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Abstract

This paper focuses on the effect of experience within an industry on wages. I use a correlated random effects simultaneous equation model that allows individual and match heterogeneity to affect wages, job tenure and industry experience. I estimate my model separately for men and women using a large panel of young Italian workers for the years 1986–2004. Results show that wage returns to industry experience are much higher than wage returns to job seniority. The hypotheses of exogeneity of job seniority and industry experience in the wage equation are rejected: high-wage workers and high-wage matches last longer.

JEL Code: J31, J62.
Keywords: Wage growth and industry experience, firm tenure, simultaneous equation models, random effects, Worker History Italian Panel (WHIP) dataset.

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1 Introduction

Workers are paid more the longer they stay in the same sector and the longer they work for the same firm. This suggests that sector- and employer-specific human capital are important for wage growth and that mobility might have costs in terms of wage trajectories. On the other hand, individuals who earn high wages are more mobile than average. This *prima facie* conflicting results suggest that both human capital accumulation and match quality considerations are important in the wage determination process: workers learn useful skills as they keep their jobs longer and as they work longer in the same industry, but can also benefit from finding a better match by moving more. Estimating returns to firm tenure and industry experience needs to take account that movers and not movers may differ in ways that cannot be typically observed in our data, and that not all transitions are equivalent. Yet quantifying the role of firm tenure and industry[1] experience for wage growth is critical for researchers and policy makers alike. For researchers it sheds light on the role of different types of human capital for mobility and wages, and on the role of mobility on life-cycle earnings. In particular it speaks to the anecdotal evidence of long unemployment spells and high wage losses following the decline of an industry. These results have also implication for the design of labour market policies. For policy-makers, knowing the "rewards" of tenure and industry experience is valuable for policies concerning labour market mobility, contracts and compensation levels. In particular, allowing for a separate role of industry experience can be informative for the relative earnings loss associated with different labour market transitions. For example, public policy might consider specific interventions for displaced workers employed in a shrinking sector as opposed to displaced workers in a booming sector.

The main goal of this paper is to estimate the effect of labour market experience, industry experience and firm tenure on wages, allowing individual unobserved heterogeneity to affect wages and mobility. In particular, I estimate a three-equation simultaneous random effects model including a wage equation and two hazard equations for job and industry employment durations, for males and females separately. To estimate this multilevel correlated random effects model I use administrative data for a large sample of young Italian workers (I choose to focus on young workers so that I can observe all of their labour market history within my dataset) from the *Worker Histories Italian Panel* dataset for the years 1986-2004. This paper offers the first estimate of the returns to industry experience using Italian panel data. To the best of my knowledge it is also the first simultaneous estimation of wage growth, firm tenure and industry experience. My main results show that industry experience is important for wage determination: wage returns to industry experience (at around 6.8 percent for the first ten years for males, 1.5 for females) are much larger than wage returns to job seniority (2.4 percent for ten years of job tenure for males, 2.5 for females). This implies that mobility across sectors is associated with a much larger wage penalty than mobility within the same economic sector. Returns to labour market experience dominate the effects of

[1] I use "industry" and "sector" interchangeably here.

industry experience and of job tenure (29 percent for the first ten years for males, 11 for females). I also find evidence that wages and employment duration are simultaneously determined: individuals with characteristics that are associated with higher wages also stay on the job longer, and "good" matches (matches with conditionally higher wages) are less likely to be destroyed.

The possibility of omitted variable bias affecting a simple OLS estimate of the wage returns to job tenure has been considered since Abraham and Farber (1987). They find positive returns to seniority to be an artefact of sample selection in the sense that matches that pay conditionally higher wages from the start are more likely to survive. Altonji and Shakotko (1987) propose an Instrumental Variable (IV) technique to account for this endogeneity.[2] Under instrument's validity, this IV procedure allows us to relax the assumption of random match destruction that would be needed in an OLS framework. However, treating all mobility as equivalent does not allow us to investigate the role of experience at the level of the industry. Neal (1995) first argues that industry experience might also be an important determinant of wage growth. If industry experience is important, Altonji and Shakotko (1987) might misinterpret some of the estimated returns to job seniority. Following the same intuition, Parent (2000) uses the same IV technique as Altonji and Shakotko (1987) to investigate the return of job seniority once industry experience is accounted for, and finds that return to job seniority are close to zero. More recently, Dustmann and Meghir (2005) employ a similar strategy to study the wage impacts of different sources of human capital using data of displaced workers from Germany. They find that wage returns to sector tenure are positive for skilled workers, but are not significantly different from zero for unskilled workers. While studies that use displaced workers allow us to isolate involuntary match destructions, samples of displaced workers are typically not representative of the working population as a whole. In particular, the sample tends to be disproportionally comprised of workers employed in shrinking sector and employed by low performing firms. Altonji et al. (2009) develop a complex empirical strategy for modelling wage dynamics focusing on the role of occupations (rather than industry) and unemployment spells.[3]

I estimate a multilevel correlated random effects model of wages, industry experience and firm tenure. This model builds upon Lillard (1999) and Dostie (2005) for estimation strategy and identification. Using a simultaneous equation model means that unobserved components that affect wages can be correlated with those that affect job and sector duration, which needs to be

[2] A similar technique is used also in Altonji and Williams (2005), who find wage returns of ten years of job tenure around 11 percent. Among many others, Topel (1991) offers related evidence of the importance of firm-specific human capital while using longitudinal datasets to account for the endogeneity problem discussed above. They find that lower bounds for wage returns of firm seniority are around 2.5 percent a year on average. Topel and Ward (1992) on the other hand stress the importance of job mobility as a source of wage growth for young American males.

[3] Cingano (2003) uses data from two Italian provinces to estimate the effects of experience in a certain industrial district on wages. He finds negative and insignificant effects, concluding that district-specific skills do not seem to matter for wage growth. Kambourov and Manovskii (2009) include the role of occupations as well as industries and firms for human capital accumulation of workers using the PSID for 1968-1980. Because of data limitations, I am not able to control for occupations.

assumed away in a single equation random effects model. Lillard (1999) uses U.S. data to estimate a simultaneous model with a wage equation and an job duration equation. Dostie (2005) using French data finds that wages and job tenure are simultaneously determined. Both Lillard (1999) and Dostie (2005) focus on the returns to firm tenure and do not include industry experience, which is the main focus of this paper.

2 Empirical Strategy and Hypotheses

Estimating the returns to job tenure and industry experience with observational data is relatively complex in terms of econometrics and data requirements. It may be useful to start from describing the ideal thought experiment one would run to identify causal effects with a trivial estimation strategy. In this thought experiment there is a fixed set of workers and a fixed set of jobs. Workers are assigned to jobs randomly, and transition between jobs randomly. Matches that we created randomly are also terminated in a random fashion, so that experience and tenure accumulated by a workers do not depend on her characteristics. Under these conditions, an OLS regression of wages on experience, industry-experience and seniority identify causal effects.

Let us view this in the context of a regression equation. Let $i = \{1, ..., N\}$ identify a worker, and $t = \{1, ..., T\}$ a time period. Let $J(i,t)$ be the employer of worker i at time t. In the following, $j \equiv J(i,t)$ is used for simplicity.[4] Equivalently $K(J(i,t))$ denotes the sector of worker i in period t, and $f \equiv K(J(i,t))$. A useful starting point is a linear wage model such as:

$$w_{ijt} = \gamma_1(seniority_{ijt}) + \gamma_2(sectorseniority_{ikt}) + \gamma_3(experience_{it}) + \epsilon_{ijt} \tag{1}$$

where w_{ijt} is the real wage of worker i in match j in period t; $seniority_{ijt}$ denotes the duration of the match j up to period t; $sectorseniority_{ikt}$ is the experience accumulated by worker i in sector k up to period t; $experience_{it}$ is the total labour market experience of worker i up to time t.[5]

The error term ϵ_{ijt} can be decomposed into an individual-specific time-invariant component θ_i, capturing the effect of person-specific time-invariant characteristics, a match-specific component δ_{ij} (which captures a firm and sector effect as well) and a component that is match-, time- and person-specific, denoted by ν_{ijt} below:

$$\epsilon_{ijt} = \theta_i + \delta_{ij} + \nu_{ijt} \tag{2}$$

An OLS procedure yields unbiased estimates of γ_1, γ_2 and γ_3 in equation (1) only if experience, industry experience and job seniority are uncorrelated with θ_i, with δ_{ij} and with ν_{ijt}. In other

[4] Although I sometimes refer to the match j as a "job", it is intended simply as the match of one firm and one worker: promotions and contract changes inside the firm do not determine the end of a spell.

[5] Because firms do not change sectors in my dataset, I drop the subscript k when redundant in equation (1) and in other equations below. For example, I write ϵ_{ijt} instead of ϵ_{ijkt}.

words, OLS estimates are biased unless workers were randomly assigned to sectors and firms, and matches were randomly destroyed. My empirical strategy on the other hand allows individual level unobservables to affect wages, job duration and sector duration at the same time. It also allows job-level unobservables to affect length and profitability of the job.

In reality, a number of selection processes may violate the assumptions of the thought experiment described above. A suggested in Jovanovic 1979, workers do not choose their job randomly and firms do not hire workers randomly. Over time, the set of jobs that survives is self-selected. For example, workers might keep searching for new opportunities while employed as in Pissarides (1994), and quit their current job if they receive a sufficiently attractive offer. Therefore, higher wages may increase the probability of staying in the current job. Moreover, both firms and workers can decide to interrupt a match and will not do so randomly. Either side of the market may learn about productivity over time as in Postel-Vinay and Robin (2002), or characteristics of the worker may be observable but not contractible as in Peters (2010). A model with asymmetric information in which it takes time for a firm to get to know a worker's productivity would predict that individual unobservables associated with higher wages should also have longer permanence in a job and in an industry. Therefore, I should expect high-wage individuals to have longer spells. Consistent with the implication of a search model *à la* Mortensen and Wright (2002) where matches that last longer are of higher quality in terms of productivity, we would also expect 'good' (high wage) matches to also last longer. We will also be able to interpret the estimates within the context of a framework where where it might take time for employers and employees learn about match-specific productivity as in Jovanovic (1979) and Jovanovic (1984), which would imply that lower-quality matches will last some time but less than higher-quality matches.

My empirical model estimates the effect of firm tenure, industry experience and labour market experience on wages thereby shading light on the theoretical hypotheses discussed above. This model needs a much weaker set of conditions than those described above for a simple OLS procedure.[6] As described in details below, I estimate the effects of interest allowing unobserved individual characteristics and unobserved match characteristics to affect wages as well as mobility of workers. In addition, it will be possible to investigate whether the theoretical hypothesis outlined above hold in my data.

3 Empirical Model

My empirical model is a multilevel correlated random effects model composed of a wage equation, a tenure hazard equation modelling job-to-job transitions, and an industry hazard equation modelling sector-to-sector transitions.

[6]For a comprehensive discussion on how to treat unobserved worker, firm, and match heterogeneity in a model of wage differentials see Woodcock (2008).

3.1 Wage Equation

I specify the wage equation as follows

$$\begin{aligned} ln(w_{ijt}) = &\alpha_0 + \alpha_1' \mathbf{seniority_{ijt}} + \alpha_2' \mathbf{sectorseniority_{ikt}} + (1+\theta_{1i})\alpha_3' \mathbf{experience_{it}} \\ &+ \sum_{t=2}^{T} \iota_t^w year_t + \sum_{t=2}^{T} \kappa_t^w sector_t + \theta_{2i} + \delta_{ij} + \nu_{ijt} \end{aligned} \tag{3}$$

where w_{ijt} is the real wage of person i at time t.[7] The regressors $\mathbf{seniority_{ijt}}$, $\mathbf{sectorseniority_{ikt}}$ and $\mathbf{experience_{it}}$ are parameterised as piecewise-linear splines, where nodes (break points) are chosen to provide the best fit to the data while maintaining a parsimonious specification.

In equation (3), α's, ι's and κ's above are parameters to be estimated; θ_{1i} and θ_{2i} are random person effects with zero conditional mean; $year_t$ denotes a dummy variable for year t. I include year fixed effects to control for unobserved macroeconomic trends affecting both wages and worker mobility. The variable $sector_t$ is a dummy for each industry to control for unobserved sector characteristics that may be correlated with industry experience. For example, some sector may be characterised by high wages and low mobility (implying higher sector experience). Match-specific unobserved heterogeneity is captured by δ_{ij}. Finally, ν_{ijt} is the person-match-time specific error term, which is assumed to have mean zero conditional on all the other regressors.

3.2 Job Duration Hazard Model

Employment duration is estimated using a hazard model based on Kiefer (1988). The baseline hazard duration dependence is piecewise linear.[8] For person i employed in job j in year t, the hazard model is

$$ln(h_{ij}(\tau^j)) = \beta_0 + \beta_1' \mathbf{seniority_{ijt}} + \beta_2' \mathbf{experience_{it}} + \sum_{t=2}^{T} \iota_t^j year_t + \sum_{t=2}^{T} \kappa_t^j sector_t + \theta_{3i} + \phi\delta_{ij} \tag{4}$$

where $ln(h_{ij}(\tau^j))$ is the conditional log hazard rate, i.e. the probability to observe a job separation for a match of duration τ^j at time t, conditional on that match being active. I can control for time-invariant personal unobserved characteristics affecting job mobility through the person effect θ_{3i}. As discussed below, the match effect δ_{ij} from equation (3) with the load parameter ϕ accounts for potential cross-equation correlation between the job-level wage components and the job-level turnover hazard. The remaining regressors and parameters are defined as in equation (3).

[7] Unless stated otherwise, I use the same notation as above.

[8] I.e. piecewise generalised Gompertz. See Pollard and Valkovics (1992) and Lillard and Panis (2003b) for additional information on the Gompertz distribution.

3.3 Sector Duration Hazard Model

For person i employed in sector k in year t, the hazard model for sector duration is

$$ln(h^s_{ik}(\tau^s)) = \gamma_0 + \gamma'_1 \mathbf{sectorseniority_{ikt}} + \gamma'_2 \mathbf{experience_{it}} + \sum_{t=2}^{T} \iota^s_t year_t + \sum_{t=2}^{T} \kappa^s_t sector_t + \theta_{4i} \quad (5)$$

where $ln(h^s_{ik}(\tau^s))$ is the conditional log hazard, i.e. the probability of employment in sector k ending at time t, conditional on that sector spell not having been destroyed earlier. Equivalently as above, θ_{4i} is a person random effect, which captures skills that are portable across sectors.[9] Equation (5) does not include the match random effect: match quality may affect the probability of changing jobs, but having taken this effect into account, it has no further effect on the probability of changing sectors. Since match effects are constructed to be transitory in nature, this assumption simply states that workers are aware that the quality of the match does not include information concerning other firms, and so will not affect mobility across sectors. The other regressors and parameters are equivalent to equation (3).[10]

3.4 Error Structure and Assumptions on Parameters

Beyond individual and match heterogeneity, there may be person-specific autocorrelation in the residual wage variation. For example, there may be shocks to an individual wage that have some degree of persistence. I therefore assume a first-order autoregressive error in equation (3):

$$\nu_{iJ(i,t)t} = \omega \cdot \nu_{iJ(i,t-1)t-1} + u_{iJ(i,t)t} \quad (6)$$

where $u_{iJ(i,t)t} \sim N(0, \sigma^2_u)$. Errors may be correlated within a worker's career, beyond the correlation induced by the presence of a person effect. The random match effect is normally distributed:

$$\delta_{ij} \sim N(0, \sigma^2_\delta) \quad (7)$$

Random effects estimations do not require restrictions on the joint distribution of person and match effects across equations, so that I can evaluate the presence and magnitude of systematic cross equation correlations. Two sets of elements introduce simultaneity in the three-equation

[9] The alternative modelling choice would have been perhaps more general, but it would likely have been infeasible to estimate. In addition, it would have resulted in the need to estimate one hazard equation separately for each sector and would have made it impossible to compare the role of unobserved time-invariant ability across equations.

[10] The two hazard models described above concern the overall probability of job transitions and sector transitions. Therefore, the job hazard model of equation (4) includes both job transitions within a sector and transitions of job and sector. The sector hazard model of equation (5) includes transitions of job and sector (sector-only transitions are not possible). This introduces a positive correlation between the person effects in the job hazard model θ_{3i} and in the sector hazard model θ_{4i}, since some of the transitions are the same transitions in both models. The reader should keep this in mind when interpreting the magnitude of my estimate of that correlation. In particular, my estimate is larger than what I would find if I estimated the job hazard model using transitions within a sector only.

model described above. First, the individual effects are allowed to be correlated across equations (3), (4) and (5) for the same individual i:

$$(\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i})' \sim N(\mathbf{0}, \mathbf{\Sigma}_{\theta,\theta}) \tag{8}$$

If industry experience and job tenure were exogenous in the wage equation there would be no cross-equation correlation between the $\theta_{\bullet i}$'s. I allow for time invariant characteristics that affect wages to influence match duration and sector experience as well, and I will be able to estimate the empirical correlation between the $\theta_{\bullet i}$'s.[11] Secondly, I include δ_{ij} in equation (4) with load factor ϕ. A significant estimate for ϕ suggests that unobserved match-level factors that affect wages also influence job duration. The hypotheses on the correlation between the $\theta_{\bullet i}$'s and on ϕ are tested separately using t-tests as well as jointly using a Likelihood Ratio test.

All parameters of interest are identified off a mix of within person and match variation (i.e. variation that comes from observing multiple matches for each worker and multiple wage observations for each match) and between person and match variation (i.e. variation that comes from the fact that I observe multiple worker for each year and for each sector). Therefore, technically all effects would be identified off functional form even if I did not observe multiple jobs in multiple sectors, and many wage observations for each worker's match. However, since I observe multiple jobs per person and yearly wage observations for each job, I am not relying on functional form for identification. I use wage variation within a job as a source of identification of the effects of job seniority on wages, and wage variation within a person's career across sectors helps me to separately identify the wage effects of industry experience and of labour-market experience. The effects of labour-market experience are in turn identified off in part using workers for whom I observe more than one employer. A more comprehensive discussion of identification of random effects models is available in in Greene (2003, pages 295-298) and Lillard (1999). For equations (4) and (5) the individual component is identified in part using multiple spells for each worker before the last spell observed, which may be right-censored because the most recent match might be alive at the end of the dataset. Since workers may or may not change sector when they change jobs, I can identify all parameters in the sector hazard equation separately from those of the job tenure equation. The variance of the person-specific heterogeneity term can be identified because we observe multiple jobs for each worker.

[11] Instrumental variables techniques such as in Kambourov and Manovskii (2009) need to identify instruments that need to be correlated to all fixed effects, and therefore need to make stronger assumptions concerning the form that the endogeneity can take, as discussed in Pavan (2011).

4 Data

4.1 Wage Setting

The empirical investigation in this paper uses a long panel of young Italian workers. Collective bargaining is often viewed as the main mechanism for wage determination in Italy. In reality, there are many sources of wage heterogeneity across workers and across firms (Erickson and Ichino, 1993). National regulations concern general issues common to all sectors and all firms, and are typically silent on specific compensation levels. Contracts signed with trade unions are typically at the industry level, and specify non-binding minimum wage levels, representing an industry-specific floor for total compensation. In addition, because minimum wages are occupation and rank-specific, promotions can affect the relevance of the contractual minimum wages (Cingano, 2003). At the firm level, both firm-level agreements and individual bargaining are important, and wage premia are found to be highly heterogeneous across firms (Erickson and Ichino, 1993), and higher for small firms (Cingano, 2003).[12]

4.2 The WHIP Dataset

I estimate the simultaneous equation model described above using the *Work Histories Italian Panel* (WHIP). WHIP is a database of individual work histories for the years 1985-2004, based on administrative archives from the *Istituto Nazionale della Previdenza Sociale*[13] (INPS), which is the main institution for social security in Italy.[14] By law, all employees in the private sector, some categories of employees of the public sector and most self employed need to be enrolled in INPS, with the exception of specific categories of professionals, such as doctors, lawyers, notaries and journalists, who have alternative social security funds.

The reference population of WHIP consists of all individuals who worked in Italy in any of the years of the panel. From this population, the WHIP sample is constructed using four birth dates for each year, so that the sampling ratio is around 1:90. This results in a dynamic population of about 370,000 people. WHIP includes information about the main episodes of the working careers of people in the sample, such as duration of each employment spell, wage received, benefits received

[12] An extensive description of the institutional features of the Italian labour market is beyond the scope of this paper. Addessi and Tilli (2009), Beccarini (2009) and Schindler (2009) offer a more comprehensive analysis.

[13] National Institute for Social Security.

[14] WHIP is managed by Laboratorio Revelli Centre for Employment Studies - that has been constructed thanks to an agreement between the INPS and the University of Torino. See http://www.laboratoriorevelli.it/whip. Detailed descriptions of the WHIP dataset are available from Contini (2002) and Contini and Trivellato (2005). I use the restricted-access version of WHIP, which can only be accessed in person form the Laboratorio Revelli.

by the employee such as unemployment benefits,[15] occupation[16], location. Individual data also include gender, year and region of birth. Being an administrative registry of employment relations, the WHIP dataset does not include educational attainments of workers.[17] All jobs are identified by a unique job identifier.[18] This paper uses employees of the private sector only, for which the database also provides some information about employers such as firm size, region, sector[19] where each worker is employed.

After a long period of high unemployment despite positive economic growth in the 1980s, in the 1990s Italy experienced an increase in labour force participation and and a fall in the unemployment rate. This can be traced back to the consistent growth of temporary and part-time employment, especially for young workers. Increased flexibility has been introduced "at the margin" through a series of reforms that affected primarily new entrants in the labour force Schindler (2009). The empirical analysis below is based on a younger-than-average segment of the working population, who face a labour market that is more flexible in terms of wages and job security, and where short-term contracts are increasingly common.

4.3 Sample Restrictions

Industry experience, labour market experience and job tenure are left-censored for all individuals in WHIP because no information is available on employment spells before 1985. In order to avoid imputing key variables in my analysis, which would results in overestimating labour market experience and therefore underestimates its returns, I restrict the sample to younger workers whom I can observe for their whole careers. I drop all individuals that are employed in the first year of the panel, 1985, and then I restrict the sample to individuals that are born in 1961 or later. All of the results below are based on a population of workers that are on average younger than the overall Italian labour force: the oldest worker in the regression sample is 25 years of age is 1986, and thus is 43 years of age in 2004, the last year of the panel.

The final sample consists of 82,114 male workers and 56,914 female workers. The total number of job spells is 207,501 for males, of which 20.5 percent are right-censored, and 134,941 for female, of which 21.1 percent are right-censored. It includes 536,277 yearly wage observations for male

[15]This work does not model unemployment specifically. This is equivalent to assuming that unemployment has no effect on the set of skills of workers: I do not investigate the possibility that unemployed workers might acquire labour market skills, and also that their skills deteriorate. If that was the case in reality, my estimate of the effect of labour market experience may be biased upwards. For young workers it is hard in the data to identify unemployment spell, since that depends on eligibility.

[16]However, only five different occupations are possible, and so are of limited usefulness and capture contractual pay scale as opposed to occupation in terms of a set of tasks. I am not using this information in this version of the paper. Including occupational dummies does not substantially affect the results.

[17]I try to exclude students from the sample based on age and working status. The returns to education will be captured by the individual fixed effect, apart from education acquired while working.

[18]For confidentiality reasons firm identifiers are not included in the dataset, and thus it is not possible to identify workers that share the same employer.

[19]The classification used for this version of the dataset includes 34 sectors and it is based upon the Ateco91 system.

workers, and 358,591 for female workers. Wage measures are converted into year-2004 Euros by using aggregate data of the Consumer Price Index from Istat (2009). To make spells of different lengths comparable in terms of wages, I construct annual *Full Time Equivalent* wages for all workers.[20] As mentioned above, WHIP includes information about start date and end date of each job but wages are recorded only once a year. I identify a a *dominant* job for every worker and every year[21] to avoid overweighting observations for short employment spells and to avoid imputing wage patterns within a year.

5 Summary Statistics

In my sample, 61 percent of the workers are male and 39 percent are female. Around 90 percent of the workers are in a full-time job. As shown in Table 1, for males, *Construction* is the largest sector (18.2 percent of workers), followed by *Wholesale and Retail Trade* (13.8 percent) and by *Banking and financial intermediaries* (10 percent).[22] Comparing the distribution of workers across sectors in my regression sample with that of the 2001 Italian Population Census Istat (2005) we note that construction, wholesale and retail trade are over-represented in my sample, while banking and other services are slightly under-represented. In my sample, females are most likely to be employed in the *Wholesale and Retail Trade* sector (19.9 percent), and in the *Banking* sector (16.0 percent). Compared to the 2001 Italian Census, I find that Hotels and restaurants are over-represented in my sample of females, while industry in general is slightly under-represented. The discrepancies are likely to be due to the fact that workers in my regression sample are much younger than workers in the overall population.

The extent of worker mobility in my sample is investigated in table 2, which shows that we observe one employment spell for 37.6 percent of male workers in the sample, two spells for 24.3 percent, three spells for 15.4 percent of the sample. Therefore, more than 60 percent of workers in my sample move at least once. Figure 3 shows that we observe around 44 percent of males in more than one sector, and around 17 percent in at least three sectors. The corresponding figure for females are only slightly smaller. Table 4 shows that employment spells of males last on average just over two years. In the sample used here, about 20 percent of the spells are right-censored. Male workers enter employment spells with about 20 months of experience on average, and with around 8 months of experience in the same sector. Equivalent figures for female workers are presented in table 5. Females stay on the job slightly longer than males, and enter an employment spell with slightly less experience in the labour market and in the sector.

As shown in Tables 6 and 7, male and female workers in this sample have an average gross

[20] I divide total wages by the number of days worked and then multiply the result by 312, the total number of days of full time workers in one year.

[21] I eliminate all jobs with less than five *full-time equivalent* working days, then I rank jobs by number of effective full-time-equivalent days and then by duration and wages.

[22] Additional information on the codification of sectors in WHIP is available in Leombruni and Quaranta (2011).

income of 19,700 Euros and 17,900 Euros respectively. These incomes are calculated on a full-time full-year equivalent using real wages in 2004 Euros. At the start of the year, male (female) workers have on average 3.66 years (3.56 years) of experience in the labour market, 2.72 years (2.72 years for females) of experience in the sector, and have accumulated tenure on the job of 2.02 years (2.02 years for females). Italian firms tend to be relatively small: around 45 percent of workers are employed in a firm that has less than 10 employees, only 15 percent of workers are employed by firms that have more than 300 employees.

5.1 Wage Profiles

Figure 1 shows that there is a strong positive unconditional correlation between labour market experience and log wages. The difference in wages between males and females is large and increases with the level of experience for the first ten years. At the beginning of their careers, males and females have similar wage levels, but at around ten years of experience males earn around 20 percent more than females. Women with 15 years of experience have average wages that are similar to those of men with around half as much labour market experience.

Figure 2 presents the unconditional correlation between log wages and experience accumulated in the same industry. The pattern is similar to Figure 1, although the gap between males and females is larger and increasing for all levels of industry experience. Figure 3 shows the equivalent log wage profile for match duration. In this case all of the gap between males and females is accumulated in the first few years of job tenure, and it is constant afterwards.

5.2 Hazard Kernel Estimates of Firm Tenure

Dropping right-censored spells,[23] the median duration of a job is around one year for males and 1.17 years for females. The 75th percentile is 3.25 years for males, 3.59 for females. Median tenure in a sector is 1.83 years for males and 2 years for females. The 75th percentiles is 5.94 years for males, 6.16 for females. Figure 4 shows that the survival probability of jobs falls very rapidly in the first years of spell duration and declines very gently afterwards. Around one fourth of the matches observed in the regression sample last more than four years. These patterns are almost indistinguishable between men and women. A kernel density estimation[24] of the hazard rate constructed in Figure 5 shows the probability of match destruction at each level of tenure, conditional on that match having survived up to that point in time. The hazard rate is high in the first few years of a match, starting off at over 0.3 and falling to 0.2 at four years of job tenure. Afterwards it keeps diminishing falling to 0.1 at 12 years of tenure. While patterns are very similar between males and females, Figure 5 does reveal that matches of female workers are significantly

[23]I.e. matches that are still active the the of my panel, such that I do not observe their end date and therefore their duration. Censored spells are 20.7 percent of all spells.

[24]All of these kernel estimations use the Epanechnikov kernel.

less likely to be destroyed in the first four years of tenure, consistently with the mobility patterns described above.

6 Regression Results

I estimate the three-equation model described above using aML (Applied Maximum Likelihood), a freely-available software developed by Lillard and Panis (2003a). Because the likelihood of hazard models does not have a closed form solution, I approximate the integrals in the likelihood function using a numerical integration algorithm based upon the Gauss-Hermite Quadrature, which selects a number of support points (I use 4 points for my main simultaneous equation model) and weights such that the weighted points approximate a normal distribution (Abramowitz and Stegun, 1972).[25] Estimates of equations (3), (4) and (5) are presented in three separate tables for male and female workers separately.[26] For all regression tables discussed below, the first column refers to a model in which each of the three equations is separately estimated and in which I do not include random effects. The second column introduces random effects for individual and match heterogeneity, controlling for unobserved heterogeneity at the individual and match level, but does not allow for cross equation correlation among these random effects. The third column (column SIM) refers to the most general specification: the three- equation simultaneous model where individual and match effects are allowed to be correlated across equations. Therefore, for column SIM all three tables refer to a single estimation. Unless mentioned otherwise, all coefficients described below are statistically significant at the 1 percent level.

6.1 Males

Table 8 presents estimates from equation (3) for male workers. In the column SIM, the first two years of industry experience are associated with an average wage increase of 2.1 percent per year. The years between the second and the fifth are associated with slightly negative marginal effect on wages: while some industry experience has positive returns, workers with an intermediate level of industry experience are not paid more than workers with less industry experience. It is possible that while highly mobile workers might be driven by choice and high motivation, intermediate levels of industry experience might signal a previous layoff. The average marginal effect of industry experience on wages is small, positive and stable after the fifth year at 0.7 percent a year.

[25] As suggested in Lillard and Panis (2003a) and since the distribution of the individual random effects is of dimension four, I transform the covariance matrix into Cholesky-decomposed parameters in order to ensure that the covariance matrix remains positive definite.

[26] There are two main reasons for having estimated this model for females and males separately. Firstly, it is of direct interest to look at the estimates for males and females separately because of the overall differences between labour-market performances and dynamics for the two genders. Secondly, possible dynamic selection effects might reduce the generality of results for females. This concern may be especially relevant in the Italian context where females have among the lowest participation rates among OECD countries.

Controlling for industry experience, job tenure has a small effect on wages: the first two years are associated with an average wage increase of 0.5 percent per year; the equivalent effect falls to 0.3 percent per year in the following three years, and it is not significantly different from zero for the years 5th-10th. After the tenth year on the job, the effect is slightly negative, and significant at the 5 percent level, suggesting that staying on the same job for very long may be detrimental for wages. The effect of labour market experience on wages are large and stable across our three specifications. The marginal yearly effect for the SIM specification is 4.3 percent for the first five years and around 1.5 percent afterwards. The total effects over the first ten years of a worker's career are 6.8 percent for industry experience, 2.4 percent for job tenure and 29 percent for general work experience. If wages reflect marginal productivity of workers, which in turn is a function of human capital accumulation, these results suggest that general human capital and sector-specific human capital are both more important that firm-specific human capital.

Comparing column W2 and column SIM allow to look at the impact of endogeneity on my estimates. Failing to control for endogeneity does not lead to a large overestimation of the effect of tenure on wages, compared to typical estimates using datasets from the US and from other European countries (Kambourov and Manovskii, 2009). This difference may be due to the lower level of mobility in the Italian labour market compared to the US labour market, which might generate a lower correlation between the firm effect (which is embedded in the match effect in this paper) and the level of job tenure workers acquire. In other words, in the US low-wage firms might be more likely to lose workers to to lay them off, and might not be able to attract high-wage workers. In Italy, it seems that labour market frictions for firing decision might mitigate these tendencies.

Table 9 presents the results for the hazard regression for spell duration. The first two years of job seniority are associated with a lower probability of match destruction. However, the estimates are much closer to zero once individual heterogeneity and simultaneity are introduced, falling from around 32 percent in model J1 to around 5 percent in SIM. The average worker that is in a longer lasting jobs differs systematically from the average worker that has shorter employment spells. Therefore, in a model that does not control for unobserved heterogeneity tenure acts largely as a proxy for worker quality and match quality.

Focusing on the SIM column, seniority has a negative impact on the probability of match destruction especially for the years second to fifth. The longer a match survives the more likely it is that it survives further. The years between the second and the fifth have the largest effect, which in the context of Jovanovic (1979, 1984) would suggest that there may be substantial learning in that range of spell duration. Estimates for the effect of labour market experience on the employment hazard rate for SIM show that each of the first five years in a worker's career is associated with a 4.4 percentage-point lower log hazard rate. The following five years on the other hand are associated with a rise in the exit rate. Workers have the highest probability of leaving their job either very early in their careers or after more than five years. While the former might be driven by lower-quality short-term matches for young inexperienced workers, the latter may be related to the fact that workers with more than five years of experience are in a better bargaining position with a new employer. Their better outside option might in turn increase their exit rates.

The estimates for the sector seniority hazard model (equation 5) for male workers are outlined in Table 10. In column SIM, the effect of industry experience on the conditional probability of leaving a sector is negative and large for the first two years and positive and smaller afterwards. If it takes time for the agents involved to learn the relevant productivity parameters, then lower levels of industry experience are associated with a lower exit probability, while as industry experience gets higher it is associated with a higher exit probability, even higher than the initial exit rate after around eight years of sector tenure. Similar patterns can be observed for labour market experience: ceteris paribus, more labour market experience increases the conditional probability of leaving a certain sector. Workers with the same experience in one sector but more labour market experience are more mobile. This is not surprising given that opportunities in other sectors might increase with labour-market experience.

Tables 11 presents the estimates for the variances and covariances of the heterogeneity components and of the error structure. Unobservable worker characteristics have a large effects on the returns to labour market experience, as suggested by σ_{θ_1}.[27] I estimate wage returns to labour market experience to be highly heterogeneous across workers: workers with a draw of θ_1 that is one standard deviation above the mean earn a marginal return of 8.7 percent for each of the first five years of labour market experience. A worker with a draw that is one standard deviation below the mean receives a return to labour market experience that is very close to zero. The parameter σ_{θ_2} shows that there are individual unobservables that matter for wages above and beyond heterogeneity in returns to labour market experience. The parameters suggest that individual unobservables affect match duration and the accumulation of industry experience. These results are similar to those of Abowd et al. (1999), Lillard (1999) and Dostie (2005).

All correlation coefficients between individual heterogeneity variance components are significantly different from zero: I can reject the null hypothesis of no simultaneity across the three equations at all conventional significance levels. The correlation coefficient between the person random effect in the job hazard model and in the wage equation $\rho_{\theta_2\theta_3}$ is negative and significant, which implies that on average high-wage individuals also have a lower conditional probability of job destruction. The estimate for $\rho_{\theta_2\theta_4}$ shows that the equivalent is true also for industry experience: workers who have conditionally lower wages are also more likely to leave a sector. Looking at the match heterogeneity variance component, the negative and significant estimate for the parameter ϕ imply that there are "good" matches[28] with higher conditional wages and lower average conditional probability of destruction.

[27] One obvious example is educational attainments.

[28] As in Lillard (1999) and Dostie (2005) the match effect includes both a firm effect and a *pure* match effect.

These results are similar to the estimates in Cornelissen and Hubler (2011) and also consistent with the hypothesis of a search model with asymmetric information in which uncertainty about individual and match heterogeneity is resolved over time. Longer-lasting matches are not a random sample of all matches, and this is due in part to unobservables. Quantitatively, I find that a job that has a match effect that is one standard deviation higher than zero in the wage equation, equivalent to a wage gap from average of around 4,600 Euros, has a predicted probability of destruction that is around 9.5 percentage points lower.[29]

The hypotheses of exogeneity of job and industry experience in the wage equation can also be tested jointly using a Likelihood Ratio test that compares the likelihood function of the restricted model that assumes away simultaneity (column "W2+J2+S2" in the regression tables) against the three-equation simultaneous model (column SIM). This test easily rejects the null hypothesis of no simultaneity at any conventional significance level.

6.2 Females

Table 12 presents the estimates of equation (3) for female workers.[30] The estimates of the SIM model show that the first two years of industry experience are associated with an average wage premium of 2.5 percent a year. The years between the second and the fifth are associated with slightly negative marginal effect on wages, and the effect is stable thereafter at 0.5 percent. This is largely in line with results for males. Wage returns for the first two years of job seniority are higher than males' at 1.2 percent; they fall to a negative 0.3 percent for years 3-5, and levels off at positive 0.4 percent a year after more than ten years. The wage returns of labour market experience are much lower for females than for males. Focusing on the results of the simultaneous model in column SIM, the first five years show an average yearly effect of 1.6 percent and at 0.6 percent afterwards. This is consistent with the unconditional experience wage profile shown in figure 1 where the gap between males and females is growing in the number of years of labour market experience. Endogenous selection into the labour force is a more serious concern for females than males, who are typically found to have a rather inelastic labour supply. Therefore, these estimates suggests that the reason for large returns to experience is not simply an artefact of endogenous selection into employment.

Sectors and jobs that are more common for males value previous labour market experience more than those that are dominated by females'. The total wage returns over ten years are 1.5 percent for industry experience, 2.5 for firm tenure and 11 percent for labour market experience for females workers. In other words, sector experience and firm tenure seem to have a very small effect on the wages of female workers. Further research is required to investigate the consistency of these findings and to identify the specific mechanisms by which females' wages are much less affected by

[29] Calculated as $(-0.455) \times (0.209)$.

[30] The focus here is specifically on the aspects of the estimates in which males and females show different patterns.

labour-market experience.

Tables 13 presents the results for the hazard model of employment duration for females. Estimates are qualitatively very similar to those for males, albeit magnitudes are smaller. These differences could be due to shocks outside the labour market (such as parental leave, health problems in the family, elderly care etc.) that may affect mobility and labour market participation of females disproportionally. The estimates for equation (5) for females are in Table 14. The marginal effects of industry experience on the probability of changing sectors is qualitatively similar to the estimates for males, and the smaller coefficients for females are similar to those discussed above for the case of job tenure. Having between five and ten years of experience increases the hazard rate more for females than for males. This is not surprising since the effect of labour market experience on wages is significantly smaller for females.

Estimates in Table 15 suggest that individual unobservables are important for wages, sector and job mobility of females as well. All correlation coefficients between individual random effects are significantly different from zero. Two coefficients have the opposite sign in comparison to the estimates for males ($\rho_{\theta_1\theta_3}$ and $\rho_{\theta_1\theta_4}$ are both positive for females while they are negative for males): female workers with higher conditional returns to experience also have higher probability of leaving the job and the industry they are employed in. Overall, female workers have low returns to experience compared to males. The females that have higher returns to experience seem to be more similar to males in terms of mobility patterns, in that they have higher job and sector mobility than other females.

The estimate for the match heterogeneity component ϕ is negative and significant. The estimated coefficient implies that a job that has a match effect one standard deviation higher than zero in the wage equation, equivalent to a gap from the average of around 3,600 Euros of year 2004, has a predicted probability of destruction that is around 7.2 percentage points lower.[31] The Likelihood Ratio Test rejects the null hypothesis of no simultaneity at any conventional significance level.[32]

7 Concluding Remarks

In this paper I use panel data for a sample of Italian workers in years 1986-2004 to estimate the effect of industry experience on wages taking account of heterogeneity at the individual and match level. My results show that industry experience has a much stronger impact on wages than job tenure. Estimates show that wage returns to job seniority are very small, and that the returns to industry experience are highly nonlinear, concentrated in the first years of the employment spell, and very small afterwards. Wage returns to labour market experience dominate returns to seniority.

[31] $(-0.394) \times (0.183)$.

[32] I have run some additional specifications for males and females. Including firm size in the wage regression shows that, consistent with previous literature (see e.g. Troske 1999 for evidence using matched data), larger firms pay higher wages. However, its inclusion does not have any sizeable effect on the other estimates. The inclusion of occupation controls changes the estimates very marginally.

My empirical model also allows to test for whether job and sector durations are endogenous in the wage regression. I find that the null hypothesis of no endogeneity is rejected: high-wage workers stay on the job longer, "good" matches last longer.

The Italian labour market is considered among the most rigid in the OECD.[33] Nevertheless, job search and job match considerations are found to be important determinants of wages of workers in the early part of their careers. These results imply that earning losses from a lay-off depend on the opportunity that the worker has within the same sector, because mobility across labour-market sectors is associated with a higher short-term wage penalty than mobility within the same sector. Labour market policies might consider differentiated interventions for displaced workers employed in a shrinking sector as opposed to displaced workers in a booming sector.

This paper has an empirical focus and is largely silent about the possible mechanisms through which labour-market experience, experience within one industry and job seniority affect wages, largely due to data limitations. Assuming experience and seniority affect wages through human capital accumulation, my results suggest that industry-specific human capital is more important than firm-specific human capital. There are however a number of competing explanations, and future research is needed to discriminate among some of these explanations. Estimates may at least in part be driven by the role of labour market networks: industry experience might matter for wages through its possible effect on a worker's outside option, which may depend on a worker's network. It would also be interesting to investigate the role of trade unions, which are in some cases sector-specific, but for the most part operate across sectors in Italy.

[33] See for example Contini and Trivellato (2005).

8 Tables and Figures

8.1 Tables

Table 1: Distribution of workers by economic sector of the firm

Economic sector	Males	Females
Farming and hunting	0.2	0.1
Fishing and fish farming	0.1	0.0
Extraction of energy material	0.0	0.0
Extraction of non-energy material	0.3	0.0
Food, beverages and Tobacco	3.5	4.0
Textile and clothing	2.3	8.5
Leather and fur	1.3	2.0
Wood Industries	1.8	0.5
Paper and press	1.6	1.3
Oil refineries	0.1	0.0
Chemicals and related industries	1.2	1.0
Rubber and plastic industries	1.7	1.2
Products for working non-metal minerals	1.9	0.9
Production of metals and metal products	9.5	3.2
Production of machineries	3.4	1.3
Production of electrical and optical machinery	4.6	3.5
Production of means of transportation	1.3	0.5
Other manufacturing	2.7	2.1
Electrical power, water and natural gas	0.3	0.2
Construction	18.2	1.9
Wholesale and retail trade, auto reparations	13.8	19.9
Hotels and restaurants	7.9	12.1
Transport, warehouses and communications	5.2	2.4
Banking and financial intermediaries	10.0	16.0
Computing, rental services, research	1.0	1.8
Public administration and defense	2.3	5.0
Education	0.6	2.7
Health	0.5	1.8
Other Public, Social and personal services	2.0	5.5
Missing values	0.4	0.4
Number of observations	82,114	56,914

Source: Calculations from WHIP dataset, calculated from each worker's first job

Table 2: Number of Jobs and Conditional Average Duration

	Males		Females	
Number of jobs	**Percentage**	**Job Duration**	**Percentage**	**Job Duration**
One job	37.6	2.95	40.4	2.99
Two jobs	24.3	2.60	24.6	2.64
Three jobs	15.4	2.14	15.4	2.18
Four jobs	9.5	1.80	8.9	1.83
Five jobs	5.8	1.54	5.0	1.56
More than five jobs	7.4	1.10	5.8	1.04
Total	100.0	2.01	100.0	2.10
Frequencies	82,114		56,914	

Unit of observation is the worker

Source: Author's calculations from WHIP dataset.

Table 3: Number of Sectors

	Percentages	
Number of sectors	**Males**	**Females**
One sector	55.7	58.1
Two sectors	27.4	27.6
Three sectors	11.3	10.3
More than three sectors	5.6	4.0
Total	100.0	100.0
Frequencies	82,114	56,914

Unit of observation is the worker.

Source: Author's calculations from WHIP dataset.

Table 4: Summary statistics for Job Covariates - Males

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Job duration (years)	2.01	(2.82)	0.08	18.92	208208
Dummy for censored job spell	0.20	(0.40)	0	1	208208
Sector spell duration	3.60	(3.89)	0.04	18.87	208208
Experience at the start of the spell	1.62	(2.62)	0	17.91	208208
Experience in the sector	0.71	(1.76)	0	17.91	208208

Unit of observation is the job.

Source: Author's calculations from WHIP dataset.

Table 5: Summary statistics for Job Covariates - Females

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Job duration (years)	2.10	(2.83)	0.08	18.92	135408
Dummy for censored job spell	0.21	(0.41)	0	1	135408
Sector spell duration	3.60	(3.90)	0.04	18.87	135408
Experience at the start of the spell	1.56	(2.60)	0	17.78	135408
Experience in the sector	0.69	(1.77)	0	17.34	135408

Unit of observation is the job

Source: Author's calculations from WHIP dataset.

Table 6: Summary statistics for Year-level Covariates - Males

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Real FTE wage	19738.47	(9207.73)	107.49	199393.5	537127
Experience	3.66	(3.83)	0	17.91	537127
Sector tenure	2.72	(3.39)	0	17.91	537127
Job tenure	2.02	(3.00)	0	17.91	537127

Unit of observation is the worker-year. FTE: Full Time Employment

Source: Author's calculations from WHIP dataset.

Table 7: Summary statistics for Year-level Covariates - Females

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Real FTE wage	17859.53	(7454.51)	101.13	198854.67	359186
Experience	3.56	(3.74)	0	17.91	359186
Sector tenure	2.72	(3.37)	0	17.91	359186
Job tenure	2.02	(2.93)	0	17.91	359186

Unit of observation is the worker-year. FTE: Full Time Employment

Source: Author's calculations from WHIP dataset.

Table 8: Wage Equation for Males

Dependent variable: $ln(w_{iJ(i,t)t})$			
Variables	Models		
	W1	W2	SIM
Constant	9.700***	9.628***	9.603***
	(0.016)	(0.017)	(0.017)
Industry Experience			
0-2nd year	0.034***	0.024***	0.021***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.003***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.004***	0.005***	0.007***
	(0.001)	(0.001)	(0.001)
11th year +	0.004*	0.004***	0.007***
	(0.002)	(0.001)	(0.001)
Job Seniority			
0-2nd year	0.004***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.007***	0.002*	0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.007***	0.000	0.001
	(0.001)	(0.001)	(0.001)
11th year +	0.000	-0.003**	-0.003**
	(0.002)	(0.001)	(0.001)
Experience			
0-5th year	0.034***	0.042***	0.043***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.017***	0.015***	0.015***
	(0.001)	(0.000)	(0.000)
11th year +	0.015***	0.014***	0.014***
	(0.001)	(0.000)	(0.000)
Number of yearly wage observations: 536,277			

Time and sector fixed effects in all regressions

W1: Wage model without Unobserved Heterogeneity components

W2: Wage model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 9: Job Hazard Equation for Males

Dependent variable: $ln(h_{iJ(i,t)t}(\tau))$			
Variables	Models		
	J1	J2	SIM
Constant	0.06	0.000	0.398***
	(0.043)	(0.052)	(0.062)
Job Seniority			
0-2nd year	-0.317***	-0.140***	-0.051***
	(0.005)	(0.005)	(0.006)
3rd-5th year	-0.114***	-0.078***	-0.140***
	(0.005)	(0.005)	(0.005)
6th-10th year	-0.069***	-0.054***	-0.072***
	(0.006)	(0.006)	(0.007)
11th year +	-0.011	-0.004	-0.007
	(0.012)	(0.012)	(0.013)
Experience			
0-5th year	-0.141***	-0.170***	-0.044***
	(0.002)	(0.002)	(0.003)
6th-10th year	-0.018***	-0.003	0.059***
	(0.003)	(0.003)	(0.004)
11th year +	-0.066***	-0.061***	-0.007
	(0.006)	(0.006)	(0.007)
Number of job observations: 207,501			

Time and sector fixed effects in all regressions

J1: Job Hazard model without Unobserved Heterogeneity components

J2: Job Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 10: Sector Hazard Equation for Males

Dependent variable: $ln(h^s_{ik}(\tau))$			
Variables	Models		
	S1	S2	SIM
Constant	-0.414***	-0.360***	-0.015
	(0.042)	(0.055)	(0.072)
Industry Experience			
0-2nd year	-0.421***	-0.260***	-0.152***
	(0.005)	(0.005)	(0.006)
3rd-5th year	-0.028***	0.054***	0.008*
	(0.004)	(0.004)	(0.004)
6th-10th year	-0.002	0.067***	0.061***
	(0.003)	(0.004)	(0.005)
11th year +	0.002	0.079***	0.096***
	(0.005)	(0.006)	(0.007)
Experience			
0-5th year	-0.092***	-0.092***	0.036***
	(0.003)	(0.003)	(0.004)
6th-10th year	-0.022***	-0.017***	0.056***
	(0.003)	(0.004)	(0.004)
11th year +	-0.006	-0.037***	-0.008
	(0.005)	(0.005)	(0.007)
Number of job observations: 207,501			

Time and sector fixed effects in all regressions

S1: Sector Hazard model without Unobserved Heterogeneity components
S2: Sector Hazard model with Unobserved Heterogeneity components
SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis
Significance: *=10%; **=5%; ***=1%
Source: Author's calculations from WHIP dataset.

Table 11: Variance components and Parameters for Males

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity Variance and Covariance Components			
σ_{θ_1}		1.013***	1.023***
		(0.014)	(0.014)
σ_{θ_2}		0.221***	0.222***
		(0.001)	(0.001)
σ_{θ_3}		0.500***	0.898***
		(0.005)	(0.005)
σ_{θ_4}		0.719***	1.283***
		(0.005)	(0.007)
$\rho_{\theta_1\theta_2}$		-0.402***	-0.408***
		(0.005)	(0.005)
$\rho_{\theta_1\theta_3}$			0.158***
			(0.006)
$\rho_{\theta_2\theta_3}$			-0.114***
			(0.005)
$\rho_{\theta_1\theta_4}$			0.205***
			(0.005)
$\rho_{\theta_2\theta_4}$			-0.194***
			(0.004)
$\rho_{\theta_3\theta_4}$			0.947***
			(0.001)
Match Heterogeneity variance components			
σ_{δ}		0.209***	0.209***
		(0.000)	(0.000)
ϕ			-0.455***
			(0.017)
Error structure			
ω	0.881***	0.409***	0.407***
	(0.000)	(0.001)	(0.001)
σ_{ν}	0.161***	0.140***	0.139***
	(0.000)	(0.000)	(0.000)
ln-L	-1423933.75	-1397664.25	-1368727.7

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 12: Wage Equation for Females

Dependent variable: $ln(w_{iJ(i,t)t})$			
Variables	Models		
	W1	W2	SIM
Constant	9.618***	9.579***	9.570***
	(0.018)	(0.019)	(0.019)
Industry Experience			
0-2nd year	0.032***	0.027***	0.025***
	(0.002)	(0.001)	(0.001)
2nd-5th year	0.000	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)
5th-10th year	0.006***	0.002**	-0.004***
	(0.001)	(0.001)	(0.001)
10th year +	0.000	0.000	-0.005***
	(0.003)	(0.002)	(0.002)
Job Seniority			
0-2nd year	0.014***	0.013***	0.012***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.006***	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.006***	0.001	0.002
	(0.002)	(0.001)	(0.001)
11th year +	0.007***	0.004*	0.004*
	(0.003)	(0.002)	(0.002)
Experience			
0-5th year	0.020***	0.025***	0.016***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.004***	0.008***	0.006***
	(0.001)	(0.000)	(0.000)
11th year +	0.011***	0.010***	0.006***
	(0.002)	(0.001)	(0.000)
Number of yearly wage observations: 358,591			

Time and sector fixed effects in all regressions

W1: Wage model without Unobserved Heterogeneity components

W2: Wage model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 13: Job Hazard Equation for Females

Dependent variable: $ln(h_{iJ(i,t)t}(\tau))$			
Variables	Models		
	J1	J2	SIM
Constant	-0.200***	-0.305***	-0.041
	(0.066)	(0.074)	(0.135)
Job Seniority			
0-2nd year	-0.311***	-0.143***	-0.059***
	(0.006)	(0.007)	(0.007)
3rd-5th year	-0.072***	-0.031***	-0.088***
	(0.006)	(0.006)	(0.006)
6th-10th year	-0.050***	-0.034***	-0.060***
	(0.007)	(0.007)	(0.008)
11th year +	0.014	0.026*	0.016
	(0.013)	(0.014)	(0.015)
Experience			
0-5th year	-0.136***	-0.165***	-0.034***
	(0.003)	(0.003)	(0.004)
6th-10th year	-0.010***	0.004	0.073***
	(0.004)	(0.004)	(0.005)
11th year +	-0.055***	-0.051***	0.01
	(0.008)	(0.008)	(0.009)
Number of job observations: 134,941			

Time and sector fixed effects in all regressions

J1: Job Hazard model without Unobserved Heterogeneity components

J2: Job Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 14: Sector Hazard Equation for Females

Dependent variable: $ln(h^s_{ik}(\tau))$			
Variables	Models		
	S1	S2	SIM
Constant	-0.540***	-0.587***	-0.350**
	(0.062)	(0.076)	(0.145)
Industry Experience			
0-2nd year	-0.358***	-0.207***	-0.093***
	(0.006)	(0.007)	(0.007)
3rd-5th year	-0.019***	0.061***	0.017***
	(0.004)	(0.005)	(0.005)
6th-10th year	-0.024***	0.026***	0.020***
	(0.004)	(0.005)	(0.006)
11th year +	-0.003	0.048***	0.071***
	(0.007)	(0.008)	(0.009)
Experience			
0-5th year	-0.099***	-0.105***	0.033***
	(0.004)	(0.004)	(0.005)
6th-10th year	0.004	0.013***	0.088***
	(0.004)	(0.004)	(0.005)
11th year +	0.000	-0.014*	0.017*
	(0.007)	(0.007)	(0.009)

Number of job observations: 134,941

Time and sector fixed effects in all regressions

S1: Sector Hazard model without Unobserved Heterogeneity components

S2: Sector Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

Table 15: Variance components and Parameters for Females

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity variance components			
σ_{θ_1}		1.327***	2.059***
		(0.039)	(0.086)
σ_{θ_2}		0.191***	0.193***
		(0.001)	(0.001)
σ_{θ_3}		0.496***	0.927***
		(0.006)	(0.006)
σ_{θ_4}		0.666***	1.290***
		(0.007)	(0.009)
$\rho_{\theta_1\theta_2}$		-0.373***	-0.372***
		(0.009)	(0.008)
$\rho_{\theta_1\theta_3}$			-0.294***
			(0.009)
$\rho_{\theta_2\theta_3}$			-0.058***
			(0.007)
$\rho_{\theta_1\theta_4}$			-0.252***
			(0.008)
$\rho_{\theta_2\theta_4}$			-0.125***
			(0.006)
$\rho_{\theta_3\theta_4}$			0.952***
			(0.001)
Match Heterogeneity variance components			
σ_δ		0.183***	0.183***
		(0.000)	(0.000)
ϕ			-0.394***
			(0.029)
Error structure			
ω	0.718***	0.277***	0.277***
	0	(0.002)	(0.002)
σ_ν	0.237***	0.207***	0.207***
	(0.000)	(0.000)	(0.000)
ln-L	-1010086.9	-994355.35	-975799.48

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Source: Author's calculations from WHIP dataset.

8.2 Figures

Figure 1: Experience Profile based on annual data

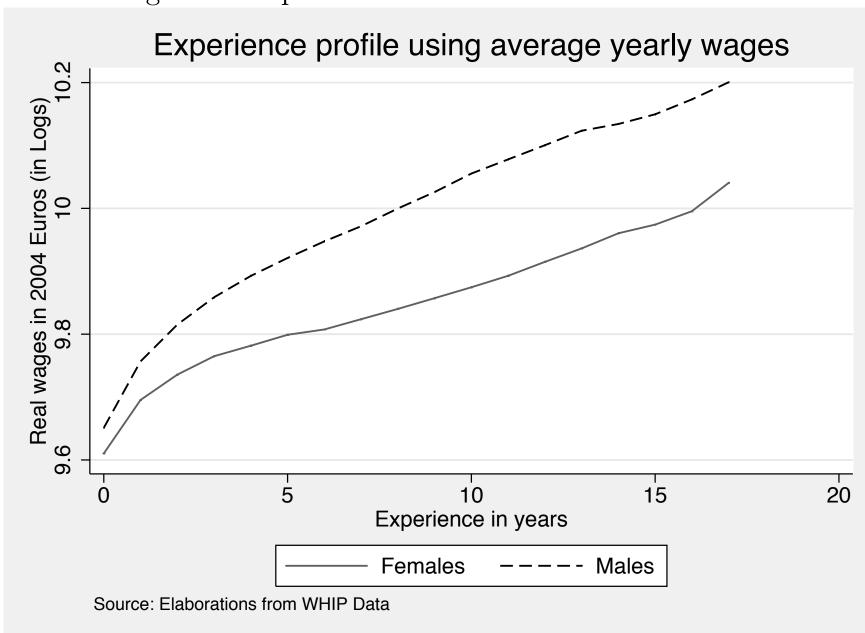


Figure 2: Industry Experience Profile based on annual data

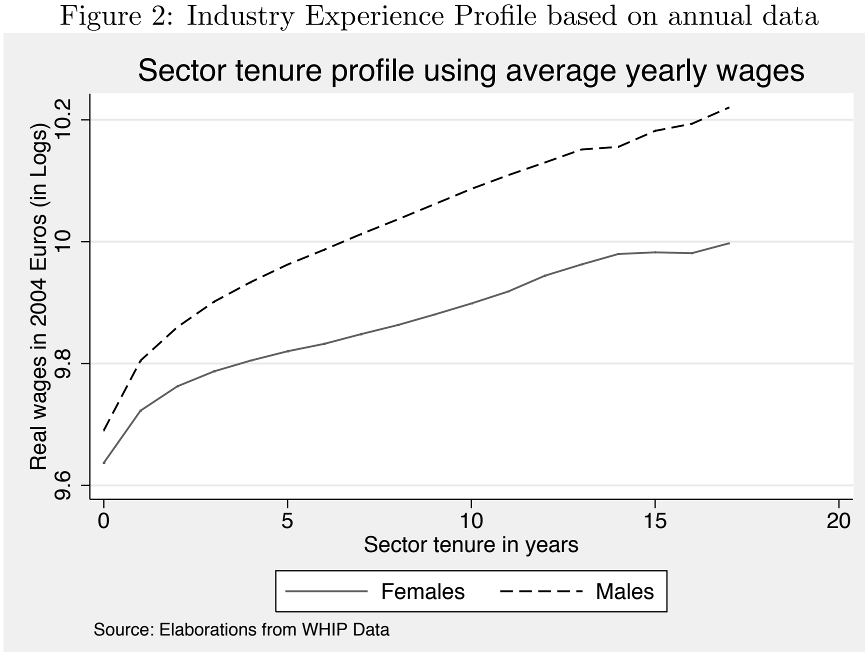


Figure 3: Job Tenure Profile based on annual data

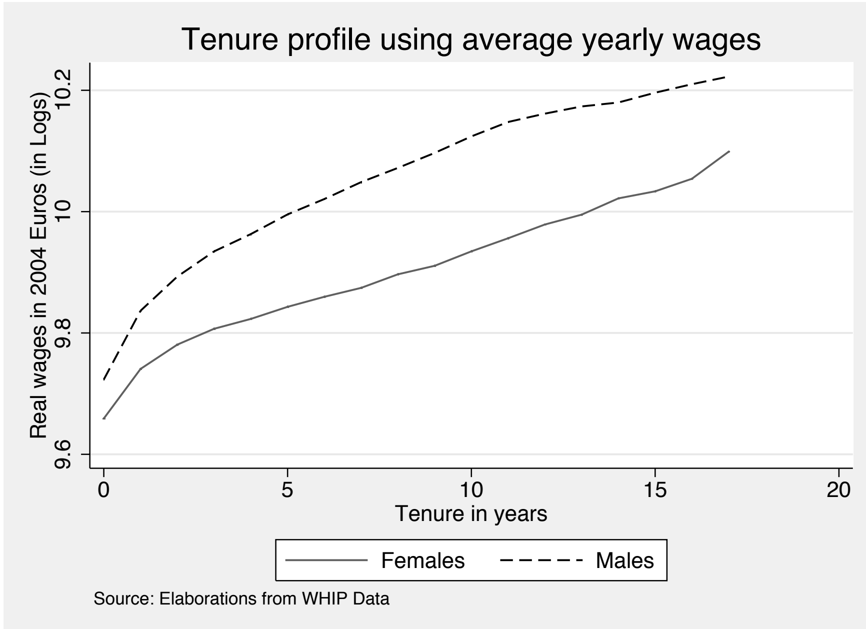
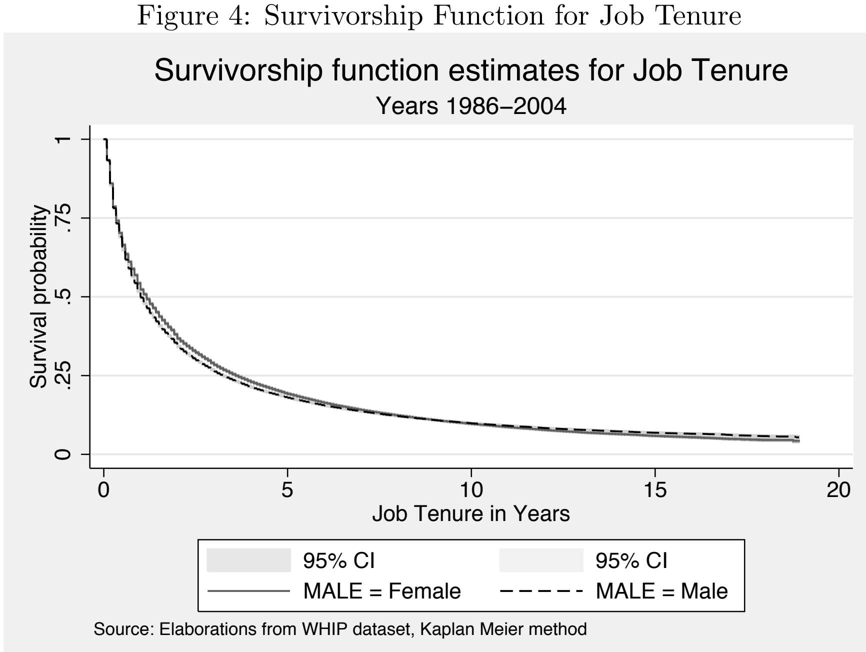
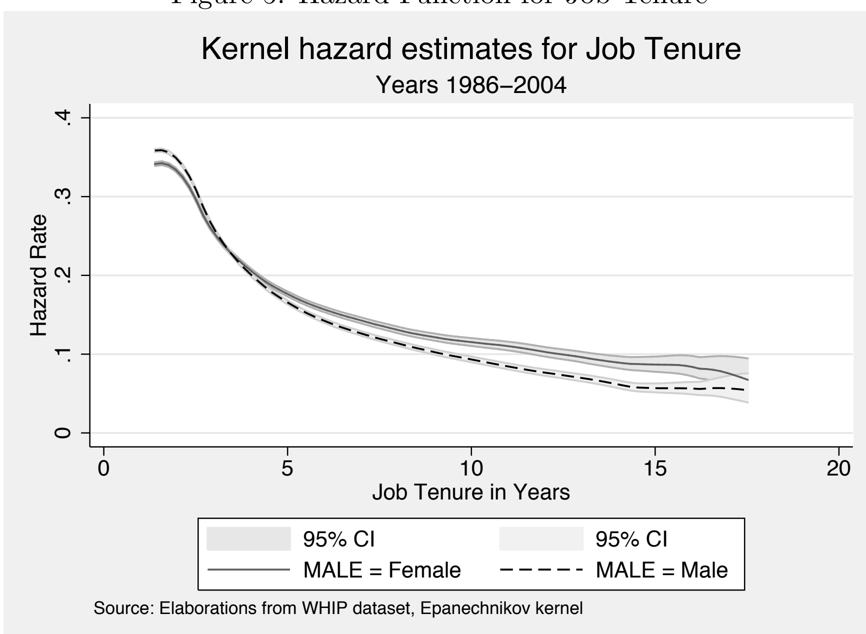


Figure 4: Survivorship Function for Job Tenure



The Kernel estimations above are constructed using the Epanechnikov kernel.

Figure 5: Hazard Function for Job Tenure



The Kernel estimations above are constructed using the Epanechnikov kernel.

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