Risky jobs and wage differentials: an indirect test for segregation

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ABSTRACT

Social scientists have developed several indicators to address the existence of segregation processes. This paper deals with labor market segregation in risky jobs and suggests a simple *indirect way* to detect segregation based on battery of statistical tests in a well-established microeconomics setting: the theory of compensating wage differentials. The test is based on matching estimator and the Rosenbaum bounds test and allows us to detect segregation while correcting for the selection bias that affect standard estimates, commonly based on OLS. We apply our test to the Italian labor market and we detect a strong segmentation in risky jobs. According to the theory, workers segregated in risky jobs, earn a lower wage.

Keywords: wage differentials; risky jobs; segregation; propensity score matching, Rosenbaum bounds.

JEL Classification: C14; J31; J28; I19

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1.Introduction

In the last three decades, the interest on compensating wage differentials in labor and health economics has been extensive. The hedonic theory of wages shows that perfect competition in the labor markets leads to wage heterogeneity, which is a result of the marked differences in working conditions.[2] Rosen (1974) formalized such idea and showed that competitive labor market provides an implicit mechanism for trading in job unpleasantness, which leads to reimbursement for the workers employed in the hardest jobs.[3] This mechanism also allows us to detect a measure of the worker willingness to take an arduous job. Indeed, wage compensating differentials have been the main source of information on which building an estimate of the so-called value of statistical life (see Viscusi and Aldy 2003b for a comprehensive review).[4]

For nearly thirty years scholars tried to find empirical evidence of such wage differentials, attempting to disentangle the pure wage risk premium from other supply- and demand-side factors that affect wage (e.g. human capital, ability, industry-specific differentials and so forth). The methodology used so far was mainly a wage equation estimated by ordinary least square, where holding “risky job” is taken as one of the possible determinants. As a consequence, the test for risk premium was simply based on a t-test applied to the coefficient of “risky job” in this equation. The main effort of the applied literature was to refine the risk measure, using both subjective and objective risk measures calculated at position levels rather than at more aggregate levels (e.g.. industry level) (see Dorman and Hagstrom, 1998; Viscusi and Moore, 1987; Viscusi, 2004), while leaving the assumption of homogenous individuals unaltered. Other papers took into account preferences heterogeneity by using information directly available on individual’s attitudes or tastes such as seat-bealt users, smokers, alcohol abusers and so on (Hersch and Viscusi, 1990; Viscusi and Hersch, 2001). More recently, scholars have also examined difference in the wage risk premium across the distribution of earnings, finding that it varies elastically with income (Evans and Smith, 2010; Kniesner et al., 2010).

Arguably, the methodology of the wage equation is weak in this context, because it implicitly assumes that people are randomly selected in risky jobs. This assumption cannot hold (see Heckman et al., 1998, 1999). Firstly, people do not value equally their safety, as the individual heterogeneity in the estimates of the statistical value of life suggests. Secondly, differences in wage hide differences in worker productivity, levels of unionization and ability to avoid risk on the job place. If both situations apply, a selection process must be taken into account in order to reveal a causal relation between risk and wage. Finally, a more nuanced exploration of the mechanism driving the sorting of individuals into risky jobs helps to detect any form of segregation in the labor market. A segregation process in the labor market is at play when differences in individual’s tastes or characteristics lead to the acceptance of a lower compensation for risky jobs. This concept, despite 20 years of research on compensating wage differentials, has been advanced and detected only by Hersch and Viscusi (1990) and Viscusi and Hersch (2001).

This paper explores the selection mechanism and the existence of segregation in risky jobs using some econometric methods, which have never used so far in this context, namely the propensity score matching estimator (PSM) (Rosenbaum and Rubin, 1985) and the Rosenbaum bounds test (RBT) (Rosenbaum, 2002). The first method performs a selection on observables characteristics and it enables us to infer the causal

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2 The human capital theory predicts that wage heterogeneity may also arise from differences linked to individual competence. The focus of this paper is only on the demand side of the labor market.

3 Adam Smith described the premises of the hedonic theory at the end of the eighteenth century, noting that workers with the same level of competence should be paid different wages if their working conditions were different.

4 Put it differently, the value of statistical life is a measure of how much people care about their own safety. This measure is helpful in political economy, to evaluate the monetary gains of health policy for instance.

relation between "holding risky position" (treatment) and "hourly wage" (the outcome), thus overcoming the bias of OLS estimates. The second method is a sensitivity test based on propensity score matching estimates and detect whether the estimates are affected by hidden bias due to selection on the unobservable heterogeneity. Moreover, it suggests the direction of a possible hidden bias. We aim to clarify the extent of this selection process - and its nature - by comparing a battery of estimates: OLS, PSM and RBT. In other words, we try to disentangle the differences in the wage-risk tradeoff due to both observables characteristics (i.e. education, age, gender and many other covariates) and unobservable traits (i.e. differences in taste for risk). To detect the magnitude of the latter in the segregation process, we use the number of unmet medical care needs for non-financial reasons between individuals as a proxy for the taste for risk; we investigate whether individuals with taste for risk are actually more prone to accept lower compensation for risky jobs. Our results suggest that all of these estimates provide a bare-bone test for the presence of segregation in the labor market.

Our exploration is based on European Union Statistics on Income and Living Conditions (EU-SILC) data collected in 2004 in Italy. We focus on the Italian labor market, which provide an unparalleled setting to build our test. In particular, the Italian legislation provides for a compulsory insurance against injuries occurring at the working place. The insurance premium varies according to the level of on-the-job exposure to danger and it is set by the national agency for the insurance against work-related injuries (INAIL). Further, the premium is entirely paid by employers so that workers are fully covered in case of work-related injuries with no costs. Given these characteristics, we settle the case in which theory suggests a wage differential equal to zero, providing us with a "benchmark" of the wage differential that should prevail if no selection process is at work. In other words, it represents a "null hypothesis".

Our empirical test suggests the presence of a strong selection in risky jobs both on observable and unobservable characteristics. By accounting for differences in taste for risk, estimates reveal that people with taste for risk receive a lower compensation. These results show that in the Italian labor market a strong segregation process is at play. We can reasonably argue that most of the detected unobserved heterogeneity in wage-risk estimates is due to this segregation process, reconciling our empirical findings with the theory on compensating wage differentials.

The paper is structured as follows: section 2 provides the theoretical framework of compensating wage differentials. Section 3 explores the segregation concept and describes the strategy we use to detect it. Section 4 highlights the econometric strategy in details. Section 5 describes data and gives some descriptive statistics. Section 6 shows the results. Some final remarks are given in the last section.

2.Theoretical framework

A good starting point to build our theoretical framework – which in turn drives our empirical investigation - is provided by Viscusi (2003b). Consider that risk can 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 exchange wage-job risk bundles (w,r) within an implicit labor market.

Consider that workers' decision about their supply of labor depends on both the wage as well as the level of risk they are exposed to. 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 rather 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 expected utility are such that the following holds:

$$(1-r)U(w)+rV(w)=u \qquad (1)$$

The above indifference curve is showed in figure 1 (Appendix) and labeled as EU_1 for worker 1 and for worker 2 (worker 2 is unambiguously more prone to accept risky jobs).

Firms' demand for labor is decreasing in the total cost of employing a worker. Considering that the cost of a worker includes provision of a safe working environment, then the cost of employing a worker is increasing in the level of safety which has to be provided. As a result, for any given level of profit, firms must pay lower wages to workers to compensate for a safer working condition. This is represented by an increasing offer curve in the wage-risk space. Figure. 1 displays two firms with wage-risk offer curves OC_1 and OC_2. The envelope of those offer curves detects the market opportunities locus.

Workers maximize expected utility choosing the wage-risk combination along the market opportunities locus. As a result, worker 1's optimal job risk choice is found in the tangency between EU_1 and firm 1's offer curve while worker 2 maximizes his expected utility at the tangency between EU_2 and OC_2.

By differentiating equation 1 with respect to w and r, it can be shown that the wage rate is increasing in the risk level:

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

Equation 2 shows the customary wage risk trade-off[5].

A crucial assumption in this model is that workers are not fully covered in case of injuries. This is not unreasonable since, if employer or the government provides the worker with an insurance against accidents, there would be no on-the-job risk to be compensated by higher wages. Conversely, when in the presence of a compulsory insurance, we can argue that such insurance might not be complete, because it is difficult to estimate all the disutility costs incurred by workers after an accident (e.g., pain, suffering); in this case, a positive wage risk premium may even arise in labor market providing already a form of insurance against injuries. We argue that a positive risk premium is not the most likely outcome in Italian labor market for two reasons. Firstly, if disutility costs are dramatically high and hard to fully cover, the standard wage compensating hypothesis does not hold, because any marginal increase in wage would never be enough to accept the risk. Secondly, nowadays employer-provided insurance takes into account the so-called "biological risk", namely the permanent loss of ability as a result of some accidents at work. Such insurance covers both the productivity losses and any kind of long-term health disease following an injury. Thus, in a setting where insurance is provided free of charge to the workers, we can rationally assume either that i) the

[5] It is noteworthy to observe that all these points of tangency reflect the joint influence of supply and demand of labor 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 XXXX, thus worker 2 should be paid more than individual 2 at same risk r_2. Moreover, the only aspect that we can observe and then estimate is the marginal change in risk, which is expected to be positively associated with wage, as showed above.

wage risk premium equals zero or ii) it is positive when the hypothesis of complete insurance is relaxed. This is the case in the Italian labor market, where there exists a mandatory insurance, entirely paid by the employer, which covers workers both against accidents at work and against biological risks. Such insurance is provided by INAIL, which calculates the premium according to the average yearly injuries registered in each industrial sector. Italy is therefore an ideal environment to empirically test our assumptions on segregation; these assumptions build on and follow directly our theoretical framework, which gives external validity to the test.

3.Defining segregation

Segregation generally conveys the practice of forcibly separating people based upon their race, ethnicity or gender. We can distinguish two types of segregation: *de jure* and *de facto* segregation. *De jure* segregation means racial separation forced by specific laws. Under modern civil rights law, such form *segregation* is not observed anymore. *De facto* segregation relates to any racial or other group-based separation that happens by fact rather than by legal requirements, e.g. by school enrollment. According to its definition, *de facto* segregation refers to an homogenous racial grouping, i.e., a group of individuals that are predominantly of one race . The racial homogeneity of such group is generally assumed to be "bad" and to have been caused by some form of "racism", i.e., limited opportunity, economic , political or social disadvantage, and/or the effects of historic discrimination[6].

Social sciences have used this wide concept of (*de facto*) segregation in several fields. Labor economists have used this notion to indicate under- (or over-) representation of a given group in occupations or sectors, not ordered by any particular criterion. This is often referred to as segregation *tout court* or *horizontal* segregation, while *vertical* segregation usually denotes the under- (over-) representation of one group in certain levels of the professional hierarchy based on 'desirable' attributes, e.g. income, prestige, job stability. The definition of segregation allows us to determine a statistical indicator of segregation to track its changes over time. A variety of indices are commonly used: the Karmel and MacLachlan index, the index of dissimilarity and the classification of occupations into feminized (or other group specific), mixed and male-dominated (or other group specific) (for a survey of gender based indicator of segregation see Bettio and Verashchagina, 2008).

The economic theory of labor market segmentation, which should be considered as the counter part of segregation[7], contrasts with the view of perfect competition. Perfect competition posits the existence of a unified market for labor, consisting of buyers and sellers in open competition with each other. In this framework, wage heterogeneity purely arises from both individual differences in human capital (skills, experience, or formal education) and differences in job characteristics. In fact, according to the theory of compensating wage differentials, those who prefer risky jobs receive higher wages or salaries than those who take safer ones. The absence of a unified labor market is also confirmed by the empirical evidence. The so-called *dual labor marker* model provides a much better approximation of the empirical wage distribution than the *single labor market* model does (Dickens and Lang, 1988) and the theories relying on the existence of one market structure seem to be even more unrealistic in the case of risky jobs (see Viscusi and Hersch, 2001).

Viscusi and Hersh (2001) offer a clearer view of what may happen in presence of segregation for risky jobs. They consider workers heterogeneity in their taste for risk. For people more prone to risk, supply curve are flatter and the compensating wage lower. Moreover, in the theory of labor market segmentation, there exist

[6] The definition of *de facto* segregation does not apply if the homogenous racial group is economically, politically, socially better-off. In this case the group is homogenous because of voluntary choice and it is considered as "good" segregation.

[7] Labor market is segmented when a group of worker is segregated in specific sector or occupations.

important differences on the demand side, such as differences in compensations that are not explained by individual workers' characteristics. Since labor markets are far from perfect, non-market institutions can play an important role in producing different outcomes for workers with similar characteristics, as do the different strategies employed by employers. In a simple monopsonistic view, the results derived by Viscusi and Hersh (2001) could be seen as the consequence of an employer strategy, i.e. employer knows that risky jobs are usually non-qualified jobs and that labor market is segmented by risk. In this setting employers can offer a lower wage for those positions without losing the opportunity of hiring risk-lover workers.

As a consequence of the theories and the relevant literature discussed above, we derive the following hypothesis:

Workers that are more prone to risk self-select themselves into segments that are worker-specific. Vice-versa, in a labor market that provides a complete insurance, a negative wage risk premium for risk-prone workers is a signal of labor market segmentation.

Based on this hypothesis, we provide an indirect test to determine the existence of *de facto* segregation. Our approach is thus different from the approach of other social sciences' fields, as it does not make use of statistical indicators but derives an indirect test of segregation based on the economic theory. As we said, we are interested in segregation in risky jobs. We assume that for a variety of reasons-such as preferences, attitudes, or limited information set - a certain group of workers is more prone to accept a risky job. A risky job is defined as a job position in which the probability of suffering from an injury is high (or more generally higher than a given threshold). After performing an accurate selection on observable characteristics and assessing the influence of unobservable ones, we aim to test whether a negative wage risk premium arises for individuals who are employed in risky sectors. It can be argued that other factors may influence our estimates and leading to a negative wage risk premium. For example, endowment of skills might make a worker more willing to avoid the on-the-job risk. However, without any loss of accuracy, we can credibly assume that these behaviors/choices are a consequence of the segmentation in labor market. Therefore, even if we acknowledge that our definition of *de facto* segregation may be too broad in scope, we believe that it holds in the majority of cases accordingly, we rely on it to carry out our empirical test.

4. Empirical test

Given the above discussion, and supposing the existence of a full coverage insurance system, we should expect a null wage risk premium. Our aim is thus to verify this hypothesis. Any deviations from this benchmark - i.e. a negative or a non-negative wage premium - would suggest either a statistical bias (inadequacy of the econometric model, unobservable traits affecting the parameters of interest, measurement errors) or some hidden labor market effects. The first contribution of our paper is to deal with these statistical issues. We address the selection process underlying the choice of working in a job with higher odds of injury faced by the employees. In this section we show our empirical strategy.

Observing a positive wage premium would indicate that there exists a market for risk, in which workers and employers trade off wage and job-related safety. Finding a null wage premium would confirm the theory, while a negative wage premium could rise apparently for two different reasons:

a) A statistical problem: in this case we would not be able to solve the selection on observable problem or other unobservable factors at work.

b) The labor market for risky job is segmented, or some workers decide to work in riskier sectors

Solving the heterogeneity bias is therefore the main dish of our analysis. Once demonstrating that no bias from selection affects our estimates we can read our results in the following way:

1. Wage risk premium = 0 implies there is no market for risk and the compensating wage differentials theory is confirmed.
2. Wage risk premium > 0 implies that there is a market for risk (in this case we should relax forcefully our assumption of a complete insurance provided by Italian employers).
3. Wage risk premium < 0 implies segregation.

Therefore, we use a battery of estimates that allow us to detect the bias and its nature. First, we estimate an OLS, based on simply Mincerian equation, as follows:

$$\ln(w) = \beta_1 r + \beta'_2 X + \varepsilon_i \qquad (3)$$

Where w is the log of hourly wage, r takes on the value of 1 if individuals is employed in a risky position, and X is a matrix of covariates controlling for workers specific characteristics (see summary statistics section below).

The coefficient β_1 in equation (3) is the semi-elasticity of wage to the risk on the job-place. Such coefficient should be positive in the case of the classical trade-off between safety and wage and it should be zero in our setting, considering that individuals are insured for free against injuries and assuming that such insurance is complete. A negative value of β_1 can be caused by two factors. Firstly, it can capture a different composition in the observable characteristics of individuals who are employed in risky positions *vs* those working in a safe environment. The lack of what is called "common support" (Rosenbaum and Rubin, 1983) in covariates between these groups may generate a bias in OLS estimates. For example, consider the case in which all people not educated are prone to accept risky positions while more educated people may want to avoid risky jobs. As education is a positive determinant of wage, a simple OLS estimates may suggest a spurious negative wage premium for risky job. Secondly, β_1 could be negative because of unobservable characteristics that select individuals in the risky jobs.

4.1.Selection on observables

In order to figure out the selection on observables, we make use of a propensity score matching. One might compare the estimation problem in the risk wage differentials framework with the construction of a counter-factual in the literature on evaluation. Assuming that the treatment status is "working in a risky job", we want to construct the corresponding counter-factual for an individual with similar characteristics i.e. "working in a non-risky job" ; 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, as a result, 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 risky job and $T_i = 0$ for worker employed in non-risky job. For any individual i in the set of individuals that receive the treatment the earning outcome is:

$$\ln w_i^1 = \alpha_i + \beta_i T_i + \varepsilon_i \text{ for } i \in \{T_i = 1\} \qquad (4)$$

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

$$\ln w_i^0 = \alpha_i + \varepsilon_i \text{ for } i \in \{T_i = 0\} \qquad (5)$$

the superscript 0 refers to the counter-factual earnings of an individual i for whom $T_i = 1$ in the observed data. 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 chooses 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 assumptions that all the outcome-relevant differences between two individuals are captured by their observable characteristics, the only remaining difference between the two groups is the "program participation". Thus, it enables us to purge the relationship between "working in a 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 Rosenbaum and Rubin (1983): rather than matching individuals on specific characteristics, a balancing score is implemented. More precisely, we make use of the propensity score, which gives us the propensity of being selected in a very risky job given the full set of observed characteristics of individuals $X_i : P(X_i) \equiv P(T_i \mid X_i)$. To construct the counterfactuals of interest, we estimate a propensity score through a Probit regression (PS), where the dependant variable is the probability of being selected into the treatment group – i.e."filling a risky position" - using the set of covariates discussed in section 5. We perform several specifications through the inclusion/exclusion of some covariates and we achieve a satisfactory selection by using the covariates depicted in table 8. In doing so, we are able to pair each treated individual to some group of comparable non-treated individuals and then to associate the outcome $\ln(w)$ of treated i to, a matched outcome $\ln \hat{w}_i^0$ 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:

$$\hat{\beta}_T = \sum_{i \in T_i = 1} \{\ln w_i^1 - \ln \hat{w}_i^0\} \frac{1}{n_1} \qquad (6)$$

Where T represents the treatment group, n_1 the number of treated individuals and $\ln w_i^0 = \sum_{i \in C} \ln w_i^0$. We use three different matching estimators, which differ in the way they construct the matched outcome $\ln w_i^0$. More precisely, we make use of the nearest neighbour, the nearest neighbour with oversampling (five matches) and a kernel-based matching (see Heckman et al., 1997; 1999). The rationale behind using three different approaches is simply to check that our estimates are not procedure-contingent. The uniformity among the estimates' magnitude should allay concerns about imprecise matching between the treatment and comparison groups.

4.2.Selection on unobservables

In order to take into account the possibility that our estimates are affected by other factors non-observed in the data, we follow the procedure proposed by Rosenbaum (2002). Such procedure allows us to calculate the Wilcoxon sign rank tests, which gives the upper and lower bound estimates of the significance levels; these levels are then used to test the null hypothesis of no wage premium-ascribable to risky jobs - for different values of unobserved selection bias. Even if we use many background variables, it is likely that other unmeasurable factors influence the selection of people in risky jobs. As we explained above, one of these factors might be the different taste for risk. We devote more attention on this factor later on. The Rosenbaum test we carry out is capable of ruling-out the effect of unobservables; it also allows us to test whether such unobservable are altering the inference we make about the wage-risk trade-off in the matching estimates.

After having established the extent of selection on unobservable, we test the influence of taste for risk on the wage premium. Arguably, the heterogeneity in taste for risk is the main unobservable factor that can affect the estimates of the wage-risk trade-off; it is also particularly useful to test for the presence of labor market segmentation. As we have just mentioned above, if people who have a taste for health risk are paid *ceteris paribus* less than risk-averted individuals, they are segregated in such job places. We estimate an OLS and a matching estimate (PSM) differentiating for people that have different taste for risk. Such strategy has been already carried-out by other scholars (among others Hersch and Viscusi, 1990; Viscusi and Hersch, 2001). We consider as health risk-lovers those individuals who have unmet medical needs. Basically, we consider a population of workers in need of medical care who did not go to the physician for reasons other than their poor income . We then estimate separate model like (3) and (6), for workers that are assumed to be more prone to risk vis-a--vis workers that are less prone to risk. A penalization in terms of wage for people with a taste for risk would prove the hypothesis of segregation in the labor market based on differences in taste for risk.
To sum up, if a negative wage risk premium arising from the first battery of tests (OLS, PSM and RBT) still holds for people with a taste for risk - when the whole sample is considered we can prove the existence of a segregated market, namely:

Take two sub-groups of workers with different taste for risk, the group with the higher taste for risk will earn, on average, a lower wage.

5.Data and Summary statistics

We have a population of 14277 workers observed in 2004 and collected by the Italian version of the European survey EU-SILC. We can discriminate the sector in which the worker is employed. In table 9 we show the injury rate per sector on 1000 workers in 2004; we use this distribution to discriminate employees working in risky sectors. In our analysis, working in sector whose injury rate is above the median of this distribution would mean performing a risky job (as robustness check we will use also the upper quartile). According to the threshold chosen, we develop our propensity score using a dummy variable to identify treated individuals[8]. Manufacturing, Construction and Transportation are those sectors that are considered more risky in our analysis. The set of covariates we use for the propensity score are shown in Table 8. According to the econometric section, these variables explain observable heterogeneity in workers characteristics. We use a wide number of controls, almost fifty: twenty regional dummies; the age and its square; a dummy for gender; EU vs non EU citizenship; the household income; the age at the first job; seven variables controlling for different educational status of the employee; two covariates detecting the urban area where the employee lives; three dwelling type control variables; eight variables to account for the household composition; and some tenure specific covariates. Our choice respects the unconfoundedness criteria. Indeed, we have several controls, generally imputable to pre-treatment characteristics, so that, conditional on these controls, treatment assignment can be considered as randomized (Rosenbaum and Rubin, 1983). Also, our

[8] Workers that are employed in risky sectors.

variables are chosen in order to be *pre-treatment* covariates in line with the average treatment effect theory. Our outcome variable is the logarithm of hourly wage, computed by exploiting information on workers yearly net wage, weekly hours worked and yearly weeks worked.

6. Results

In this section, we present the empirical results of our test based on the data presented in section 5. In Table 1 and table 2 we present the estimates of wage premium for risky jobs, i.e. sectors with an average injury for 1000 workers above the median and the upper quartile, respectively. The estimates are based on the whole sample of workers. The first row of table 1 and 2 displays the OLS estimates of equation (3). All the other rows in the tables refer to a propensity score matching estimates of the equation (6) using different matching techniques, such as the nearest neighbor (row 2), th nearest neighbor with oversampling (row 3) and the kernel matching (row 4). The second and third columns of the tables 1 and 2 contain the values of the mean absolute standardized bias, which is a measure of the heterogeneity in observables characteristics of the individuals treated, before and after the estimates, respectively. As expected, we find a negative and significant wage risk both in OLS and PSM estimates. What is important here is that PSM estimates are closer to 0 than the OLS; this can be explained by the fact that PSM estimator is able to strongly reduce the heterogeneity in the observables characteristics of the treated group. For instance, OLS estimates suggest an hourly wage penalization for risky jobs of 6.4%, while propensity score estimates suggest a penalization of around 4.9% (or 5.8% depending on the matching technique used). More importantly, the propensity score matching is able to reduce the heterogeneity from around 10 to 1 in terms of mean standardized bias. The same picture emerges from table 2 where we consider very risky jobs (sectors in the last quartile of the distribution of injuries across sectors). The magnitude of the negative wage risk premium is considerably lower both in OLS and PSM estimates. This is probably due to the fact that we are considering more homogenous and riskier sectors. Even in this case PSM estimates are closer to 0 than OLS ones and PSM is able to considerably reduce the heterogeneity in observables characteristics of the treated group (from 9 to 1 in terms of mean standardized bias). To sum up, estimates for the whole sample suggest that Italian labor market is segmented in risky jobs, given that they show the presence of observables characteristics which contribute to generate a wage penalization for risky jobs; indeed, when selection on such characteristics is carried out, wage premium becomes closer to zero which is the benchmark value if no segregation process were at work.

In the same direction go the estimates of wage risk premium when we split the sample for males and females (table 3). For females, a very strong wage penalization emerges. On average, women in risky jobs gain almost 9% less than women working in non-risky jobs. Such penalization becomes smaller when selection on observables is carried out, but it is still high (around 8%). For males, wage penalization is around 5% and it becomes around 4% when selection on observables is carried out. These results suggest that segregation in risky jobs is more penalizing in terms of wage for women than men.

The picture is less clear in the manual-workers sub-sample (table 4.a). While for non manual workers the same results of a negative wage premium apply- confirming also the direction of the bias and ability of PSM to reduce such bias- for manual workers it appears a positive wage premium even if not always significant and close to 0. Anyway, table 4.b, where the 4th quartile as a measure of risk is used, confirm our previous results (i.e. the negative sign of the coefficient and OLS downward bias): the manual workers sub-sample shows no significant wage penalization for risky jobs. According to these last results, we can argue that a segregation process in risky jobs is less severe when it comes to manual workers. We believe that this result is not difficult to reconcile, since manual positions are segmented *per se* and therefore the safety of the job place is not the main driver of segmentation.

In table 5 and 6, we look at the segregation for unobserved characteristics. In such tables we show the results of Rosembaum bounds test for every propensity score estimates showed in table 1-4. Such test is usually used as a sensitivity test of PSM estimates, as discussed in section 4.2, but it helps to understand indirectly the role of unobservable characteristics in the segregation in risky jobs. Results of table 5 show that PSM estimates are significant and robust up to a 20% of changes in probability of holding a risky job due to unobservable characteristics (Γ=1.2). On one side, such result is telling that PSM estimates are robust to a very strong unobservable factor which changes the distribution of treated and untreated up to 20%; on the other side, RBT results suggest that whatever unobservable characteristics would have the effect of pushing our estimates close to zero. In economic terms, this means that wage penalization for risky jobs disappears if unobservable characteristics would be present and taken into account.

To give a better idea of which type of unobservables could affect the segregation process, we make use of a specific question in the survey, which may give information about individual health risk aversion. The variable we use to identify risk aversion is unmeet medical care for reasons other than income. Basically, we consider as more prone to risk those individuals declaring that they did not take a medical examination even if they would have needed it, for reasons other than poor income . We perform a last estimate of wage risk trade-off, by splitting the sample in worker that are assumed to be more prone to risk and workers that are less prone to risk. Results of this estimate are shown in table 6. OLS and PSM show that workers giving less importance to their health receive a more negative wage premium than workers caring more. The results for very risky jobs (right column of table 6) show that, while individuals more prone to risk are clearly penalized in terms of wage, individuals who are not prone to risk do not experience forms of penalization for risky jobs. These results show the essence of segregation process that we have previously discussed. It is the different value that individuals attach to their life, together with observable characteristics, that drive the mechanism of sorting in risky jobs. In absence of such mechanisms we would observe no differences in wage between risky and non-risky jobs in Italy. Thus, our empirical findings suggest the following dynamics : i) a negative wage premium emerges (OLS); ii) the premium tends to zero when a selection on observables is carried out (PSM); iii) the premium would be closer to zero when taking into account unobservable characteristics (RBT); iv) individuals more prone to risk accept a lower wage for risky jobs. These unprecedented results jointly demonstrate that risky jobs are strongly segmented in Italian labor market.

7.Final Remarks

In this paper we propose a simple *indirect way* to detect segregation in the labor market. We base our analysis on wage differentials existing between risky and non- risky jobs. Our idea is quite simple: a negative wage premium for workers employed in risky jobs has to be interpreted as a proof of segmentation in these sectors, once the selection on observable characteristics of workers has been performed. Thus, our main attention is to perform an accurate selection on observable characteristics using an econometric method, which, to the best of our knowledge, has never employed so far in this context: the propensity score matching. The advantage of this method is to ensure a "common support" in the observable characteristics of individuals employed in a risky positions *vs* individuals working in a safe job. In other words, such method purges the wage-risk relation from a different composition in the observables characteristics, which is not taken into account in a simple OLS estimate. Subsequently, we conduct a sensitivity analysis on our PSM estimates using the Rosembaum bounds test, which is a sensitivity test that allows us to detect whether the estimates are affected by hidden bias due to selection on the unobservable heterogeneity. Our test of segmentation is thus based on the comparison of a battery of estimates: OLS, PSM, RBT. We derive the following implications from the result of the test: if a negative wage premium arises even when selection on observables is adequately carried out, then segregation in risky jobs is at work. Further, the RBT allows us to detect which is the magnitude of the unobservable factors that would have the effect to push these estimates towards zero. We assess our test for segregation to Italian labor market using a population of 14277 workers observed in 2004 and collected from the survey EU-SILC. The Italian labor market is a convenient environment to develop our test given that in Italy a mandated insurance for risky jobs exists and it is entirely paid by the employer. If we assume that such insurance is complete, we are in a case where theory of compensating wage differentials predicts a wage premium equals to zero. If we relax the hypothesis of complete insurance, a positive wage premium would come out. Thus, a negative wage premium is not compatible with the theory of wage differentials unless we admit the existence of a dual labor market.

After a careful selection on observed heterogeneity (PSM) and a check for unobserved factors (RBT), we detect that wage risk premium is always negative. In addition, we find that such estimates are robust to very strong unobservable factors which change the distribution of treated and untreated by up to 20%. To give a better sense of which type of unobservable characteristic affects this segregation process, we perform a last estimate by splitting the sample according to the level of risk aversion; in doing so, we use unmeet medical care needs for non financial reasons as a proxy for taste for risk. These additional results show that, while individuals prone to risk are clearly penalized in terms of wage, individuals who are not prone to risk do not have wage penalization for risky jobs (or they are less penalized, when considering a less strong definition of risk sector).

To the best of our knowledge, this approach of detecting segregation in the labor market is novel in the literature. As any other approach, it has some advantages and limitations. On one side, it is an indirect way to detect segregation in all situations where the researcher has a clue that it may present. We have based our analysis on risky jobs, but the same approach can be easily extended to detect sexual segregation or racial segregation in the labor market. Basically, the approach allows us to assess whether, after performing a careful selection on observable characteristics, a negative premium still emerges for those categories, which are likely to be segregated. In addition, the RBT test is a useful tool to assess the potential extent of unobservable factors and the direction toward which such factors would move the estimates.

The main limitation of the approach is the difficulty to assess whether segregation or segmentation in the labor market is voluntary or not (see Dickens and Lang, 1988). Basically, we are not able to completely discern if workers' preferences drive the choice of working in more hazardous jobs or if such choice is involuntary. The last exercise attempts to draw some conclusion along this direction by performing separate estimates for risk-lover and risk-averse people. We observe an important role of preferences in such choice, as individuals more prone to risk accept a lower wage to work in risky jobs than individuals not prone to risk.

A second limitation of the approach is that the type of work may influence preferences or tastes (Dickens and Lang, 1988 offer a nice discussion on this topic). In our case it is likely that individuals employed in risky jobs develop higher taste for risk while they are working in risky sectors. If this is the case, preferences are endogenous, that is, they are the consequence of such choice rather that its determinants.

However, even in the case of endogenous preferences, the extent of segregation would remain if more prone-to-risk individuals are more likely to work in risky jobs; in fact, by working in these sector they reinforce these preferences. In this case segmentation would be a self-generating process. Future research is required to address these limitations and develop a more sophisticated approach to detect segregation in the labor market. The approach presented in this paper must be considered as a bare-bone test for researchers who aim at detecting the existence of segregation in the labor market.

References

Bettio, F., & Veraschagina A. (2008). *Occupational Segregation and Gender Wage Disparities in Developed Economies*. In F., Bettio, & A., Veraschagina (Eds.), Frontiers in the Economics of Gender (pp. 167–191). London and New York: Taylor and Francis, Routledge.

Dickens, W. T., and Lang, K. (1988). The reemergence of segmented labor market theory. The American Economic Review, *Papers and Proceedings of the One-Hundredth Annual Meeting of the American Economic Association*, 78,(2), 129–134.

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

Evans, M. F., and Smith, V., K. (2010). Measuring how risk tradeoffs adjust with income, *Journal of Risk and Uncertainty*, 40(1), 33–55.

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(4), 605–654.

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

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.

Hersch, J., and Viscusi W. K. (1990). Cigarette smoking, seatbelt use, and differences in wage-risk tradeoffs. *Journal of Human Resources*, 25(2), 202–227.

Kniesner T. J., Viscusi W. K., Ziliak J. P. (2010). Policy relevant heterogeneity in the value of statistical life: New evidence from panel data quantile regressions, *Journal of Risk and Uncertainty*, 41(1), 15–31.

Rosen, S. (1974). Hedonic prices and implicit markets, *Journal of Political Economy*, 82, 34-55.

Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70(1), 41–55.

Rosenbaum, P., R. 2002. *Observational Studies*. 2nd edition. New York, NY: Springer

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.

Viscusi, W. K. (2004). The value of life: estimates with risks by occupation and industry, *Economic Inquiry*, 42(1), 29–48.

Viscusi, W. K., and Hersch J. (2001). Cigarette smokers as job risk takers, *Review of Economics and Statistics*, 83(2), 269–280.

Viscusi, W. K., and Aldy J. E. (2003). The Value of a Statistical Life: a critical review of market estimates throughout the world. *The Journal of Risk and Uncertainty*, 27(1), 5–7

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

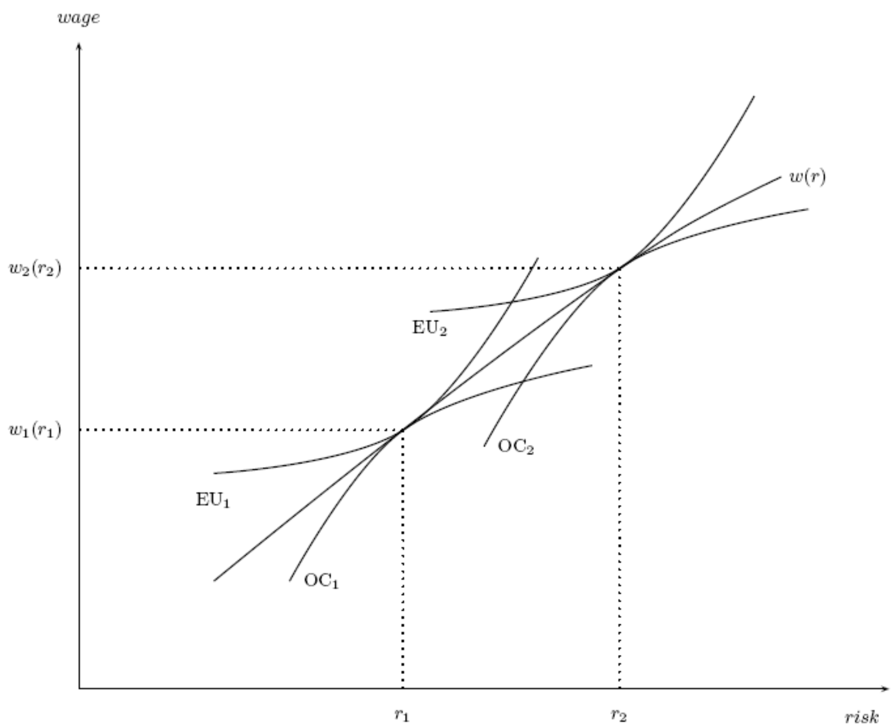

Table 1. Wage premium estimates for jobs above the *median* of the risk distribution (OLS and PSM).

	ATT (s.e.)	Mean absolute standardized bias		No observations	
		Before	After		
OLS	-.064*** (.006)			14108	
PSM nn	-.058*** (.011)	10.83	1.54	Treated	6,762
				Control	7,345
PSM 5nn	-.049*** (.009)	10.83	1.08	Treated	6,762
				Control	7,345
PSM kernel	-.052*** (.007)	10.83	1.003	Treated	6,762
				control	7,345

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table 2. Wage premium estimates for jobs above the *4th quartile* of the risk distribution (OLS and PSM).

	ATT (s.e.)	Mean absolute standardized bias		No observations	
		Before	After		
OLS	-.040*** (.008)			14108	
PSM nn	-.045*** (.015)	9.31	1.68	Treated	2,275
				Control	11,830
PSM 5nn	-.037*** (.011)	9.31	1.21	Treated	2,275
				Control	11,830
PSM kernel	-.045*** (.008)	9.31	0.85	Treated	2,275
				control	11,830

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table 3.a. Wage premium estimates for jobs above *the median* of the risk distribution, female and male sample (OLS and PSM).

	Female					Male				
	ATT (s.e.)	Mean absolute standardized bias		No observation		ATT (s.e.)	Mean absolute standardized bias		No observations	
		Before	After				Before	After		
OLS	-.093*** (.010)			5,396		-.050*** (.008)			8,712	
PSM nn	-.085*** (.017)	11.00	2.25	Treated	1,660	-.043*** (.013)	10.10	1.74	Treated	5,100
				Control	3,733				Control	3,612
PSM 5nn	-.084*** (.013)	11.00	1.77	Treated	1,660	-.045*** (.010)	10.10	1.47	Treated	5,100
				Control	3,733				Control	3,612
PSM kernel	-.089*** (.011)	11.00	1.15	Treated	6,762	-.042*** (.008)	10.10	0.92	Treated	5,100
				Control	7,345				Control	3,612

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table 3.b. Wage premium estimates for jobs above the *4th quartile* of the risk distribution, female and male sample (OLS and PSM).

	Female					Male				
	ATT (s.e.)	Mean absolute standardized bias		No observation		ATT (s.e.)	Mean absolute standardized bias		No observations	
		Before	After				Before	After		
OLS	-.122*** (.020)			5,396		-.025*** (.004)			8,712	
PSM nn	-.116*** (.042)	6.82	4.78	Treated	335	-.024*(.015)	7.55	1.86	Treated	1,934
				Control	5,042				Control	6,777
PSM 5nn	-.123*** (.030)	6.82	2.65	Treated	335	-.033***(.011)	10.10	1.13	Treated	1,934
				Control	5,042				Control	6,777
PSM kernel	-.137*** (.021)	11.00	2.53	Treated	335	-.035*** (.008)	10.10	0.88	Treated	1,934
				Control	5,042				Control	6,777

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table 4.a Wage premium estimates for jobs above the *median* of the risk distribution, manual and non-manual sample (OLS and PSM).

	Manual					Non-manual				
	ATT (s.e.)	Mean absolute standardized bias		No observation		ATT (s.e.)	Mean absolute standardized bias		No observation	
		Before	After				Before	After		
OLS	.022*** (.008)			6,555		-.061*** (.009)			7,553	
PSM nn	.015 (.013)	6.36	1.90	Treated	4,636	-.051*** (.016)	7.74	2.09	Treated	2,125
				Control	1,917				Control	5,428
PSM 5nn	.021* (.011)	6.36	1.50	Treated	4,636	-.050*** (.012)	7.74	1.16	Treated	5,100
				Control	1,917				Control	3,612
PSM kernel	.023*** (.009)	6.36	1.15	Treated	4,636	-.054*** (.008)	7.74	0.73	Treated	5,100
				Control	1,917				Control	3,612

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table4.b. Wage premium estimates for jobs above the *4th quartile* of the risk distribution, manual and non-manual sample (OLS and PSM).

	Manual					Non-manual				
	ATT (s.e.)	Mean absolute standardized bias		No observation		ATT (s.e.)	Mean absolute standardized bias		No observation	
		Before	After				Before	After		
OLS	.004 (.010)			6,555		-.065*** (.013)			7,553	
PSM nn	-.001 (.016)	9.95	2.88	Treated	1,523	-.058** (.026)	6.05	2.50	Treated	742
				Control	5,006				Control	6,811
PSM 5nn	-.002 (.013)	9.95	1.47	Treated	1,523	-.062*** (.018)	6.05	1.21	Treated	742
				Control	5,006				Control	6,811
PSM kernel	-.005 (.011)	9.95	0.87	Treated	1,523	-.062*** (.012)	6.05	1.20	Treated	742
				Control	5,006				Control	6,811

***, **, * Significant at 1, 5, 10% respectively. Standard errors for OLS are clustered at household level. Bootstrapped standard errors for PSM, 300 replications.

Table 5. Rosenbaum bounds test. (p-value Wilcoxon's signed rank test)

Overall Estimates			Female			Male		
Γ	Median	4th quartile	Γ	Median	4th quartile	Γ	Median	4th quartile
1	<.001	<.001	1	<.001	<.001	1	<.001	.012
1.05	<.001	.004	1.1	<.001	.020	1.1	<.001	.329
1.1	<.001	.048	1.2	<.001	.085	1.2	.266	.887
1.15	.001	.226	1.3	.001	.230	1.3	.967	.996
1.2	.003	.550	1.4	.045	.433			
1.25	.093	.833	1.5	.307	.645			
1.3	.526	.962	1.6	.728	.809			

Table 6. Rosenbaum bounds test. (p-value Wilcoxon's signed rank test)

Manual			Non-manual		
Γ	Median	4th quartile	Γ	Median	4th quartile
1	<.001		1	<.001	.001
1.05	<.001		1.05	<.001	.008
1.1	.072		1.1	<.001	.031
1.15	.441		1.15	.037	.089
1.2	.865		1.2	.174	.199

Table 7. Wage premium estimates for risky jobs according to differences in taste for risk.

	Median		4th quartile	
	Prone to risk	Not prone to risk	Prone to risk	Not prone to risk
OLS	-.085* (.046)	-.063*** (.006)	.028 (.053)	-.041*** (.008)
PSM nn	-.064 (.094)	-.047*** (.010)	-.043 (.096)	-.034*** (.015)
N	335	13773	335	13773

Table 8. Descriptive statistics of the variables

Variable	Mean	Standard deviation
Female	.3818029	.4858456
Age	39.84787	10.62305
Age^2	1700.694	862.2538
Non-native from European country	.0149233	.1212502
Non-native from country outside EU	.0451202	.2075749

Age at first job	17.96645	4.87101
Household capital income	793.3865	3016.517
Single	.3936401	.4885737
Education (control group: illiterate)		
Primary school	.0681516	.2520147
Junior high school	.304966	.4604092
High school (3 year)	.1118582	.315203
High school (5 years)	.3628914	.4808507
Not university diploma	.0070743	.0838138
College graduate	.118092	.3227284
Post-graduate course	.0130279	.1133981
Phd	.0027317	.0521957
Degree of urbanization (control group: densely populated area)		
Intermediate area	.396792	.4892493
Thinly populated area	.2260979	.4183179
Dwelling type (control group: detached house)		
Semi-detached or terraced house	.2304314	.4211239
Flat in a building with less than 10 dwellings	.2435362	.4292311
Flat in a building with 10 or more dwellings	.2528866	.4346819
Tenure status (control group: owner)		
Accommodation is rented at a prevailing rate	.1347622	.3414814
Accommodation is rented at a reduced rate	.050851	.2197011
Accommodation is provided free	.0894446	.2853944
Household type (control groups: one person household)		
2 adults, no dependent children, both adults under 65 years	.1463193	.3534384
2 adults, no dependent children, at least one adult 65 years or more	.0231841	.1504933
Other households without dependent children	.2329621	.4227331
Single parent household, one or more dependent children	.0212229	.1441318
2 adults, one dependent child	.1552147	.3621219

2 adults, two dependent children	.1583666	.3650972
2 adults, three or more dependent children	.0300483	.1707263
Other households with dependent children	.1357428	.3425272
Regional dummies (control group: Piemonte)		
Valle d'Aosta	.0201723	.1405943
Lombardia	.1349723	.341706
Bolzano	.0247951	.1555057
Trento	.0214331	.1448281
Veneto	.0908454	.2873992
Friuli-Venezia Giulia	.0469286	.2114934
Liguria	.0392239	.1941341
Emilia-Romagna	.078658	.2692136
Toscana	.0780976	.2683346
Umbria	.0434265	.2038223
Marche	.0527422	.2235261
Lazio	.0780976	.2683346
Abruzzo	.022904	.1496026
Molise	.0154094	.1231788
Campania	.0481894	.2141737
Puglia	.0348112	.1833078
Basilicata	.0173706	.1306524
Calabria	.0219934	.146667
Sicilia	.0334104	.179712
Sardegna	.0291378	.1681985
# of observations	14277	

Table 9. Injury rate per 1000 workers per sector, 2004.

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

In parenthesis NACE rev 1.1 classifications. Source: our calculations based on INAIL data, www.Inail.it