Individual Wage Growth: The Role of Industry Experience*

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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.

Introduction

There is strong evidence that wages increase throughout the working life of individuals. In particular, studies as far back as Becker (1962) and Mincer (1974) find that wages increase across firm tenure. This has been viewed as evidence that firm-specific human capital is important for wage growth. At the same time, workers tend to benefit from job mobility in terms of wage growth (see for example Bartel and Borjas 1982; Topel and Ward 1992). Taken together, this suggests 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 work longer in the same industry, but can also benefit from finding a better match by moving more.

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A more recent literature, inspired by McCall (1990) and by Neal (1999), recognizes that firm switches are not homogeneous, and that occupations and sectors are also important dimensions to look at. Parent (2000) and Kambourov and Manovskii (2009) estimated wage returns to industry experience, addressing the possible endogeneity of job seniority and sector experience in a wage equation with an instrumental variable strategy. They found industry experience to be important for wage determination, while also finding wage returns to firm tenure to be very small or negative. However, Pavan (2011) developed a novel search model showing that the IV technique previously utilized might underestimate the importance of firm tenure, and found larger structural estimates of the wage effects of firm tenure.

In this paper I estimate the effect of labor-market experience, industry experience, and firm tenure on wages, allowing individual unobserved heterogeneity to affect wages and mobility of workers, taking account of the critique of Pavan (2011). While empirically complex, quantifying the role of firm tenure and industry experience for wage growth is important for researchers and policymakers alike. It sheds light on the role of different types of human capital for wages and tenure, and on the role of mobility on life-cycle earnings. For policymakers, knowing the "rewards" of tenure and industry experience is valuable when creating policies concerning labor market mobility, contracts, and compensation levels. In particular, allowing for a separate role of industry experience can be informative for the relative earnings losses associated with different labor-market transitions. For example, public policy might consider targeted interventions for displaced workers employed in shrinking sectors.

In order to evaluate the wage effects of industry experience, I estimate a three-equation simultaneous random effects model, for females and males separately. The model consists of a wage equation and two hazard equations for job and industry employment durations. To estimate this model I use administrative data from a large sample of young Italian workers (I chose to focus on young workers so that I can observe all of their labor market history within my dataset) from the Worker Histories Italian Panel (WHIP) dataset for the years 1986–2004. To the best of my knowledge, this paper offers the first estimate of the returns to industry experience using Italian panel data. Although I am unable to reproduce the definition of a "career" used in Pavan (2011) because of data limitations, I believe my results can be informative when compared to those of this literature. I find industry experience to be important for wage determination: Wage returns to industry experience for male workers is over twice as large as returns to job seniority (7.5 percent for 10 years, compared to 2.6 percent). This implies that mobility across sectors is associated with a much larger wage penalty than mobility within the same economic sector. Returns to labor market experience dominate the effects of industry experience and of job tenure (29 percent for the first

10 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 at the firm and sector level) are less likely to be destroyed.

The possibility of omitted variable bias affecting a simple ordinary least squares (OLS) estimate of the wage returns to job tenure has been considered since Abraham and Farber (1987). They found positive returns to seniority to be an artifact 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) proposed an instrumental variable (IV) technique to account for this endogeneity.[1] This IV procedure allows us to relax the assumption of random match destruction that would be needed in an OLS framework, if the instrument is valid. However, treating all mobility as equivalent does not allow us to investigate the role of experience at the level of the industry. Neal (1995) argues that industry experience might also be an important source of wage growth. If industry experience is important, some of the estimates of Altonji and Shakotko (1987) may be misleading. Following the same intuition, Parent (2000) used the IV technique of Altonji and Shakotko (1987) to investigate the return of job seniority once industry experience is accounted for, and found that returns to job seniority are close to zero. More recently, Dustmann and Meghir (2005) employed a similar strategy to study the wage impacts of different sources of human capital using data of displaced workers from Germany. They found 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. Altonji, Smith, and Vidangos (2013) developed a complex empirical strategy for modeling wage dynamics focusing on the role of occupations (rather than industry) and unemployment spells.[2]

[1] Altonji and Williams (2005) used a similar technique, and found wage returns of 10 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. Topel (1991) found 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.

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

As discussed above, Pavan (2011) developed a search model that includes career ("careers" are a combination of industry and occupation) and firm choice, and provided a structural estimation of the model. His evidence showed that previous IV estimates underestimate the role of firm-specific matches for wage growth by failing to take account of the two-stage search process for careers and firms. Pavan (2011) found significant returns to both career and firm tenure, and argues that the negligible or negative returns to firm tenure found in Parent (2000) and Kambourov and Manovskii (2009) is an effect of the particular assumptions of their IV technique. As discussed below, my estimation technique produces consistent estimates under a weaker set of assumptions as the IV techniques frequently used in the literature.

Empirical Strategy and Hypotheses

In this paper, I estimate a multilevel correlated random effects model of wages, industry experience, and firm tenure. My estimation strategy builds upon Lillard (1999) and Dostie (2005), who focus on the returns to firm tenure and do not include industry experience, using U.S. and French data, respectively. In a simultaneous equation model, unobserved components that affect wages can be correlated with those that affect job and sector duration, which needs to be assumed away in a single-equation random-effects model.

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 by 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, so that experience and tenure accumulated by a worker do not depend on her characteristics. Let us view this in the context of a regression equation. Let $i = \{1, \ldots, N\}$ identify a worker, and $t = \{1, \ldots, T\}$ 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.[3] Equivalently $K(J(i, t))$ denotes the sector of the current employer of worker i in period t, and I define $k \equiv K(J(i, t))$ for simplicity. A useful starting point is a linear wage model such as:

$$w_{ijt} = \gamma_1(seniority_{ijt}) + (sectorseniority_{ikt}) + \gamma_3(experience_{it}) + \varepsilon_{ijt} \qquad (1)$$

[3] 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.

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 labor market experience of worker i up to time t (because firms do not change sectors in my dataset, I drop the subscript k when redundant).

It is possible to decompose the error term ε_{ijt} into an individual-specific time-invariant component θ_i, capturing the effect of person-specific time-invariant characteristics; a match-specific component δ_{ij}, a component denoting the match with a particular industry λ_{ik} and a component that is match-, time-, and person-specific, denoted by v_{ijt} below:[4]

$$\epsilon_{ijt} = \theta_i + \delta_{ij} + \lambda_{ik} + v_{ijt} \qquad (2)$$

An OLS procedure yields unbiased estimates of γ_1, γ_2, and γ_3 of equation (1) only if all regressors were uncorrelated with θ_i, δ_{ij}, λ_{ik}, and v_{ijt}. In other words, OLS estimates are biased unless workers were randomly assigned to sectors and firms, and matches were randomly destroyed, which is unlikely to be the case in reality. Workers do not typically choose their jobs randomly and firms do not hire workers randomly, so that over time, the set of jobs that survives is self-selected (Jovanovic 1979). 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. In addition, matches are unlikely to be broken at a random period. Either side of the market may learn about certain aspects of the worker's productivity over time as in Jovanovic (1979) and Gibbons et al. (2005), so that lower quality matches may not last as long as higher quality matches. On-the-job search might result in offers that the current firm will decide not to match (Postel-Vinay and Robin 2002); some characteristics of the worker may be observable but not contractible (Peters 2010). If asymmetric information on workers' productivity exists, one can expect high-wage individuals to have longer spells, and consistent with Mortensen and Wright (2002) we would also expect high-wage matches to last longer. My empirical model estimates the effect of firm tenure, industry experience, and labor market experience on wages under a much weaker set of conditions than those of a simple OLS procedure. I estimate the effects of interest allowing unobserved individual characteristics and unobserved match characteristics to affect wages as well as mobility of workers.

[4] The findings of Neal (1999) imply that it is important to account for workers' searches over jobs as well as careers. Consistently, Parent (2000), Kambourov and Manovskii (2009), Pavan (2011), and others include a sector/career term in their error structure.

Empirical Model

My empirical model is a three-equation multilevel correlated random effects model composed of a wage equation, a tenure hazard equation modeling job-to-job transitions, and an industry hazard equation modeling sector-to-sector transitions. Below, I describe them separately and then discuss how they are simultaneously estimated.

Wage equation. I specify the wage equation as follows:

$$\begin{aligned}\ln(w_{ijt}) =& \alpha_0 + \boldsymbol{\alpha}_1'\boldsymbol{seniority_{ijt}} + \boldsymbol{\alpha}_2'\boldsymbol{sectorseniority_{ikt}} + (1+\theta_{1i})\boldsymbol{\alpha}_3'\boldsymbol{experience_{it}} \\ &+ \sum\nolimits_{t=2}^{T} \iota_t^w year_t + \sum\nolimits_{t=2}^{T} \kappa_t^w sector_t + \theta_{2i} + \delta_{ij} + \lambda_{ik} + v_{ijt}\end{aligned} \tag{3}$$

where w_{ijt} is the real wage of person i at time t. The regressors $\boldsymbol{seniority_{ijt}}$, $\boldsymbol{sectorseniority_{ikt}}$, and $\boldsymbol{experience_{it}}$ are parameterized as piecewise-linear splines, where nodes (break points) are chosen following the procedure suggested in Lillard and Panis (2003b) with the goal of capturing the main trends of the data under a relatively parsimonious specification.[5]

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, and $year_t$ 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. Unobserved match quality, at the firm and at the sector level, are denoted by δ_{ij} and λ_{ik}, respectively. Finally, v_{ijt} is the person-match-time–specific error term, which is assumed to have mean zero conditional on all the other regressors.

Job duration hazard model. Employment duration is estimated using a hazard model based on Kiefer (1988). The baseline hazard duration dependence is piecewise linear.[6] For person i employed in job j in year t, the hazard model is

$$\begin{aligned}\ln\left(h_{ij}\left(\tau^j\right)\right) =& \beta_0 + \boldsymbol{\beta}_1'\boldsymbol{seniority_{ijt}} + \boldsymbol{\beta}_2'\boldsymbol{sectorseniority_{ikt}} + \boldsymbol{\beta}_3'\boldsymbol{experience_{it}} \\ &+ \sum\nolimits_{t=2}^{T} \iota_t^j year_t + \sum\nolimits_{t=2}^{T} \kappa_t^j sector_t + \theta_{3i} + \phi_\delta\delta_{ij} + \phi_\lambda\lambda_{ik}\end{aligned} \tag{4}$$

where $\ln\left(h_{ij}(\tau^j)\right)$ 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

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[5] I start with a larger number of nodes, and then drop nodes when consecutive coefficients are very similar to each other, until predictive power falls significantly.

[6] That is, piecewise generalized Gompertz. See Pollard and Valkovics (1992) and Lillard and Panis (2003b).

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} and sector match effect λ_{ik} from equation (3) with load parameters φ_δ and φ_λ account for potential cross-equation correlation between the job-level and sector-level wage components and the job-level turnover hazard.[7] The remaining regressors and parameters are defined as in equation (3).

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

$$\ln\left(h^s_{ik}(\tau^s)\right) = \gamma_0 + \boldsymbol{\gamma}_1' \boldsymbol{sectorseniority}_{ikt} + \boldsymbol{\gamma}_2' \boldsymbol{experience}_{it} + \sum\nolimits_{t=2}^{T} \iota^s_t year_t + \sum\nolimits_{t=2}^{T} \kappa^s_t sector_t + \theta_{4i} \tag{5}$$

where $\ln\left(h^s_{ik}(\tau^s)\right)$ is the conditional log hazard; i.e., the probability of employment in sector k ending at time t, conditional on the sector spell being active. The individual random effect θ_{4i} captures skills that are portable across sectors. In equation (5) I do not account for the possibility that job tenure and match quality may affect the probability of changing sectors. While I am therefore unable to test this implication of the search structures of Neal (1999) and Pavan (2011) here, the job tenure hazard model allows me to relate to that model.[8] The other regressors and parameters are equivalent to equation (3).[9]

Error structure and assumptions on parameters. Beyond individual and match heterogeneity, 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): $v_{iJ(i,t)t} = \omega v_{iJ(i,t)t-1} + u_{iJ(i,t)t}$, where $u_{iJ(i,t)t} \sim N(0, \sigma^2_u)$. Errors

[7] As discussed in Lillard (1999), a job-specific heterogeneity component cannot be identified, because only one duration per job can be observed. However, because the mean of all random effects is zero, the coefficient on the match heterogeneity from the wage equation characterizes the covariance.

[8] 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. To the extent that this assumption may be violated, wage effects and tenure duration, which take account of the role of sector match quality, may be more reliably estimated. Unfortunately, the empirical procedure that I use does not allow me to include regressors that vary at a higher level than the dependent variable.

[9] 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 and in the sector hazard model, because 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.

may be serially correlated within a worker's career, beyond the correlation induced by the presence of a person effect. The firm and sector match effects are normally distributed: $\delta_{ij} \sim N(0, \sigma_\delta^2)$ and $\lambda_{ik} \sim N(\mathbf{0}, \boldsymbol{\sigma}_\lambda^2)$.

Random effects estimations do not require restrictions on the joint distribution of person and match effects across equations, so I can evaluate the presence and magnitude of systematic cross-equation correlations. Two sets of elements introduce simultaneity in the three-equation model described above. First, the individual effects are allowed to be correlated across equations (3), (4), and (5) for the same individual i: $(\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i},)' \sim N(0, \boldsymbol{\Sigma}_{\theta,\theta})$.

If industry experience and job tenure were exogenous in the wage equation there would be no cross-equation correlation between the θ_i's. I allow for time-invariant characteristics that affect wages to also influence match duration and sector experience, and estimate the empirical correlation between the θ_i's.[10] Second, I include δ_{ij} (with load factor φ_δ) and λ_{ik} (with load factor φ_λ) in equation (4). A significant estimate for φ_δ or φ_λ would suggest that unobserved match-level or sector-match–level factors that affect wages also influence job duration. The hypotheses on the correlation between the θ_i's and on φ_δ and φ_λ are tested separately using *t*-tests and jointly using a likelihood ratio test.

Identification. The identification of this model follows naturally from Lillard (1999) and Dostie (2005), with the addition of industry experience. All parameters of interest are identified from a mix of within-person and match variation (i.e., variation that comes from observing multiple matches at the firm and sector level and multiple wage observations for each match) and between-person and match variation (i.e., variation that comes from observing multiple workers for each year, each firm, and for each sector). 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 labor-market experience. The variance of the person-specific heterogeneity term can be identified from multiple jobs for each worker. For equations (4) and (5), the individual component is identified using multiple spells for each worker before the last spell observed, taking account of censorship. Since workers may or may not change sector when they change jobs, I can identify the

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

parameters in the sector-hazard equation separately from those of the job-tenure equation (see Greene 2003: 295–98 and Lillard 1999).

Data

In this section I present some background information on wage settings in the Italian context. I then describe the school security dataset that I use in the Empirical section.

Wage setting and gross job flows in Italy. My empirical investigation 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 (Contini et al. 2007; Erickson and Ichino 1995). National regulations concern general issues common to all sectors and all firms, and are typically silent on specific compensation levels. Trade-union contracts are typically at the industry level, and specify nonbinding 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). Both firm-level agreements and individual bargaining are important, and wage premia are found to be highly heterogeneous across firms (Erickson and Ichino 1995), and higher for small firms (Cingano 2003).[11] Job-to-job transition probabilities are 15.2 percent for males and 16.2 for females in each year.[12] Intersectoral transitions represent 42.7 percent of all job-to-job transitions, and in particular 43.5 percent for male workers and 41.2 percent for females. Employment-to-nonemployment transition probabilities are 11.5 percent for males and 12.9 percent for female workers.[13]

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

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

[12] The author's calculations are from the full WHIP dataset.

[13] These statistics are in line with those presented in related work on Italian data. Contini et al. (2007) used WHIP data, Cefis and Gabriele (2009) used data for the population of firms of one region of Italy. See Burda and Wyplosz (1994) and Contini and Revelli (1997) for a background discussion on job flows and a cross-country comparison.

archives from the Istituto Nazionale della Previdenza Sociale (National Institute for Social Security, 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 people need to be enrolled in INPS, with the exception of specific categories of professionals.[15]

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,[16] so that the sampling ratio is around 1:90. WHIP includes information about the main episodes of the working careers of people in the sample, such as duration of each employment spell, wages, unemployment benefits,[17] and occupation.[18] Individual data also include gender, year, and region of birth. Being an administrative registry of employment relations, WHIP does not include educational attainments of workers.[19] All jobs are identified by a unique job identifier.[20] This paper uses employees of the private sector only, for which the database also provides information about employers such as firm size, region, and sector.[21]

After a long period of high unemployment despite positive economic growth in the 1980s, in the 1990s Italy experienced an increase in labor-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 labor force Schindler (2009). The empirical analysis below is based on a younger-than-average segment of the working population, who face a labor market that

[14] WHIP is managed by Laboratorio Revelli Centre for Employment Studies, which has been constructed thanks to an agreement between the INPS and the University of Torino. Detailed descriptions of the WHIP dataset are available from Contini (2002) and Contini and Trivellato (2005).

[15] These categories include doctors, lawyers, notaries, and journalists, primarily, who have alternative social security funds.

[16] Each year a new cohort of workers enters the labor market, and our panel. In other words, although the panel is very long in total each worker is observed for half of the length of the panel on average.

[17] 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 labor-market skills, and also that their skills deteriorate. If that was the case in reality, my estimate of the effect of labor-market experience may be biased upward. For young workers it is hard in the data to identify unemployment spell, as that depends on eligibility.

[18] 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. Including occupational dummies does not substantially affect the results.

[19] 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.

[20] For confidentiality reasons firm identifiers are not included in the WHIP dataset.

[21] The classification used for this version of the dataset includes thirty-four sectors and it is based upon the Ateco91 system.

is more flexible in terms of wages and job security, and where short-term contracts are increasingly common.

Sample restrictions. Industry experience, labor market experience, and firm tenure are sometimes be left-censored because no information is available on employment spells before 1985. In order to avoid imputing key variables in my analysis, which may result in overestimating labor-market experience, I restrict the sample to younger workers whom I can observe for their whole careers.[22] All of the results below are therefore based on a population of workers that are on average younger than the overall Italian labor force: the oldest worker in the regression sample is twenty-five years of age is 1986, forty-three years of age in 2004.

My regression sample consists of 82,114 male and 56,914 female workers. The number of job spells is 207,501 for males, of which 20.5 percent are right-censored, and 134,941 for females, of which 21.1 percent are right-censored. It includes 536,277 yearly wage observations for male workers, and 358,591 for female workers. 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[23] to avoid imputing wage patterns within a year.

Summary Statistics

All of the summary statistics below refer to my regression sample. In this 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. Among males, *Construction* is the largest sector (18.2 percent of workers), followed by *Wholesale and Retail Trade* (13.8 percent) and by *Banking* (10 percent). 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 and wholesale and retail trade are overrepresented in my sample, while banking and other services are slightly underrepresented. 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 overrepresented in my sample of females, while industry in general is slightly underrepresented. The discrepancies are likely to

[22] In particular, 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.

[23] 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.

be due to the fact that workers in my regression sample are much younger than workers in the overall population.

In Italy, employment in small and medium-sized enterprises (SMEs) represents a large share of total employment: approximately 45 percent of workers are employed in a firm that has fewer than ten employees, and only 15 percent of workers are employed by firms that have more than three hundred employees. Table 1 reports means and standard deviations of job covariates of interest, by gender. For males, it shows that employment spells last on average just over 2 years, and that about 20 percent of the spells are right-censored. Male workers enter employment spells with 1.62 years (about 20 months) of labor-market experience on average, and with 0.71 years (around 8 months) of experience in the same sector. Equivalent figures for females show that they stay on the job slightly longer than males, and enter an employment spell with slightly less experience in the labor market and in the sector.

As shown in Table 2, male and female workers in this sample have an average gross income of 19,700 Euros and 17,900 Euros, respectively.[24] At the start of each year, male workers have on average 3.66 years of experience in the labor market, 2.72 years of experience in the sector, and have accumulated tenure on the job of 2.02 years. Statistics for females are very similar.[25] The yearly job-to-job transition probabilities (probability of being in a different match at t+1 compared to t, conditional on being observed at t+1 and t; i.e., the share of movers among employed workers) are 22.7 percent for males and 21.1 percent for females. Sector-to-sector transition probabilities (probability of being in a different sector at t+1 compared to t, conditional on being observed at t+1 and t) are 11.1 percent for males, 9.9 percent for females. This implies that among job-to-job transitions, around half (49.2 percent for male, 46.9 for female workers) are intersectoral transitions, the other half being transitions inside the same industry.

The extent of worker mobility in my sample is further investigated in Table 3, 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. We observe approximately 44 percent of males in more than one sector, and approximately 17 percent in at least three sectors. The corresponding figure for females are only slightly smaller.

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[24] These incomes are calculated on a full-time full-year equivalent using real wages in 2004 Euros. I convert wages into year-2004 Euros real wages using Consumer Price Index (CPI) data from Istat data. To make spells of different lengths comparable in terms of wages, I construct annual *Full Time Equivalent* wages for all workers: 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 1 year.

[25] The reader should bear in mind that a new cohort of workers enters the labor market each year. The median worker is observed for 5 years; 25 percent of workers are observed for 10 years or more.

TABLE 1

SUMMARY STATISTICS FOR JOB COVARIATES

	Males		Females	
Variable	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Job duration (years)	2.01	(2.82)	2.10	(2.83)
Dummy for censored job spell	0.20	(0.40)	0.21	(0.41)
Sector spell duration (years)	3.60	(3.89)	3.60	(3.90)
Experience at the start of the spell (years)	1.62	(2.62)	1.56	(2.60)
Experience in the sector (years)	0.71	(1.76)	0.69	(1.77)
N	208,208		135,408	

SOURCE: Author's calculations from WHIP dataset. Unit of observation is the job.

TABLE 2

SUMMARY STATISTICS FOR YEAR-LEVEL COVARIATES

	Males		Females	
Variable	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Real FTE wage (2004 Euros)	19,738	(9207.73)	17,859	(7454.51)
Experience (years)	3.66	(3.83)	3.56	(3.74)
Sector tenure (years)	2.72	(3.39)	2.72	(3.37)
Job tenure (years)	2.02	(3.00)	2.02	(2.93)
Job to job transition probability	22.7		21.1	
Sector to sector transition probability	11.1		9.9	
N	537,127		359,186	

SOURCE: Author's calculations from WHIP dataset. Unit of observation is the worker-year.

TABLE 3

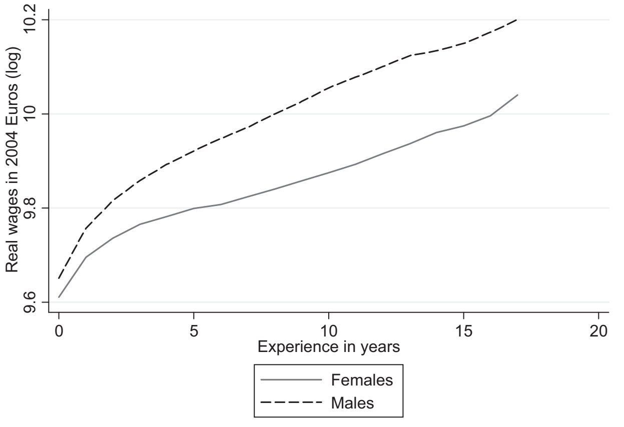
DISTRIBUTION OF WORKERS BY NUMBER OF JOBS AND DURATION

	Males		Females	
Number of jobs	Share of Workers	Job Duration	Share of Workers	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
N	82,114		56,914	

NOTE: Job duration is expressed in years, excluding censored spells.
SOURCE: Author's calculations from WHIP dataset. Unit of observation is the worker.

FIGURE 1

EXPERIENCE WAGE PROFILE



Source: Elaborations from WHIP dataset, using average yearly wages.

Wage profiles. Figure 1 shows that there is a strong positive unconditional correlation between labor 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 10 years. At the beginning of their careers, males and females have similar wage levels, but at around 10 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 labor-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.

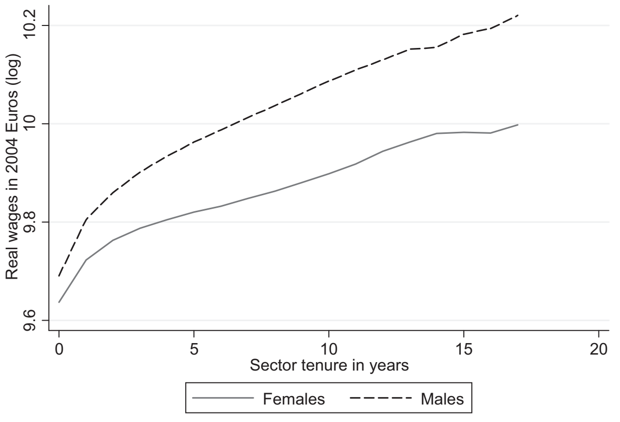
Hazard kernel estimates of firm tenure. Dropping right-censored spells,[26] the median duration of a job is around one year for males, slightly longer for females.[27] Figure 4 shows that the survival probability of jobs falls rapidly in the first years of

[26] That is, spells that are still active at the end of the last year of my panel, for which I do not observe their end date and therefore their duration. Right-censored spells are 20.7 percent of all spells.

[27] The twenty-fifth 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 seventy-fifth percentile is 5.94 years for males, 6.16 for females.

FIGURE 2

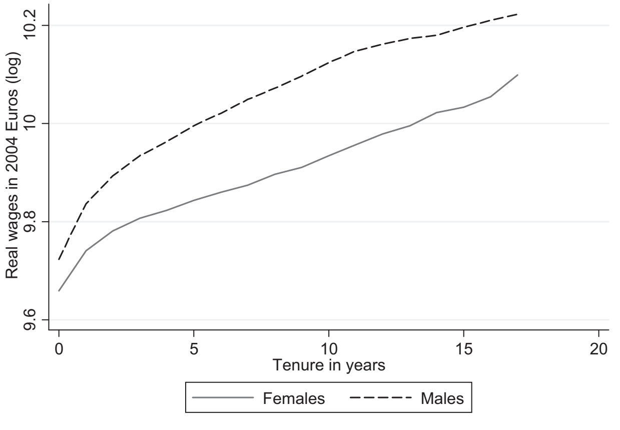
Sector Experience Wage Profile



Source: Elaborations from WHIP dataset using average yearly wages.

FIGURE 3

Job Tenure Wage Profile

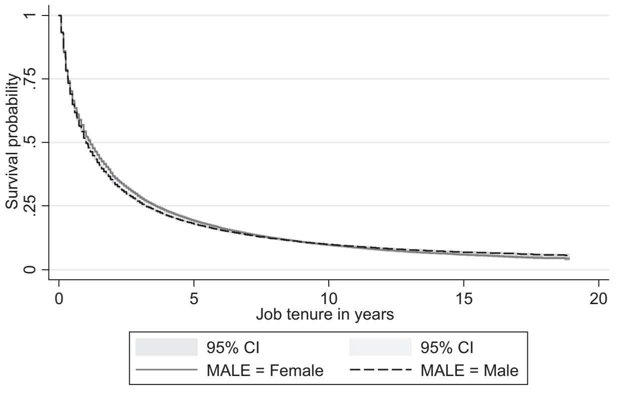


Source: Elaborations from WHIP dateset, using average yearly wages.

spell duration and declines gently afterward. Approximately one fourth of the matches last more than 4 years. These patterns are almost indistinguishable between men and women. A kernel density estimation (using the Epanechnikov kernel) 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

FIGURE 4

SURVIVORSHIP FUNCTION ESTIMATES FOR JOB TENURE



Source: Elaborations from WHIP dataset, Kaplan Meier method, years 1986-2004.

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 4 years of job tenure, and keeps diminishing afterward. Jobs of female workers are less likely to be destroyed in the first 4 years of tenure, consistent with the mobility patterns described above.

Regression Results

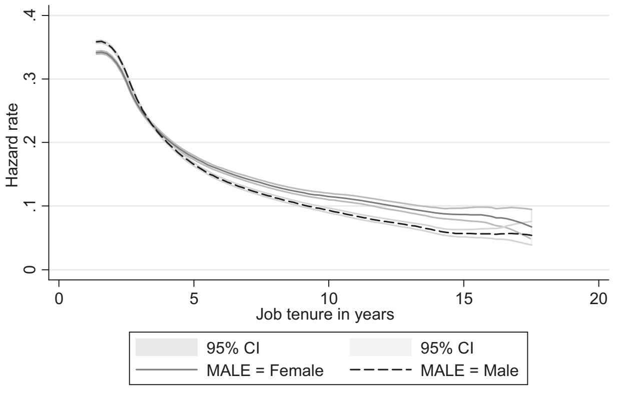
I estimate the three-equation model described above using aML (Applied Maximum Likelihood), a software developed by Lillard and Panis (2003a).[28] Estimates of equations (3), (4), and (5) are presented for men and women separately.[29] For

[28] Because the likelihood of hazard models with normally distributed residuals does not have a closed-form solution, I approximate the integrals in the likelihood function using the Gauss–Hermite quadrature, which selects a number of support points and weights such that the weighted points approximate a normal distribution (Abramowitz and Stegun 1972). For the job and sector match effect and for the residual, I use six support points. For the individual heterogeneity component I use four support points for each of the dimensions (i.e., function evaluations) in order to keep computing time manageable. An elegant alternative for tackling the curse of dimensionality is discussed in Pavan (2011), who uses a nonlinear state-space approach. As suggested in Lillard and Panis (2003a) and because the distribution of the individual random effects is of dimension four, I also transform the covariance matrix into Cholesky-decomposed parameters in order to ensure that the covariance matrix remains positive definite.

[29] There are two main reasons for having estimated this model for females and males separately. First, it allows us to investigate the overall differences between labor-market performances and dynamics for the two genders. Second, 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 in the Organisation for Economic Co-operation and Development (OECD).

FIGURE 5

KERNEL HAZARD FUNCTION FOR JOB TENURE



Source: Elaborations from WHIP dataset, Epanechnikov kernel, years 1986-2004.

all regression tables discussed below, the first column refers to a model without random effects in which each equation is separately estimated. The second column introduces random effects for individual, sector match, and firm match heterogeneity, still estimating the three equations separately. The third column (column SIM) refers to the most general specification: the three-equation simultaneous model in which individual and match effects are allowed to be correlated across equations.

Males. Table 4 presents estimates from equation (3) for male workers. In the column SIM, the first 2 years of industry experience are associated with an average wage increase of 2.3 percent per year.[30] The years between the second and the fifth are associated with slightly negative marginal effects 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. Controlling for industry experience,[31] job tenure has a moderate effect on wages: The first 2 years are associated with an average

[30] Unless mentioned otherwise, all coefficients described below are statistically significant at the 1-percent level.

[31] I have estimated a two-equation model equivalent to Dostie (2005) and I find larger returns to job seniority and also to labor-market experience, using the same regression sample as my full three-equation model. Failing to control for industry experience seems to have a large effect on estimated effects of the wage returns to job seniority.

TABLE 4

WAGE EQUATION FOR MALES

Dependent variable: $\ln(w_{ijt})$	Models		
Variables	W1	W2	SIM
Constant	9.700***	9.640***	9.615***
	(0.016)	(0.021)	(0.020)
Job Seniority			
0–2nd year	0.004***	0.005***	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)
Industry Experience			
0–2nd year	0.034***	0.025***	0.023***
	(0.001)	(0.001)	(0.001)
3rd–5th year	0.003***	-0.004***	-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*	0.005***	0.007***
	(0.002)	(0.001)	(0.001)
Experience			
0–5th year	0.034***	0.041***	0.041***
	(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***	0.013***	0.014***
	(0.001)	(0.000)	(0.000)

NOTES: 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 parentheses. ** =5%; *** =1%
SOURCE: Author's calculations from WHIP dataset.

wage increase of 0.5 percent per year; the equivalent effect falls to 0.3 percent per year in the following 3 years, and it is not significantly different from zero for the years 5–10. 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 a long time may be detrimental for wages. The effect of labor-market experience on wages is large and stable across our three specifications. The marginal yearly effect for the SIM specification is 4.1 percent for the first 5 years and approximately 1.5 percent afterward. If wages reflect marginal pro-

TABLE 5

Job Hazard Equation for Males

Dependent variable: $\ln(h_{ij}(\tau))$	Models		
Variables	J1	J2	SIM
Constant	0.067	0.007	0.418***
	(0.043)	(0.052)	(0.063)
Job Seniority			
0–2nd year	–0.268***	–0.046***	–0.088***
	(0.006)	(0.008)	(0.007)
3rd–5th year	–0.140***	–0.134***	–0.222***
	(0.006)	(0.006)	(0.006)
6th–10th year	–0.049***	–0.031***	–0.084***
	(0.007)	(0.007)	(0.008)
11th year +	–0.022	–0.029*	–0.085***
	(0.014)	(0.015)	(0.016)
Industry Experience			
0–2nd year	–0.073***	–0.127***	–0.081***
	(0.007)	(0.008)	(0.009)
3rd–5th year	–0.024***	0.062***	0.143***
	(0.005)	(0.006)	(0.006)
6th–10th year	–0.021***	0.017***	0.040***
	(0.006)	(0.006)	(0.008)
11th year +	0.009	0.027**	0.112***
	(0.013)	(0.013)	(0.015)
Experience			
0–5th year	–0.132***	–0.161***	–0.094***
	(0.003)	(0.003)	(0.004)
6th–10th year	–0.018***	–0.012***	0.030***
	(0.004)	(0.004)	(0.006)
11th year +	–0.065***	–0.064***	–0.042***
	(0.008)	(0.008)	(0.010)

Notes: 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 parentheses. **=5%; ***=1%.
Source: Author's calculations from WHIP dataset.

ductivity 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 columns W2 and SIM shows 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 United States and from other European countries (Kambourov and Manovskii 2009). This difference may be due to the lower level of mobility in the

Italian labor market compared to the U.S. labor market, which might generate a lower correlation between match quality and tenure.

Table 5 presents the results for the hazard regression for spell duration. The first 2 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 27 percent in model J1 to 9 percent in SIM. Workers with jobs that last longer are systematically different from workers with 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 second to fifth years. 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. The following 5 years 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 5 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 5 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 effects of industry experience are different from those of job seniority. After the first 2 years, industry experience has a significant positive effect on job destruction: When workers accumulate sector-specific experience, they are more likely to change jobs. These estimates are consistent with the view that industry-specific human capital can be transferred across firms of the same sector. Estimates for the effect of labor-market experience on the employment hazard rate for SIM show that in the first 5 years there is a large negative effect of labor-market experience on the probability of job destruction.

The estimates for the sector-seniority hazard model of equation (5) for male workers are outlined in Table 6. In the SIM column, the effect of industry experience on the conditional probability of leaving a sector is negative and large for the first 2 years and positive and smaller afterward. 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 8 years of sector tenure. Similar patterns can be observed for labor-market experience: *Ceteris paribus*, workers with more labor market experience are more mobile across sectors.

TABLE 6

SECTOR HAZARD EQUATION FOR MALES

Dependent variable: $\ln(h^s_{ik}(\tau))$

Variables	S1	S2	SIM
	Models		
Constant	–0.414***	–0.321***	–0.029
	(0.042)	(0.060)	(0.073)
Industry Experience			
0–2nd year	–0.421***	–0.219***	-0.146***
	(0.005)	(0.005)	(0.007)
3rd–5th year	–0.029***	0.055***	0.023***
	(0.004)	(0.004)	(0.005)
6th–10th year	–0.002	0.078***	0.072***
	(0.003)	(0.004)	(0.006)
11th year +	0.002	0.101***	0.108***
	(0.005)	(0.006)	(0.009)
Experience			
0–5th year	–0.092***	–0.077***	0.025***
	(0.003)	(0.003)	(0.004)
6th–10th year	–0.022***	–0.008***	0.047***
	(0.003)	(0.004)	(0.005)
11th year +	–0.006	–0.047***	–0.017**
	(0.005)	(0.005)	(0.008)

NOTES: 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 parentheses. ***=1%.
SOURCE: Author's calculations from WHIP dataset.

Table 7 presents the estimates for variances and covariances of the heterogeneity components and of the error structure. Unobservable worker characteristics have a large effect on the returns to labor-market experience, as suggested by σ_{θ_1}.[32] Workers with a draw of θ_1 that is one standard deviation above the mean earn a marginal return of more than 8 percent for each of the first 5 years of labor-market experience, against an average effect just over 4 percent. The parameter σ_{θ_2} shows that there are individual unobservables that matter for wages above and beyond heterogeneity in returns to labor-market experience: Individual unobservables affect match duration and the accumulation of industry experience. These results are in line with those of Abowd, Kramarz, and Margolis (1999); Lillard (1999); and Dostie (2005).

[32] One obvious example is educational attainments.

TABLE 7

VARIANCE COMPONENTS AND PARAMETERS FOR MALES

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity Variance and Covariance Components			
σ_{θ_1}		1.042***	1.044***
		(0.016)	(0.016)
σ_{θ_2}		0.186***	0.189***
		(0.001)	(0.001)
σ_{θ_3}		0.508***	0.904***
		(0.005)	(0.005)
σ_{θ_4}		0.858***	1.271***
		(0.006)	(0.007)
$\rho_{\theta_1\theta_2}$		–0.458***	–0.463***
		(0.006)	(0.006)
$\rho_{\theta_1\theta_3}$			0.154***
			(0.006)
$\rho_{\theta_2\theta_3}$			–0.130***
			(0.006)
$\rho_{\theta_1\theta_4}$			0.203***
			(0.005)
$\rho_{\theta_2\theta_4}$			–0.222***
			(0.005)
$\rho_{\theta_3\theta_4}$			0.951***
			(0.001)
Match Heterogeneity Variance Components			
σ_{δ}		0.162***	0.162***
		(0.000)	(0.000)
σ_{δ}		0.178***	0.177***
		(0.001)	(0.001)
φ_{δ}			–0.444***
			(0.035)
φ_{λ}			–0.297***
			(0.034)
Error Structure			
ω	0.881***	0.409***	0.406***
	(0.000)	(0.001)	(0.001)
σ_{v}	0.161***	0.140***	0.139***
	(0.000)	(0.000)	(0.000)
ln-L	–1423868.76	–1393686.23	–1364720.26

NOTES: Asymptotic standard errors in parentheses. ***=1%.
SOURCE: Author's calculations from WHIP dataset.

All correlation coefficients between individual heterogeneity variance components are highly significant. 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, which implies that high-wage individuals have a lower conditional probability of job destruction. The estimate for $\rho_{\theta_2\theta_4}$ shows that the equivalent is true for industry experience as well: Workers who have conditionally lower wages are more likely to leave a sector. Looking at the job-match heterogeneity variance components, the negative and significant estimate for the parameter φ_δ implies that there are "good" matches[33] with higher conditional wages and lower average conditional probability of destruction. These results are comparable to the estimates in Cornelissen and Hübler (2011) and also consistent with a search model with asymmetric information in which uncertainty about individual and match heterogeneity is resolved over time. A job with a match effect that is one standard deviation higher than zero in the wage equation, equivalent to a wage gap from average of around 4600 Euros, has a predicted probability of destruction that is 7.2 percentage points lower (calculated as –0.444*0.162).

The negative coefficient on φ_δ implies that, holding job-match quality constant, workers with a higher sector match are less likely to leave the job they hold. In particular, working in a sector that has a match effect that is one standard deviation higher than zero in the wage equation has a predicted probability of destruction that is 5.3 percentage points lower (calculated as –0.297*0.177). This is consistent with the theoretical set-up and empirical findings of Pavan (2011): Sector matches of low quality are more likely to be broken, even when the firm match is relatively good, because it is not possible for a worker to change sector without changing firms. The hypotheses of exogeneity of job and industry experience in the wage equation can be tested jointly using a likelihood ratio test that compares the likelihood function of the restricted model (columns W2, J2, and S2 in the regression tables) against the three-equation simultaneous model (SIM column). I can reject the null hypothesis of no simultaneity at any conventional significance level.

Females. Table 8 presents the estimates of equation (3) for female workers. The estimates of the SIM model show that the first 2 years of industry experience are associated with an average wage premium of 2.5 percent a year, which turns slightly negative between the second and the fifth year. The effect is stable thereafter, at 0.5 percent. Wage returns for the first 2 years of job seniority are higher than those of males at 1.3 percent; they fall to a negative 0.4 percent for years 3–5, and are insignificant afterward. The wage returns of labor-market experience are much lower for females than for males: 1.5 percent per year for the first 5 years, 0.6 percent afterward. This is consistent with the unconditional experience wage profile shown in Figure 1 where the gap

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

TABLE 8

Wage Equation for Females

Dependent variable: $ln(w_{ijt})$

Variables	Models W1	W2	SIM
Constant	9.618***	9.588***	9.581***
	(0.018)	(0.022)	(0.022)
Job Seniority			
0–2nd year	0.014***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)
3rd–5th year	0.006***	–0.002	–0.004***
	(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***	0.003*	0.003
	(0.003)	(0.002)	(0.002)
Industry Experience			
0–2nd year	0.032***	0.028***	0.025***
	(0.002)	(0.001)	(0.001)
2nd–5th year	0.000	–0.002	–0.004***
	(0.001)	(0.001)	(0.001)
5th–10th year	0.006***	0.002**	–0.005***
	(0.001)	(0.001)	(0.001)
10th year +	0.000	0.000	–0.006***
	(0.003)	(0.002)	(0.002)
Experience			
0–5th year	0.020***	0.024***	0.015***
	(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)

Notes: 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 parentheses. **=5%; ***=1%
Source: Author's calculations from WHIP dataset.

between males and females is growing in the number of years of labor market experience. Endogenous selection into the labor force is a more serious concern for females than males, who are typically found to have a rather inelastic labor supply. Therefore, these estimates suggest that the reason for large returns to experience is not simply an artifact of endogenous selection into employment.

Tables 9 and 10 present the results for the hazard model of employment duration for females. Estimates are qualitatively very similar to those for

TABLE 9

Job Hazard Equation for Females

Dependent Variable: $ln(h_{ij}(\tau))$	Models		
Variables	J1	J2	SIM
Constant	–0.195***	–0.292***	–0.026
	(0.067)	(0.074)	(0.139)
Job Seniority			
0–2nd year	–0.261***	–0.041***	–0.087***
	(0.008)	(0.010)	(0.010)
3rd–5th year	–0.093***	–0.084***	–0.162***
	(0.007)	(0.008)	(0.008)
6th–10th year	–0.031***	–0.009	–0.065***
	(0.008)	(0.008)	(0.009)
11th year +	–0.004	–0.003	–0.065***
	(0.016)	(0.017)	(0.018)
Industry Experience			
0–2nd year	–0.074***	–0.138***	–0.073***
	(0.009)	(0.010)	(0.012)
3rd–5th year	0.016**	0.052***	0.126***
	(0.007)	(0.007)	(0.008)
6th–10th year	–0.024***	0.023***	0.033***
	(0.008)	(0.008)	(0.009)
11th year +	0.025	0.037**	0.129***
	(0.015)	(0.016)	(0.019)
Experience			
0–5th year	–0.125***	–0.151***	–0.078***
	(0.003)	(0.004)	(0.005)
6th–10th year	–0.007	0.000	0.047***
	(0.005)	(0.007)	(0.007)
11th year +	–0.061***	–0.059***	–0.039***
	(0.010)	(0.010)	(0.013)

Notes: 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 parentheses. **=5%; ***=1%.
Source: Author's calculations from WHIP dataset.

males, albeit magnitudes are smaller. These differences could be due to shocks outside the labor market (such as parental leave, health problems in the family, elderly care, etc.) that may affect mobility and labor-market participation of females disproportionally. Estimates in Table 11 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

TABLE 10

SECTOR HAZARD EQUATION FOR FEMALES

Dependent Variable: $ln(h^s_{ij}(\tau))$

	Models		
Variables	S1	S2	SIM
Constant	–0.538***	–0.588***	–0.358**
	(0.062)	(0.078)	(0.150)
Industry Experience			
0–2nd year	–0.359***	–0.182***	–0.087***
	(0.006)	(0.007)	(0.009)
3rd–5th year	–0.019***	0.064***	0.031***
	(0.004)	(0.005)	(0.006)
6th–10th year	–0.024***	0.031***	0.032***
	(0.004)	(0.005)	(0.007)
11th year +	–0.003	0.066***	0.085***
	(0.007)	(0.008)	(0.012)
Experience			
0–5th year	–0.099***	–0.097***	0.022***
	(0.004)	(0.004)	(0.005)
6th–10th year	0.004	0.019***	0.077***
	(0.004)	(0.004)	(0.006)
11th year +	0.000	–0.022***	0.005
	(0.007)	(0.007)	(0.011)

NOTES: 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 parentheses. ***=1%.
SOURCE: Author's calculations from WHIP dataset.

the estimates for males ($\rho_{\theta_1\theta_3}$ and $\rho_{\theta_1\theta_4}$ are both negative for females while they are positive 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 job match heterogeneity component φ_δ is negative and significant.[34] The coefficient has the same sign as for males, but it is larger for males in absolute

[34] Given the importance of match heterogeneity, one would like to look at how contract types project into it. In Italy, workers with a long-term job are in a much more rigid contractual arrangement than those with a temporary job. The information on contract type in WHIP is limited, and only available from 1998. A variance decomposition of match quality (using a match effect calculated from a fixed-effects wage regression) shows that contract heterogeneity explains approximately 12 percent (for males; 6 percent for females) of the variance in estimated match quality.

TABLE 11

VARIANCE COMPONENTS AND PARAMETERS FOR FEMALES

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity Variance and Covariance Components			
σ_{θ_1}		1.335***	2.126***
		(0.043)	(0.099)
σ_{θ_2}		0.160***	0.162***
		(0.001)	(0.001)
σ_{θ_3}		0.504***	0.936***
		(0.006)	(0.007)
σ_{θ_4}		0.752***	1.279***
		(0.008)	(0.009)
$\rho_{\theta_1\theta_2}$		–0.422***	–0.413***
		(0.010)	(0.010)
$\rho_{\theta_1\theta_3}$			–0.323***
			(0.010)
$\rho_{\theta_2\theta_3}$			–0.099***
			(0.009)
$\rho_{\theta_1\theta_4}$			–0.285***
			(0.008)
$\rho_{\theta_2\theta_4}$			–0.149***
			(0.007)
$\rho_{\theta_3\theta_4}$			0.958***
			(0.001)
Match Heterogeneity Variance Components			
σ_{δ}		0.141***	0.142***
		(0.001)	(0.001)
σ_{δ}		0.157***	0.155***
		(0.001)	(0.001)
φ_{δ}			–0.750***
			(0.064)
φ_{λ}			0.299***
			(0.056)
Error Structure			
ω	0.718***	0.278***	0.278***
	(0.000)	(0.002)	(0.002)
σ_{v}	0.237***	0.207***	0.207***
	(0.000)	(0.000)	(0.000)
ln-L	–1010054.87	–992933.21	–974246.55

NOTE: Asymptotic standard errors in parentheses. ***=1%.
SOURCE: Author's calculations from WHIP dataset.

value. On the other hand, conditional on match quality, females are more likely to change jobs when they have a better sector match. This suggests that females may be employed in sectors and firms where firm-level experience is relatively unimportant compared to sector-level experience. In addition, low

TABLE 12

CUMULATIVE WAGE RETURNS FROM FULL SIMULTANEOUS MODEL

	Males			Females		
Variables	2 Years (1)	5 Years (2)	10 Years (3)	2 Years (1)	5 Years (2)	10 Years (3)
Job seniority	1.10%	2.02%	2.59%	2.51%	1.37%	2.23%
Industry experience	4.52%	3.86%	7.51%	5.05%	3.72%	0.97%
Labour market experience	8.24%	20.60%	28.15%	3.10%	7.74%	10.62%

SOURCE: Author's calculations from WHIP dataset.

returns to labor-market experience for females implies that match quality is a relatively more important source of wage growth for females.[35] Future work could be focused on the exact mechanisms behind these gender differences, perhaps with data that allow us to compare coworkers inside the same establishment.[36]

Cumulative wage returns. The wage returns to job seniority, industry experience, and labor-market experience exhibit a high degree of nonlinearity, which makes it difficult to compare these estimates to others in the literature. Table 12 reports cumulative wage effects after 2, 5, and 10 years, as in Kambourov and Manovskii (2009), Pavan (2011), and others. For both males and females, wage returns to labor-market experience dominate those of job seniority and industry experience. For space considerations I focus on the 5-year horizon. For males, 5 years of job seniority are associated with a 2-percent wage gain. On the other hand, 5 years of industry experience are associated with almost 4-percent-higher wages. Five years of labor-market experience result in a 20-percentage-point increase in wages. Compared to Pavan (2011), who looked at careers rather than sectors, I find larger returns to job tenure, smaller but comparable returns to sector tenure, and very similar returns to labor-market experience. Females exhibit lower returns for all three variables and all time horizons. Looking again at column 2, cumulative returns to job seniority are only 1.4 percent for females, due to negative marginal returns for

[35] Given that match quality and sector quality are highly correlated, the combined effect is still negative, meaning that "good" jobs and sector matches last longer.

[36] As for males, the likelihood ratio test rejects the null hypothesis of no simultaneity at any conventional significance levels. 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 sizable effect on the other estimates. The inclusion of occupation controls (only five "occupational levels" are available in my dataset, however) changes the estimates very marginally.

the years 3–5. Returns to industry experience are similar to those of males but dissipate at higher experience level. Finally, labor-market experience has much lower returns for females. The differences may be driven by sample differences and by failing to account for skill deterioration from nonemployment. These findings depict rather different labor markets for males and females.

Concluding Remarks

In this paper I use panel data for a sample of young Italian workers for years 1986–2004 to estimate the effect of industry experience on wages taking account of heterogeneity at the individual and match level. I find that industry experience has a stronger impact on wages than job tenure, and also that its returns are highly nonlinear, concentrated in the first years of the spell. Wage returns to labor-market experience dominate returns to seniority. My empirical model allows me to test whether job duration and sector duration 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. These results imply that mobility across sectors is associated with a higher short-term wage penalty than mobility within the same sector. Earning losses of displaced workers previously employed in a shrinking sector may be higher than those of displaced workers previously employed in a booming sector. Public policy could therefore consider optimal compensation schemes that differ for these two cases.

This paper has an empirical focus and is largely silent about the possible mechanisms through which labor-market experience, experience within one industry, and job seniority affect wages, largely due to data limitations. The overall patterns are largely consistent with the model of Pavan (2011). However, more research is needed to understand the possible role of nonemployment spells on this analysis, the role of institutions on wage settings, and the sizable differences between men and women in my estimates.

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