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ABSTRACT

Gender Wage Gaps and Risky vs. Secure Employment: An Experimental Analysis*

In addition to discrimination, market power, and human capital, gender differences in risk preferences might also contribute to observed gender wage gaps. We conduct laboratory experiments in which subjects choose between a risky (in terms of exposure to unemployment) and a secure job after being assigned in early rounds to both types of jobs. Both jobs involve the same typing task. The risky job adds the element of a known probability that the typing opportunity will not be available in any given period. Subjects were informed of the exogenous risk premium being offered for the risky job. Women were more likely than men to select the secure job, and these job choices accounted for between 40% and 77% of the gender wage gap in the experiments. That women were more risk averse than men was also manifest in the Pratt-Arrow Constant Absolute Risk Aversion parameters estimated from a random utility model adaptation of the mean-variance portfolio model.

NON-TECHNICAL SUMMARY

This paper is an experimental analysis of the effects of gender differences in attitudes toward risk on job choice and wages. Women were more likely than men to select the secure job with no risk of unemployment in lieu of the higher paying job with unemployment risk. This difference in job choice accounted for between 40% and 77% of the gender wage gap in the experiments.

JEL Classification: J16, J24, J31, C91, D81

Keywords: occupational choice, gender wage differentials, risk aversion, lab experiment

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I Introduction

Gender wage gaps have been the subject of a vast number of empirical studies primarily focused on field data generated by naturally occurring labor markets. The fundamental conceptual bifurcation of the gender wage gap is between discrimination and human capital. Discrimination can arise from three distinct sources: Becker tastes and preferences, market power, and statistical discrimination. The human capital explanation appeals to gender differences in productivity endowments. Gender differences in occupational outcomes can clearly contribute to the gender wage gap. Some of this component of the wage gap can arise as a result of job segregation induced by tastes for discrimination by economic agents (Baldwin et al., 2001; Shatnawi et al., 2014). The remainder of the occupational outcome gap can arise from gender differences in preferences over various job attributes that are associated with compensating differentials.

One potentially salient job attribute is the risk of involuntary unemployment. Depending on the distribution of risk attitudes pertaining to spells of unemployment, there will be some compensating differential that arises in the labor market. The degree to which men and women differentially sort themselves into risky vs. secure jobs has implications for the gender wage gap. A recent study examined this issue in the context of public vs. private sector employment and the gender wage gap (Jung, 2015). Unfortunately, in the naturally occurring labor market there are a host of factors that can be confounded with risk aversion given the multidimensional nature of the job package, e.g. family friendly policies, commuting distance, etc.

The aim of this study is to use the laboratory to identify the potential role of risk aversion in explaining gender wage gaps in a setting in which we can abstract from a myriad of factors normally present in field labor markets, including labor market discrimination. Experiments are conducted in which subjects are given the opportunity to choose between two typings tasks differentiated only by the prospect of exogenous spells of unemployment in one of the tasks. The risky task is accompanied by a wage premium. Gender gaps that arise in our experimental design can only come from gender differences in typing performance and job choices. Women were more likely than men to select the secure job, and wage decomposition analysis reveals that these job choices accounted for between 40% and 77% of the gender wage gap in the experiments.

II Literature

Adam Smith argued in *Wealth of Nations* that the wages could be determined by different characteristics of jobs such as risk (Smith, 1776). Since the time of Adam Smith, the theory of compensating wage differentials has been widely studied. Murphy et al. (1987) and Moore (1995) show that job sectors with higher unemployment and greater risk tend to have higher wages. Hence, job-sorting decisions may well vary with individuals' attitudes to risk. More recent work such as Hartog et al. (2003) also shows that jobs with greater risk are paid higher wages, contributing to the theory of compensating wage differentials. Workers who are more willing to accept a certain number of dollars for a given increase in risk are more likely to choose to work in riskier jobs than those who are less inclined to make a trade-off between wages and risk. While job-sector choice is sensitive to differences in risk attitudes, it is *a priori* also strongly correlated with education decisions.

Depending on the individual's degree of risk aversion, risk averse workers place more value on employment stability while others who are less risk averse may prefer trading off stability against the higher wage (risk premium) in the private sector. This argument has been widely studied for decades. For example, Bellante and Link (1981) used the index of innate risk aversion measure (proxies such as insurance investment, seat belt use, etc.) and showed that the probability of choosing to work in the public sector increases as the degree of risk aversion increases. A recent study using the large scale German Socio Economic Panel found that risk averse workers tend to sort into public sector employment while risk taking is rewarded with higher wages in the private sector (Pfeifer, 2011). With the use of revealed risk preferences data, Buurman et al. (2012) validate the argument that public workers are significantly less likely to choose the risky option (lotteries).

Ekelund et al. (2005) use a psychometric variable measuring harm avoidance as an indicator of risk attitudes. They find that agents with a higher harm-avoidance score (i.e. less risk averse) are more likely to become self-employed, which is considered riskier than being employed as a wage earner. In an experimental study, Dohmen et al. (2005) show that measures of subjective risk attitudes, such as self-reported risk aversion and lottery questions, provide a valid predictor of actual risk behavior. Dohmen and Falk (2011) build upon these results and use self-reported risk aversion in the German Socioeconomic Panel to see whether risk preferences explain how individuals are sorted into occupations with different earnings variation. Pissarides (1974) presents a theoretical model explaining that risk-averse workers have lower reservation wages. Cox and Oaxaca (1989) suggest a negative relationship between the degree of risk aversion and the level of reservation wages and Cox and Oaxaca (1992) and Cox and Oaxaca (1996) re-validate the argument by experimental evidence on individual search behavior. This relationship is demonstrated empirically by Pannenberg (2007). Similarly, Goerke and Pannenberg (2012) show that there is a negative relationship between risk aversion and union membership.

Given that job sorting matters in terms of the position actually held in the labor market, there is good reason to wonder whether the job-sorting decision interacts with the gender disparity observed on the labor market. Although the gender bias in education has been reduced and the education gap between men and women has narrowed in recent decades (Arnot et al., 1999), there is still concern over the considerable wage gap and other kinds of gender-based discrimination in the labor market. In a move to explain these findings, Croson and Gneezy (2009) and Bertrand (2011) argue that women may be more risk averse and less competitive than men. More interestingly for our question, Gneezy et al. (2003), Niederle and Vesterlund (2007) and Croson and Gneezy (2009) all suggest that differences in risk attitudes might partly explain the gender gap in labor-market outcomes. Similarly, Barsky et al. (1997), Dohmen and Falk (2011) and Bonin et al. (2007) show that job-sector selection and wages are correlated with risk attitudes.

III Conceptual Framework

Secure Job

Let compensation for the secure job follow a simple piece rate scheme: $W_s = \gamma_s P$, where W_s is the earnings from performance of the task, P is discrete output measure of performance (to be defined below), and γ_s is the marginal return to performance for the secure job. For any given individual, productivity/performance is a random variable: $P_i = \psi_i + \varepsilon_i$, where $\psi_i = E(P_i) > 0$ (mean productivity) and $\varepsilon_i \sim i.i.d(0, \sigma_i^2)$. Accordingly, $Var(P_i) = \sigma_i^2$.

For an individual employed in the secure job, wages are determined according to $W_{si} = \gamma_s P_i$. The mean and variance from the wage individual's wage distribution are readily obtained as

$$E(W_{si}) = \gamma_s \psi_i$$

$$Var(W_{si}) = (\gamma_s)^2 \sigma_i^2.$$

Risky Job

Conditional on productivity, let compensation in the risky job be determined according to

W_r	$Prob(W_r = k)$
w_u	ϕ
w_r	$1 - \phi$

where ϕ is the probability of drawing unemployment, w_u is unemployment compensation, $w_r = \gamma_r P$ is the earnings from employment in the risky job, and γ_r is the marginal return to performance for the risky job.

We can obtain the mean and variance of the conditional wage distribution as

$$\begin{aligned} E(W_r|P) &= \phi w_u + (1-\phi) w_r \\ &= \phi w_u + (1-\phi) \gamma_r P \end{aligned}$$

$$\begin{aligned} Var(W_r|P) &= (\phi)(1-\phi)(w_r - w_u)^2 \\ &= (\phi)(1-\phi)(\gamma_r P - w_u)^2 . \end{aligned}$$

The law of iterated expectations and the law of total variance are used to obtain the unconditional moments of the wage distribution for a given individual:

$$\begin{aligned} E(W_{r_i}) &= E_P\left[E(W_r|P_i)\right] \\ &= \phi w_u + (1-\phi)\gamma_r E(P_i) \\ &= \phi w_u + (1-\phi)\gamma_r \psi_i \end{aligned}$$

$$\begin{aligned} Var(W_{ri}) &= E\left[Var(W_r|P_i)\right] + Var\left[E(W_r|P_i)\right] \\ &= (\phi)(1-\phi)\left[(\gamma_r)^2\left(\sigma_i^2+\psi_i^2\right) + (w_u)^2 - 2\gamma_r\psi_i w_u\right] \\ &+ (1-\phi)^2(\gamma_r)^2\sigma_i^2 \\ &= (\phi)(1-\phi)(\gamma_r\psi_i - w_u)^2 + (1-\phi)(\gamma_r)^2\sigma_i^2. \end{aligned}$$

Risk Premium

One can readily solve for the compensating risk premium for a risk neutral agent:

$$E(W_{r_i}) = E(W_{s_i})$$

$\Rightarrow$

$$\phi w_u + (1-\phi)\gamma_r\psi_i = \gamma_s\psi_i$$

$\Rightarrow$

$$\gamma_r - \gamma_s = \left(\frac{\phi}{1-\phi}\right)\left(\gamma_s - \frac{w_u}{\psi_i}\right) > 0, \tag{1}$$

where $\gamma_r - \gamma_s$ is the compensating risk premium that would just render the risk neutral agent indifferent between the secure job and the risky job.

Note that $\gamma_s - \frac{w_u}{\psi_i} > 0 \Rightarrow w_u < \gamma_s\psi_i$, i.e. to ensure a positive risk premium, the unemployment compensation must be less than the expected marginal revenue product (return) on the secure job. Also, note that the compensating risk premium $\gamma_r - \gamma_s$ is increasing in ϕ (unemployment risk) and ψ_i (skill), and is decreasing in w_u (unemployment compensation).

IV Experimental Design

Subjects were recruited from the University of Paris I. At the conclusion of the experiment, a questionnaire was administered to the subjects. This was done to not only obtain basic demographic information, but also to measure risk attitudes elicited on the basis of hypothetical Holt-Laury lottery choices provided to the subjects.

Treatments

In our experiments earnings from the secure job depend only on performance. There is no risk of unemployment. By contrast earnings from the risky job depend on performance and chance (risk of unemployment). Furthermore, receipt of the unemployment benefit w_u occurs with probability ϕ. and the receipt of earnings $w_{ri} = \gamma_r P_i$ occurs with probability $1-\phi$. Subjects were fully informed about the payoffs for performance and the unemployment probability for the risky job.

Each subject participates in three treatments:

- **Treatment 1:** half of the subjects are randomly assigned to the risky job and the other half are assigned to the secure job.
- **Treatment 2:** the subjects assigned to the risky (secure) job in Treatment 1 are assigned to the secure (risky) job in treatment 2.
- **Treatment 3:** the subjects choose between the risky job and the secure job.

We conducted two sets of experiments in which Treatments 1 - 3 were run with two different risk premiums ($\gamma_r - \gamma_s$). There was no overlap of subjects between the two risk premium experiments.

Effort Tasks and Compensation

Subjects earn income from working by typing randomly generated blocks of 5 letters. Compensation is derived from a subject's performance measured by P_i which corresponds to the number of correctly typed blocks. In each period there are 40 random, 5 letter blocks, so $0 \leq P_i \leq 40$. There are 10 periods in each experimental trial. Subjects are given 90 seconds each period to type.

All subjects were confronted with the same sequence of letter blocks over the 10 periods within a given treatment (Treatments 1 - 3) but the sequences were different across the treatments.

At the end of each experimental session, a period was drawn randomly from each of Treatments 1 - 3 separately for each subject, and each subject was then compensated on the basis of their performances in the 3 randomly selected periods.

Experimental Design Parameters

It is important to set parameter design values such that sufficient numbers of subjects will be attracted to the risky job and to the secure job. Naturally, we do not know the risk attitudes of each subject ex ante, nor do we know each subject's productivity distribution ex ante. On the basis of simulations we were able to adopt reasonable values of the experimental design parameters.

For our design we fixed the values of w_u, ϕ, and γ_r and varied γ_s. The experimental design values were set according to $w_u =$ €$1, \phi = 0.3, \gamma_r =$ €0.2, $\gamma_s =$ €0.13 or €0.14. Accordingly, the two risk premium experiments corresponded $\gamma_r - \gamma_s =$ €0.07 and €0.06.

V Empirical Analysis and Results

Decomposition Analysis

Our objective is to be able to measure the effect of gender differences in job choice on any gender wage gaps that arise within our experimental setting. This is accomplished through decomposition methods. We begin with the within-job gender wage gaps and then consider the effects of job choices.

secure job

Let $w^j_{s,i}$ represent the average wage of the ith worker from group $j = m, f$ in the secure job:

$$\begin{aligned} w^j_{s,i} &= \frac{\sum_{t=1}^{T} w^j_{s,it}}{T} \\ &= \frac{\gamma_s \sum_{t=1}^{T} P^j_{s,it}}{T} \\ &= \gamma_s P^j_{s,i} \end{aligned}$$

where $T = 10$, and $P^j_{s,i}$ = the average performance/productivity of the ith worker.

The average wage over all workers in group j in the secure job is simply

$$w^j_s = \frac{\sum_{i=1}^{N^j_s} w^j_{s,i}}{N^j_s} = \frac{\gamma_s \sum_{i=1}^{N^j_s} P^j_{s,i}}{N^j_s} = \gamma_s P^j_s,$$

where N^j_s = is the number of workers in group j in the secure job, and P^j_s = the average performance of group j workers in the secure job, i.e.

$$P^j_s = \frac{\sum_{i=1}^{N^j_s} P^j_{s,i}}{N^j_s} = \frac{\sum_{i=1}^{N^j_s} \sum_{t=1}^{T} P^j_{s,it}}{N^j_s T}.$$

The gender wage decomposition for the secure job is simply

$$w_s^m - w_s^f = \gamma_s \left(P_s^m - P_s^f \right).$$

This illustrates that the only source of a gender wage gap within a given job arises from gender differences in productivity.

risky job

Wage decompositions within the risky job are calculated only over the observations for which individuals are employed. We define an indicator for employment as $E_{it} = 1$(employed). Let $w_{r,i}^j$ represent the conditional average wage of the ith worker from group $j = m, f$ in the risky job:

$$w_{r,i}^j = \frac{\sum_{t \epsilon \{E_{it}=1\}} w_{r,it}^j}{T_{r,i}^j} = \frac{\gamma_r \sum_{t \epsilon \{E_{it}=1\}} P_{r,it}^j}{T_{r,i}^j} = \gamma_r P_{r,i}^j,$$

where $T_{r,i}^j \leq T$ is the number of periods for which the ith worker was employed in the risky job, and

$$P_{r,i}^j = \frac{\sum_{t \epsilon \{E_{it}=1\}} P_{r,it}^j}{T_{r,i}^j}$$

is the individual's performance averaged over their periods of employment.

The conditional average wage over all workers in group j in the risky job is accordingly

$$w_r^j = \frac{\sum_{i=1}^{N_r^j} \sum_{t \epsilon \{E_{it}=1\}} w_{r,it}^j}{\sum_{i=1}^{N_r^j} T_{r,i}^j} = \frac{\gamma_r \sum_{i=1}^{N_r^j} \sum_{t \epsilon \{E_{it}=1\}} P_{r,it}^j}{\sum_{i=1}^{N_r^m} T_{r,i}^j} = \gamma_r P_r^j,$$

where P_r^j is average performance for all subjects in group j over all spells of employment in the risky job.

It follows that the gender wage decomposition for the risky job is

$$w_r^m - w_r^f = \gamma_r \left(P_r^m - P_r^f \right).$$

Again, the only sources of a gender wage gap within a job arise from gender differences in performance.

endogenous job choice

Ultimately, we are interested in how gender differences in choosing between secure and risky jobs impact gender wage gaps.

The average wage for group $j = m, f$ across both the secure and risky jobs is calculated as

$$\begin{aligned} w_j &= w_r^j \theta_r^j + w_s^j \left(1 - \theta_r^j\right) \\ &= \gamma_r P_r^j \theta_r^j + \gamma_s P_s^j \left(1 - \theta_r^j\right) \end{aligned}$$

where θ_r^j is the sample proportion of the observations generated from the risky job choices, i.e.

$$\theta_r^j = \frac{\sum_{i=1}^{N_r^j} T_{r,i}^j}{N_s^j T + \sum_{i=1}^{N_r^j} T_{r,i}^j}.$$

For a given risk premium within the endogenous choice treatment (Treatment 3), the gender wage gap decomposition may be expressed by

$$\begin{aligned} w_m - w_f = & \underbrace{\gamma_r \left(P_r^m - P_r^f\right) \theta_r^f + \gamma_s \left(P_s^f - P_s^f\right) \left(1 - \theta_r^f\right)}_{productivity} \\ & + \underbrace{\left(\gamma_r P_r^m - \gamma_s P_s^m\right) \left(\theta_r^m - \theta_r^f\right)}_{job\, choice}, \end{aligned}$$

or alternatively by

$$\begin{aligned} w_m - w_f = & \underbrace{\gamma_r \left(P_r^m - P_r^f\right) \theta_r^m + \gamma_s \left(P_s^m - P_s^f\right) \left(1 - \theta_r^m\right)}_{productivity} \\ & + \underbrace{\left(\gamma_r P_r^f - \gamma_s P_s^f\right) \left(\theta_r^m - \theta_r^f\right)}_{job\, choice}. \end{aligned}$$

The alternative decompositions arise from weighting the gender differences in productivity, $(P_r^m - P_r^f)$ and $(P_s^m - P_s^f)$ by either θ_r^f or θ_r^m.

With two sets of experiments corresponding to two different risk premiums, we can perform aggregate decompositions that combine the two sets of experiments. For simplicity we will denote the two risk premium experiments as (1) and (2), which correspond to risk premiums of €0.07 and €0.06, respectively .

The weight for risk premium experiment (1) for group $j = m, f$ is

$$\Omega_j = \frac{N_s^{j(1)}T + \sum_{i=1}^{N_r^{j(1)}} T_{r,i}^{j(1)}}{\left[N_s^{j(1)}T + \sum_{i=1}^{N_r^{j(1)}} T_{r,i}^{j(1)}\right] + \left[N_s^{j(2)}T + \sum_{i=1}^{N_r^{j(2)}} T_{r,i}^{j(2)}\right]}.$$

Therefore, the weighted average wage over both sets of experiments for group j is given by

$$w_j = w_j^{(1)}\Omega_j + (1 - \Omega_j)\, w_j^{(2)}$$

When considering a decomposition of the overall gender wage gap for the two sets of risk premium experiments combined, four alternatives readily come to mind. These are derived from the sample weights from the two risk premium experiments (Ω) interacted with the share of each gender group's observations from selection of the risky job (θ_r): (Ω^m, θ_r^f), (Ω^m, θ_r^m), (Ω^f, θ_r^f), (Ω^f, θ_r^m).

Conditioning on a particular choice of θ_r, we obtain two possible decompositions:

$$\begin{aligned} w_m - w_f = {} & \left[w_m^{(1)} - w_f^{(1)}\right]\Omega_m + \left[w_m^{(2)} - w_f^{(2)}\right](1 - \Omega_m) \\ & + \left[w_f^{(1)} - w_f^{(2)}\right](\Omega_m - \Omega_f)\,, \end{aligned}$$

and

$$\begin{aligned} w_m - w_f = {} & \left[w_m^{(1)} - w_f^{(1)}\right]\Omega_f + \left[w_m^{(2)} - w_f^{(2)}\right](1 - \Omega_f) \\ & + \left[w_m^{(1)} - w_m^{(2)}\right](\Omega_m - \Omega_f)\,. \end{aligned}$$

The portion of the overall wage gap arising from the gender wage gaps in each of the two sets of experiments is measured by $\left[w_m^{(1)} - w_f^{(1)}\right]\Omega_m + \left[w_m^{(2)} - w_f^{(2)}\right](1-\Omega_m)$ or by $\left[w_m^{(1)} - w_f^{(1)}\right]\Omega_f + \left[w_m^{(2)} - w_f^{(2)}\right](1-\Omega_f)$. The terms $\left[w_f^{(1)} - w_f^{(2)}\right](\Omega_m - \Omega_f)$ and $\left[w_m^{(1)} - w_m^{(2)}\right](\Omega_m - \Omega_f)$ reflect the difference in sample weights for the two experiments weighted by the average wage difference among women or men between the two sets of experiments.

As an example of the contributions of gender differences in productivity and job choice to the overall wage gaps from our two sets of experiments, we confine our attention to the decomposition corresponding to (Ω^m, θ_r^f). The other alternative decompositions are obtained in an analogous fashion. By appropriate substitution for the average wages in $\left[w_m^{(1)} - w_f^{(1)}\right]\Omega_m + \left[w_m^{(2)} - w_f^{(2)}\right](1-\Omega_m)$, we obtain

$$
\begin{aligned}
\textit{productivity} = & \left[\gamma_r^{(1)}\left(P_r^{m(1)} - P_r^{f(1)}\right)\theta_r^{f(1)}\right. \\
& \left. +\gamma_s^{(1)}\left(P_s^{m(1)} - P_s^{f(1)}\right)\left(1-\theta_r^{f(1)}\right)\right]\Omega_m \\
& + \left[\gamma_r^{(2)}\left(P_r^{m(2)} - P_r^{f(2)}\right)\theta_r^{f(2)}\right. \\
& \left. +\gamma_s^{(2)}\left(P_s^{m(2)} - P_s^{f(2)}\right)\left(1-\theta_r^{f(2)}\right)\right](1-\Omega_m)
\end{aligned}
$$

$$
\begin{aligned}
\textit{job choice} = & \left(\gamma_r^{(1)} P_r^{m(1)} - \gamma_s^{(1)} P_s^{m(1)}\right)\left(\theta_r^{m(1)} - \theta_r^{f(1)}\right)\Omega_m \\
& + \left(\gamma_r^{(2)} P_r^{m(2)} - \gamma_s^{(2)} P_s^{m(2)}\right)\left(\theta_r^{m(2)} - \theta_r^{f(2)}\right)(1-\Omega_m)\,.
\end{aligned}
$$

Identification of Individual Risk Attitudes

While it is not possible to precisely identify risk attitudes for every subject, it is possible to identify subsets of individuals who are either risk averse or risk loving. The key to this identification is to compare each subject's job choice with the difference between their predicted risk neutral premium and the experimental risk premium.

Upon substitution of an estimate for ψ_i in eq.(1) for each subject, one can estimate the compensating risk premium if the subject were risk neutral:

$$\widehat{(\gamma_r - \gamma_s)}_i = \left(\frac{\phi}{1-\phi}\right)\left(\gamma_s - \frac{w_u}{\hat{\psi}_i}\right), \tag{2}$$

where $\hat{\psi}_i$ is the average number of correctly typed blocks over the last observed five periods in the assigned treatment.

Let $R_i = 1(J_i = r)$ be an indicator for choosing the risky job. A subject's risk attitudes are identified under the following conditions:

$$\widehat{(\gamma_r - \gamma_s)}_i < \gamma_r - \gamma_s \text{ and } R_i = 0 \Rightarrow \text{risk averse} \tag{3}$$

$$\widehat{(\gamma_r - \gamma_s)}_i > \gamma_r - \gamma_s \text{ and } R_i = 1 \Rightarrow \text{risk loving.} \tag{4}$$

Condition (3) states that if a subject's estimated risk premium under risk neutrality is less than the experimental risk premium, and the subject chooses the secure job, that subject is classified as risk averse. Similarly condition (4) states that if a subject's estimated risk premium under risk neutrality exceeds the experimental risk premium, and the subject chooses the risky job, that subject is classified as risk loving.

Note that the reverse of conditions (3) and (4) is not true, i.e.

$$\text{risk averse} \not\Rightarrow \widehat{(\gamma_r - \gamma_s)}_i < \gamma_r - \gamma_s \text{ and } R_i = 0$$

$$\text{risk loving} \not\Rightarrow \widehat{(\gamma_r - \gamma_s)}_i > \gamma_r - \gamma_s \text{ and } R_i = 1.$$

The compliment of the sets of observations corresponding to conditions (3) and (4) is given by

$$\widehat{(\gamma_r - \gamma_s)}_i \leq \gamma_r - \gamma_s \text{ and } R_i = 1 \Rightarrow \text{risk attitude not identified} \tag{5}$$

$$\widehat{(\gamma_r - \gamma_s)}_i \geq \gamma_r - \gamma_s \text{ and } R_i = 0 \Rightarrow \text{risk attitude not identified.} \tag{6}$$

Satisfaction of condition (5) or (6) is consistent with risk aversion, risk neutrality, or risk loving.

Constant Absolute Risk Aversion

As part of our empirical analysis, we examine the extent to which subject job choices can be rationalized by a class of utility functions. We consider the class of utility functions corresponding to Constant Absolute Risk Aversion (CARA). In the interest of simplicity, we adapt the mean-variance portfolio Markowitz (1952) model as described in Wenner (2002) to binary selection between the secure job and the risky job. The random utilities of the job gambles are expressed as

$$U_{si} = y_{si} + \varepsilon_{si} \text{ (secure job)}$$

$$U_{ri} = y_{ri} - \frac{\alpha}{2}\sigma_{ri}^2 + \varepsilon_{ri} \text{ (risky job)},$$

where α is the Pratt-Arrow measure of constant relative risk aversion, and $\sigma_{ri}^2 = (\phi)(1-\phi)(\gamma_r \psi_i - w_u)^2$ is the conditional (on ψ_i) variance of wages on the risky job.

Let σ_{sr}^2 = variance of $\varepsilon_{si} - \varepsilon_{ri}$. The probability that one would select the risky job is given by

$$\begin{aligned}
Prob(J = r|\psi_i) &= Prob\left(U_{ri} > U_{si}\right) \\
&= Prob\left(y_{ri} - \frac{\alpha}{2}\sigma_{ri}^2 + \varepsilon_{ri} > y_{si} + \varepsilon_{si}\right) \\
&= Prob\left(y_{ri} - y_{si} - \frac{\alpha}{2}\sigma_{ri}^2 > \varepsilon_{si} - \varepsilon_{ri}\right) \\
&= Prob\left(\frac{\varepsilon_{si} - \varepsilon_{ri}}{\sigma_{sr}} < \frac{y_{ri} - y_{si}}{\sigma_{sr}} - \frac{\alpha}{2\sigma_{sr}}\sigma_{ri}^2\right) \\
&= Prob\left(\frac{\varepsilon_{si} - \varepsilon_{ri}}{\sigma_{sr}} < I_i\right) \\
&= \Phi\left(I_i\right),
\end{aligned}$$

where $I_i = \theta_1 (y_{ri} - y_{si}) + \theta_2 \left(\frac{-\sigma_{ri}^2}{2}\right)$, $\theta_1 = \frac{1}{\sigma_{sr}} > 0$, and $\theta_2 = \frac{\alpha}{\sigma_{sr}} \gtreqqless 0$. It is readily apparent that the probit standard deviation is identified from $\sigma_{sr} = \frac{1}{\theta_1}$, or the variance from $\sigma_{sr}^2 = \frac{1}{(\theta_1)^2}$. Defining the risky job variance variable as $\frac{-\sigma_{ri}^2}{2}$ allows us to directly estimate α as $\tilde{\alpha} = \frac{\tilde{\theta}_2}{\tilde{\theta}_1}$. Furthermore, with this model we can directly compare the $\tilde{\alpha}_m$ and

$\tilde{\alpha_f}$ risk aversion parameter estimates for males and females.

In order to achieve a larger sample size, a single probit model is estimated from the pooled sample of men and women. A gender interaction term for the conditional variance on the risky job is added to the probit index function in order to identify gender differences in the effects of risky job income variance on job choice:

$$I_i = \theta_1 (y_{ri} - y_{si}) + \theta_2 \left(\frac{-\sigma_{ri}^2}{2} \right) + \theta_3 \left(\frac{-\sigma_{ri}^2 F_i}{2} \right),$$

where $F_i = 1\,(female)$. Identification of the CARA risk aversion parameters for men and women comes from $\alpha_m = \dfrac{\theta_2}{\theta_1}$ and $\alpha_f = \dfrac{\theta_2 + \theta_3}{\theta_1}$.

Because an individual's conditional variance of wages on the risky job σ_{ri}^2 depends on their unobserved expected productivity ψ_i, it is necessary to estimate expected productivity for each subject. Our estimate $\hat{\psi}_i$ is calculated as the average of the subject's final 5 observed performances in their last assigned treatment. The presumption is that this estimate is a reasonable estimate of expected productivity and is a good measure of a subject's own beliefs about their productivity at the time they choose between the risky and the secure job.

Empirical findings

There was a total of 192 subjects who participated in the experiments: 97 in the €0.07 risk premium experiment (54 men and 43 women), and 95 subjects who participated in the €0.06 risk premium experiment (49 men and 46 women).

Tables 1 - 4 report the productivity and wage outcomes for the €0.07 and €0.06 risk premium experiments. For both risk premium experiments, the reported wage outcomes are by design proportional to the corresponding productivity outcomes. The results show that overall for both risk premium experiments, the typing performance of the men exceeded that of the women for both the assigned job treatments and the job choice treatments. This difference in performance directly translated into statistically significant gender wage gaps that favored the men. A closer examination reveals that for the €0.07 risk premium experiment, there was no statistically significant gender difference in typing performance and hence the wage among those who chose the secure job. On the other hand among those who selected the risky job for the €0.06 risk premium treatment, the statistically significant gender wage gap in productivity (and wages), favored women.

When examining typing performance in the assigned treatments, there is no statistically significant difference between the risky job and the secure job for either men or women in the higher risk premium treatment. For the lower risk premium treatment this is only true for men. When women were assigned the risky job, their typing performance was higher by a statistically significant amount than when assigned to the secure job. In the job choice treatment there is of course selection. For the higher risk premium treatment there was no statistically significant difference in job performance among men between the risky and secure jobs. On the other hand women who chose the secure job exhibited a statistically significant performance advantage over women who selected the risky job. The results are quite different in the lower risk premium treatment where men who selected the secure job performed much better than those who selected the risky job. For women the results were exactly the opposite: those who selected the risky job performed much better than those who selected the secure job. These performance differences were statistically significant.

Table 5 is an overview of gender differences in job choice. We report two measures of risky job choice: the proportion of individuals within each gender group who selected the risky job (n); and the proportion of wage payments within each gender group arising from the selected risky job (θ_r). For both measures in both risk premium experiments, the risk proportions for men are higher. The higher risk premium attracts higher proportions of both men and women to the risky job, but the increased attraction of the risky job is proportionately greater for women. Consequently, the gender risk proportion gaps associated with the choice of the risky job diminish when the risk premium is higher. So for example the gender difference in the proportion of individuals choosing the risky job when the risk premium is €0.06 is 19 percentage points. This gap falls to 11 percentage points with the higher risk premium of €0.07. In fact the gender gaps in choosing the risky job are statistically significant for the lower risk premium experiment and marginally insignificant for the wage payment proportions in the higher risk premium experiment. With one exception, the hypothesis that the risky job proportions are lower for men can be rejected in favor of higher risky job proportions for men. The exception for this one-tailed test occurs in the case of the proportion of individuals in the higher risk premium experiment. Failure to reject the null is marginal in this case.

Table 6 reports the results from our risk attitude classifications according to conditions (3), (4), (5), and (6). As it turned out, the predicted risk premium under risk neutrality for every subject was less than the experimental risk premium. This means that conditions (4) and (6) were never satisfied in the data. Consequently, no risk loving subjects were identified, and all of the subjects whose risk attitudes were not identified satisfied condition (5). The proportion of subjects who were identified as risk averse was higher for women in both risk premium experiments. Predictably, the proportions for both genders were lower in the higher risk premium experiment. This is consistent with the findings reported in Table 5. Furthermore, proportionately fewer women were identified as risk averse in the higher risk premium experiment. This is is also consistent with the findings reported in Table 5.

Wage decompositions generated by subject job choices are reported in Table 7. Wages on average were higher for men in both risk premium treatments. The gender wage gap in the €0.07 risk premium experiment was €0.50. Depending on which risky job wage payment fraction (θ_r^f for women or θ_r^m for men) is used to weight gender differences in performance, the propensity of women to select the secure job accounts for €0.26 (52%) or €0.20 (40%) of the wage gap. For the €0.06 risk premium treatment the gender wage gap was slightly lower at €0.47. Again depending on which risky job wage payment fraction is used to weight gender differences in performance, the propensity of women to select the secure job can account for €0.20 (43%) or as much as €0.36 (77%) of the wage gap. When the two sets of risk premium experiments are combined using the experiment sample weights for men ($\Omega_m = 0.537$) to weight gender differences in productivity within jobs, the overall wage gap averaged to €0.48. Under our two alternative overall wage decompositions, job choice accounts for an average of €0.23 (48%) or €0.27 (56%) of the gender wage gap. Rounding error and the contribution of differences in the experiment sample weights are minor and exactly offsetting. [1]

[1] Using the experiment sample weights for women ($\Omega_f = 0.463$) yielded very nearly identical decompo-

To discover what additional factors beyond gender can explain subject job choices, we estimate a probit model of risky job choice. Table 8 reports the results of this exercise. When conditioning on other factors, being a women exhibits a consistently negative effect on the probability of choosing the risky job. This negative effect is statistically significant overall and for the lower risk premium treatment but not the higher risk premium treatment. Age of the subject and the subject's average typing performance over the most recent five periods in the assigned treatment are never statistically significant. However, the productivity effect is consistently negative. This is consistent with the theoretical reasoning that suggests that the higher one's productivity, the higher risk premium would need to be to induce a risk neutral agent to choose the risky job.

Interestingly, the Holt-Laury risk aversion measure consistently exhibits a negative effect on the probability of selecting the risky job though it is only statistically significant overall but not in the individual risk premium experiments. The strongest results, however, stem from the effects of a subject's actual experience of unemployment in the assigned treatment. The more often a subject actually experienced unemployment, the less likely they were to choose the risky job. This effect is statistically significant overall and in the separate risk premium experiments. Statistical significance is exhibited despite the fact that subjects are fully informed about the probability of drawing an unemployment spell. Although the higher risk premium experiment drew more subjects to the risky job, the positive effect of the higher risk premium is not statistically significant.

We explore the determinants of typing performance beyond gender in a random effects model of performance differentiated by risk premium and risky vs. secure employment. Performance is measured each period as the number of correctly typed 5-letter blocks. In the risky job, observations are omitted when the subject draws an unemployment spell.[2] The results are reported in Table 9. After conditioning on the Holt-Laury risk measure, age, and period, the effects of being female on typing performance is negative in 6 out 8 cases. However, this effect is statistically significant only among those who selected the

sitions.

[2]When a spell of unemployment is drawn, performance is of course censored. Because unemployment spells are exogenous, there is no censoring bias arising from random effects estimation. Consequently, random effects tobit is not the appropriate estimator in this case.

risky job in the higher risk premium experiment. The effect of being female on typing performance is positive but not statistically significant for the secure job when chosen in the higher risk premium experiment and for the risky job chosen in the lower risk premium treatment.

The Holt-Laury risk measure is statistically significant in three cases. All three of these are in the higher risk premium experiment and show a negative effect on performance: the assigned risky job, the assigned secure job, and the selected risky job. The age of the subject uniformly exhibits a negative effect on performance but is statistically significant only in the higher risk premium treatments. Perhaps most interesting are the period effects. In both risk premium experiments, the variable 'Period' had a positive and statistically significant effect on performance only in the assigned treatments. This is consistent with subjects learning the typing task during the assigned treatment with no further learning taking place on average by the time the subjects are able to choose between the risky and the secure job.

We also examine whether or not the gender effects and the effects of the Holt-Laury risk measure are significantly different between the risky job and the secure job, i.e. $\beta_r^F - \beta_s^F$, and $\beta_r^R - \beta_s^R$. These differences are examined separately but not jointly and are statistically significant only for job choice in the higher risk premium experiment. Relative to men, women who chose the risky job in the higher risk premium experiment did not perform as well as those who selected the secure job. Typing performance is negatively associated with the Holt-Laury risk measure for those who chose the risky job relative to those who selected the secure job.

Table 10 reports test results for gender differences in risk preferences based on the estimated Pratt-Arrow α parameters obtained from the CARA mean-variance utility function model. The estimated α's are inferred from the model as nonlinear functions of the estimated probit parameters and the associated standard errors are obtained by the delta method. Based on two-tailed tests, we cannot reject risk neutrality for men nor can we reject the hypothesis of no gender difference in α. However, one can reject the hypothesis that women are risk neutral. A series of one-tailed tests shed additional light on gender differences in job risk attitudes as viewed through the lens of the CARA mean-variance utility function model. The hypothesis of risk loving behavior corresponds to $H_0 : \alpha \leq 0, H_1 : \alpha > 0$. We find that one cannot reject the hypothesis of risk loving behavior for men but can reject risk loving for women. The hypothesis that women are less risk averse than men corresponds to $H_0 : \alpha_f - \alpha_m \leq 0, H_1 : \alpha_f - \alpha_m > 0$. We are able to reject the hypothesis that women are less risk averse than men (in favor of the hypothesis that women are more risk averse than men).

VI Discussion

When comparing subject behavior in the higher risk premium experiment (0.07) against behavior in the lower risk premium experiment (0.06) we are relying on a cross-subject design since subjects experienced only one of the two risk premiums. Since the subjects are drawn from the same subject pool, we can think of differences in behavior between the two experiments as risk premium treatment effects. Unconditionally, the higher risk premium increases the propensity to select the risky job. When conditioning on other factors, this effect persists but loses precision in a probit model of job choice.

One might speculate about whether or not an additional incentive to choose the risky job is utility gained from the leisure time associated with drawing a spell of unemployment. Our results strongly reveal the negative impact of unemployment experienced during the assigned treatment phase on the subsequent probability of choosing the risky job. This is indicative of an aversion to income loss occasioned by unemployment as opposed to any positive utility of leisure.

In seeking to uncover the independent effects of ex ante productivity on job choice, we use an average of the five most recently observed typing performances in the assigned job phase. Our analysis of the data strongly supports the notion that this measure is a reasonable proxy for subjects' beliefs about their expected typing abilities. In the assigned job treatment rounds of the experiment, learning is evidenced by the positive and statistically significant effect of Period on (log) typing performance. Whereas in the subsequent job choice treatment rounds, there is a complete lack of statistical significance of Period on typing performance. Thus, in the assigned job treatments there is a positive trend in typing performance but in the job choice treatment there is no trend in typing performance. We therefore conclude that learning has pretty much terminated by the time subjects are exposed to the job choice treatment.

Additional evidence comes from OLS and Random Effects regressions of typing performance in the job choice treatment on our ex ante measure of productivity from the assigned job treatments. The estimated coefficients on our ex ante productivity measure are very nearly equal to 1.00 and highly statistically significant. On the other hand the constant term and subject gender are never statistically significant. The simple R^2 between typing performance in the job choice treatment and the ex ante productivity measure ranges from 0.90 to 0.95.[3]

Clearly there is no universally accepted measure of risk attitudes. Nevertheless, the Holt-Laury measure based on lottery choices has enjoyed some status as a widely accepted measure or proxy for risk preferences. While not the central theme of this paper, it was relatively costless to investigate the association between this measure of risk preferences and job choice. The HL measure of risk aversion is consistently negative in its affect on the probability of choosing the risky job, though it is statistically significant with only the combined data from the risk premium experiments. Our view is that the HL measure has some validity but is far from the only or even major determinant of risky vs. secure job choice.

It should be noted that we test for gender differences in risk preferences in only one type of setting, namely the financial risk associated with involuntary spells of unemployment. There are of course other types of risks that influence job choices, e.g. health risks and risks of bodily injury. Gender differences in these other types of risk preferences clearly could exist in the naturally occurring labor market and could further contribute to observed gender wage differentials.

[3]These estimation results are available upon request.

VII Summary and Conclusions

The research reported in this paper exploits the tight control of the laboratory environment to examine the potential for gender differences in risk attitudes to contribute to gender wage gaps in the labor market. The mechanism examined here is the selection between a risky job and a secure job defined by a known probability of unemployment in the former and the absence of unemployment in the latter. The risky job entails a risk premium in the piece-rate for accurately typed blocks of letters. Unlike the field environment, there is no wage discrimination, monopsony power, or imposed job segregation in our laboratory setting. Any gender wage gap that arises can only arise from two sources: job performance and job choice.

In our experiments a gender wage gap arose in both risk premium treatments, and these gaps favored men. The wage gap was 13.6% of the average female wage in the high premium experiment and 12.3% of the average female wage in the low risk premium experiment. Women exhibited a greater propensity to choose the secure, but lower paying, job. These choices account for between 40% and 77% of the gender wage, depending on the risk premium and which risky job wage payment fraction (θ_r^f for women or θ_r^m for men) is used to weight gender differences in job performance. While the magnitudes of gender wage gaps can be expected to be different in the field because of a whole host of additional factors at work, the experimental evidence in our case points to the potential of risk attitudes for contributing to observed gender wage gaps in naturally occurring labor markets.

We leave to future research additional investigation along the lines of a) conditioning the probability of unemployment on an individual's job performance, and b) the relationship between risk aversion and competition aversion.

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Table 1: Productivity (Number of correctly typed words): Risk Premium=0.07

	Assigned				Choice			
	Overall	Risky	Secure	$\overline{P}_r - \overline{P}_s$	Overall	Risky	Secure	$\overline{P}_r - \overline{P}_s$
Men	23.21	23.10	23.28	-0.18	23.31	23.26	23.42	-0.16
	(0.08)	(0.11)	(0.1)	(0.15)	(0.1)	(0.11)	(0.19)	(0.22)
obs	925	385	540		439	309	130	
Women	21.67	21.54	21.76	-0.22	22.07	21.29	23.00	-1.71***
	(0.08)	(0.12)	(0.1)	(0.16)	(0.12)	(0.16)	(0.17)	(0.23)
obs	729	299	430		328	178	150	
$\overline{P}^m - \overline{P}^f$	1.54***	1.56***	1.52***	0.04	1.24***	1.97***	0.42	1.55***
	(0.11)	(0.16)	(0.14)	(0.22)	(0.16)	(0.19)	(0.25)	(0.32)

* p <0.1 **p <0.05 ***p <0.01

Standard errors in differences are calculated as the square root of the sum of squared S.E from the fixed effects model.

Table 2: Wage: Risk Premium=0.07

	Assigned				Choice			
	Overall	Risky	Secure	$\overline{W}_r - \overline{W}_s$	Overall	Risky	Secure	$\overline{W}_r - \overline{W}_s$
Men	3.78	4.62	3.03	1.59***	4.18	4.65	3.04	1.61***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
obs	925	385	540		439	309	130	
Women	3.44	4.31	2.83	1.48***	3.68	4.26	2.99	1.27***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
obs	729	299	430		328	178	150	
$\overline{W}^m - \overline{W}^f$	0.34***	0.31***	0.20***	0.11***	0.50***	0.39***	0.05	0.34***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)

* p <0.1 **p <0.05 ***p <0.01

Standard errors in differences are calculated as the square root of the sum of squared S.E from the fixed effects model.

Table 3: Productivity (Number of correctly typed words): Risk Premium=0.06

	Assigned				Choice			
	Overall	Risky	Secure	$\overline{P}_r - \overline{P}_s$	Overall	Risky	Secure	$\overline{P}_r - \overline{P}_s$
Men	23.94	24.09	23.84	0.25	24.18	23.13	26.18	-3.05***
	(0.08)	(0.12)	(0.11)	(0.16)	(0.1)	(0.13)	(0.16)	(0.21)
obs	819	329	490		378	248	130	
Women	22.71	22.98	22.52	0.46***	22.8	23.84	21.95	1.89***
	(0.08)	(0.13)	(0.11)	(0.17)	(0.11)	(0.18)	(0.14)	(0.23)
obs	771	311	460		380	170	210	
$\overline{P}^m - \overline{P}^f$	1.23***	1.11***	1.32***	-0.21	1.38***	-0.71***	4.23***	-4.94***
	(0.11)	(0.18)	(0.16)	(0.24)	(0.15)	(0.22)	(0.21)	(0.31)

* p <0.1 **p <0.05 ***p <0.01

Standard errors in differences are calculated as the square root of the sum of squared S.E from the fixed effects model.

Table 4: Wage: Risk Premium=0.06

	Assigned				Choice			
	Overall	Risky	Secure	$\overline{W}_r - \overline{W}_s$	Overall	Risky	Secure	$\overline{W}_r - \overline{W}_s$
Men	3.93	4.82	3.34	1.48***	4.30	4.63	3.67	0.96***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
obs	819	329	490		378	248	130	
Women	3.74	4.60	3.15	1.45***	3.83	4.77	3.07	1.70***
	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
obs	771	311	460		380	170	210	
$\overline{W}^m - \overline{W}^f$	0.19***	0.22***	0.19***	0.03	0.47***	-0.14***	0.60***	-0.74***
	(0.01)	(0.04)	(0.02)	(0.04)	(0.03)	(0.05)	(0.03)	(0.06)

* p <0.1 **p <0.05 ***p <0.01

Standard errors in differences are calculated as the square root of the sum of squared S.E from the fixed effects model.

Table 5: Gender Differences in Job Choices
(standard errors in parentheses)

	$RP = 0.07$		$RP = 0.06$	
	n	θ_r	n	θ_r
Men	0.76	0.70	0.73	0.66
	(0.06)	(0.06)	(0.06)	(0.07)
obs	54	439	49	378
Women	0.65	0.54	0.54	0.45
	(0.07)	(0.07)	(0.08)	(0.07)
obs	43	328	46	380
Diff	0.11	0.16	0.19*	0.21**
	(0.09)	(0.10)	(0.10)	(0.10)

* p <0.1 **p <0.05
n: proportion of individuals in group j who selected the risky job
θ_r: proportion of wage payments in group j arising from the (selected) risky job

Table 6: Inferred Risk Attitudes
(percentages)

	$RP = 0.07$		$RP = 0.06$	
	Men	Women	Men	Women
Identified Risk Averse	0.24	0.35	0.27	0.46
Identified Risk Loving	0.00	0.00	0.00	0.00
Not Identified	0.76	0.65	0.73	0.54
Total	1.00	1.00	1.00	1.00
obs	54	43	49	46

Table 7: Wage Decompositions for Job Choices

	$RP = 0.07$		$RP = 0.06$		Combined	
	θ_r^f	θ_r^m	θ_r^f	θ_r^m	θ_r^f	θ_r^m
Productivity	0.24	0.29	0.26	0.11	0.25	0.21
Job Choice	0.26	0.20	0.20	0.36	0.23	0.27
Experiment Weight Diff					-0.01	-0.01
Rounding Error	0.00	0.01	0.01	0.00	0.01	0.01
Wage Gap	0.50		0.47		0.48	

a. θ_r^f and θ_r^m are the proportions of wage payments for women and men arising from the (selected) risky job.
b. The Combined decompositions use Ω^m to weight the decompositions arising from the two risk premium experiments.
c. Experiment Weight Diff = $\left[w_f^{(1)} - w_f^{(2)}\right](\Omega_m - \Omega_f)$

Table 8: Probit Selection Equation for 'Risky Job'
(standard errors in parentheses)

	Risk Premium (RP)		
	Overall	RP=0.07	RP=0.06
Female	-0.497**	-0.387	-0.603**
	(0.20)	(0.29)	(0.28)
Age	0.006	-0.031	0.048
	(0.03)	(0.04)	(0.05)
Risk Aversion (HL)	-0.093*	-0.115*	-0.088
	(0.05)	(0.07)	(0.08)
Productivity[a]	-0.022	-0.053	-0.013
	(0.02)	(0.03)	(0.02)
Unemployment History[b]	-2.619***	-2.464**	-2.682***
	(0.69)	(1.01)	(0.96)
Risk Premium (0.07)	0.067		
	(0.20)		
Constant	2.453**	4.158**	1.327
	(1.10)	(1.694)	(1.36)
chi2	25.65	11.97	15.35
N	192	97	95

* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

a. average productivity over the last observed five periods in the assigned treatment.

b. average number of unemployment periods in the assigned risky session.

Table 9: Performance: Risky vs. Secure Employment
(dependent variable: log of performance)
(standard errors in parentheses)

	Risk Premium=0.07				Risk Premium=0.06			
	Assigned		Choice		Assigned		Choice	
	Risky	Secure	Risky	Secure	Risky	Secure	Risky	Secure
Female	-0.055	-0.065	-0.120***	0.055	-0.050	-0.047	0.004	-0.116
	(0.041)	(0.040)	(0.043)	(0.079)	(0.057)	(0.056)	(0.070)	(0.107)
Risk Aversion (HL)	-0.019*	-0.021**	-0.029***	0.018	-0.003	-0.003	-0.008	0.025
	(0.010)	(0.010)	(0.010)	(0.025)	(0.014)	(0.014)	(0.016)	(0.032)
Age	-0.028***	-0.028***	-0.027***	-0.033***	-0.011	-0.012	-0.012	-0.018
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.021)
Period	0.008***	0.005***	-0.000	0.001	0.006***	0.006***	0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	3.849***	3.894***	3.948***	3.752***	3.361***	3.386***	3.412***	3.427***
	(0.138)	(0.133)	(0.168)	(0.229)	(0.210)	(0.206)	(0.232)	(0.478)
N	684	970	487	280	640	950	418	340
$\beta_r^F - \beta_s^F$	0.010		-0.175**		-0.003		0.120	
	(0.057)		(0.090)		(0.080)		(0.128)	
$\beta_r^R - \beta_s^R$	0.002		-0.047*		0.003		-0.033	
	(0.014)		(0.027)		(0.49)		(0.036)	

Results obtained from Random Effects Estimation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Results obtained from Random Effects Estimation.

$\beta_r^F - \beta_s^F$ tests whether the coefficients of 'Female' in both jobs are same.

$\beta_r^R - \beta_s^R$ tests whether the coefficients of 'Risk Aversion (HL)' in both jobs are same.

Table 10: Gender Differences in the Pratt-Arrow
CARA Risk Preferences Parameters (α)
(Mean-Variance Utility Function)

Test	p value
$H_0\colon \alpha_m = 0, H_1\colon \alpha_m \neq 0$	0.194
$H_0\colon \alpha_f = 0, H_1\colon \alpha_f \neq 0$	0.052
$H_0\colon \alpha_m \leq 0, H_1\colon \alpha_m > 0$	0.457
$H_0\colon \alpha_f \leq 0, H_1\colon \alpha_f > 0$	0.026
$H_0\colon \alpha_f = \alpha_m, H_1\colon \alpha_f \neq \alpha_m$	0.152
$H_0\colon \alpha_f \leq \alpha_m, H_1\colon \alpha_f > \alpha_m$	0.076
Men: $\tilde{\alpha}_m = 0.008, \tilde{\sigma}_{\tilde{\alpha}_m} = 0.070$	
Women: $\tilde{\alpha}_f = 0.127, \tilde{\sigma}_{\tilde{\alpha}_f} = 0.066$	