, W. K. (1978), Wealth effects and earnings premiums for job hazards, *The review of economics and statistics*, 60(3):408–416.

[25] Viscusi, W. K. and Moore, M. J. (1987), Workers' compensation: wage effects, benefit inadequacies and the value of health losses, *The Review of Economics and Statistics*, 69(2):249–261.

[26] Viscusi, W. K. (2003a), The value of life: estimates with risks by occupation and industry, *Harvard Discussion Paper*, 422.

[27] Viscusi, W. K. (2003b), The Value of a Statistical Life: a critical review of market estimates throughout the world, *The Journal of Risk and Uncertainty*, 27(1):5-76.

Appendix 1

Table 4: Injury rate per NACE (Rev.) sector, 2004 [†]

Sector	**Injury rate 1000 workers**
Agriculture and fishing (A+B)	87
Mining, manufacturing, electricity (C+D+E)	109.75
Construction (F)	178
Wholesale and retail trade, Hotels and restaurant (G+H)	92
Transport(I)	116
Financial intermediation (J)	10
Real estate(K)	64
Public administration,education, health, other social activities (L+M+N+O)	63.25

[†] Source: our calculations based on INAIL data, www.Inail.it

Table 4 depicts our calculations about injury rate per 1000 workers per sector. Risky jobs, that lie above the 70% of injury rate distribution are represented by mining, manufacturing, construction and transports.