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Abstract

Using a unique Portuguese linked employer-employee dataset, this paper offers an extension of the standard Mincerian model of wage determination by allowing for different returns to experience and tenure over the sequence of jobs that constitute a career. We also consider the possibility of distinct wage hikes each time workers change jobs, where such uplifts reflect the returns to job search investments over the life cycle and shape the curvature of the earnings profile. We further investigate how worker, firm, and job match heterogeneity influence the returns to mobility, experience, and tenure. The returns to job mobility are found to reflect sorting into better job matches. Moreover, the estimated returns to experience are upwardly biased because more productive workers tend to be more experienced.

JEL-Codes: J310, J630.

Keywords: returns to tenure, returns to experience, job mobility, high-dimensional fixed effects, job match fixed effect, job match quality effect.

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1 Introduction

This paper seeks to extend the prototypical model of wage determination that regresses individual wages on total labor market experience and current job tenure (and a vector of other explanatory variables), where the key parameters represent the average returns to an additional year of experience and tenure. It does so by including the job histories of workers while recognizing that the returns to experience and tenure are heterogenous across jobs and hence informative on job search strategies and on the intensity of on-the-job training investments by workers.

We proceed in two stages. The first step corresponds to an expansion of the conventional Mincerian wage equation (here including controls for schooling, gender, and firm size) in recognizing that total experience is simply the sum of past and current job tenure intervals (see Addison and Portugal, 1989). We take advantage of the job history of each worker by allowing for distinct returns to experience and tenure in the sequence of jobs. In other words, we assume that the returns to the first job may differ from those on the second, third, and indeed all subsequent jobs.

Furthermore, we allow for the possibility that wages change discretely whenever a worker changes (sequentially) his/her job. In this paper, we consider job sequences up to a maximum of 10 jobs. In extending the canonical Mincer equation, a distinction is drawn between the returns to experience, tenure, and match quality in a manner different from the orthodox routes pursued in the literature (e.g., the two-step estimator of Topel, 1991; the instrumental variable approach of Altonji and Shakotko, 1987; and the method of controlling for completed tenure in Abraham and Farber, 1987).

Being able to identify different experience and tenure earning profiles over the course of a career is informative on the intensity and timing of job training investments. Our focus on heterogeneities in the returns to experience over a career finds a parallel in the recent discussion surrounding the relevant unit of heterogeneity in the accumulation of human capital (Arellano-Bover and Saltiel, 2021; Jarosch et al., 2020). More importantly, the sequence of wage uplifts accompanying job changes, reflecting the return to job search investments over the life cycle, is hypothesized to shape the curvature of the earnings profile. To the best of our knowledge, this is the first time that the complete history of job sequences has been employed to estimate the returns to experience, tenure, and job mobility.

The next step is to consider job match heterogeneity in the specification of the wage equation. Proceeding in this manner, we jointly account for worker, firm, and match quality time-invariant heterogeneity (Raposo et al., 2021), thereby circumventing endogeneity problems arising from job change decisions. The task then becomes one of ascertaining the share of returns accruing from being in better-paying firms, being a more productive worker, and being in better job matches. More precisely, the goal of this exercise is to determine how much of the returns to experience, tenure, and job search reflect firm, worker, and match quality heterogeneity.

The paper is structured as follows. The next section discusses the related literature. Section 3 sets down a simple extension of the Mincerian wage model to establish our empirical design. Section 4 introduces the dataset. Our detailed results and decomposition of the sources of heterogeneity are provided in Sections 5 and 6. Findings from alternative regression model specifications are given in Section 7. Section 8 concludes.

2 Literature Review

At the heart of this essay is the Mincerian regression equation, in the wake of which development a series of influential studies have sought to obtain the pure causal effect of tenure on wages, namely the effect of an extra year's tenure on wages holding constant years of experience and job match quality. This effect is construed as a measure of the return to firm specific human capital and/or indicative of contractual mechanisms that reward tenure for incentive reasons (e.g., deferred compensation that encourages workers to supply effort and thereby improve performance). However, this interpretation is problematic because it ignores the job-changing decisions that underpin the mix of wages, job tenure, and market experience contained in survey data. Thus, for example, job changing may reflect the sorting of workers into longer lasting and more productive jobs. High wage jobs tend to survive which may mean that individuals with long job tenures simply earn more. Alternatively, the positive association between tenure and wages might simply reflect a tendency for more productive (or more able) individuals to change jobs less frequently.

The early literature has dealt with the confounding factor of match quality (or worker-firm match quality) by seeking to remove the stochastic component of wages specific to the worker-firm pair. One approach is that of Topel (1991), who first estimates a prototype model of wage determination containing the worker's current job tenure and lifetime work experience (with parameters β_2 and β_1 respectively), and a residual term decomposed into job-match quality, the individual's ability, and an idiosyncratic error term. Here the main problem is that the wage boost of worker-firm interaction is likely to be correlated with tenure. Specifically, when match quality is high separation rates will fall and expected tenure will rise, biasing the tenure coefficient estimate upward. Topel's method is to first difference incumbents' wages to remove match quality and individual effects. Within-job wage growth combines the returns to general market experience and job-specific tenure. Average within job growth is given by $\beta_1 + \beta_2$. These elements cannot be distinguished. In a second step, therefore, Topel estimates a cross-section regression of wages on initial jobs, that is, for workers at different points in their careers. This second stage gives an (upper-bound) estimate of the returns to general experience alone. Subtraction from the results from the first stage gives a consistent (lower-bound) estimate of the returns to tenure, namely $\widehat{\beta_1 + \beta_2} - \hat{\beta}_1$.

Other studies have applied similar models to obtain consistent estimates of the return to experience. Altonji and Shakotko (1987) apply an instrumental variables procedure in which tenure is instrumented by the deviation of tenure from its observed, job-specific spell mean (i.e., it being argued that job effects are not time varying). Although this procedure is prima facie equivalent to Topel's second-step model, the authors obtain much smaller tenure effects than does Topel, who in turn attributes this in part to the IV procedure producing a greater upward bias in the return to experience and hence a greater downward bias in the returns to tenure.

Using a different approach, Abraham and Farber (1987) report equally small effects of tenure. They add the final ex post tenure of the worker at the firm to the total labor market experience and current job tenure variables, arguing that the ultimate duration of a job is a good proxy for its unobserved dimensions or worker quality. As ultimate duration is unobserved for most observations, they use expected completed tenure for the censored observations based on the frequency of job endings in the data. They then add the estimate of completed tenure on the last job to the standard model of wage determination to capture the effects of unobservables representing the quality of the worker, job, or worker employer match. The outcome is that the effects of tenure are again negligible.

Topel (1991; 166-172) directly confronts his findings with those in the last two studies and concludes that both understate the returns to tenure because of measurement error and methodological biases, respectively, after correction for which the reported shortfalls in the estimated returns to tenure across studies are effectively eliminated, with 10 years of job seniority elevating wages by more than 25 percent on average. However, in a companion study, Snell et al. (2018) argue that there remain uninvestigated sources of bias in the rate of return to tenure, and in particular the positive co-movement of firm employment and firm wages. If a firm's employment and wages rise (fall) together its average tenure will fall (rise), and tenure will be endogenous. This co-movement stems from unobservable wage shocks that produce a time-varying wage component that is common to all a firm's workers and moves in parallel with its employment. Specifically, aggregate and firm-specific shocks are seen as impacting firms that have a relatively high wage at time t coupled with high employment, high hiring, and low average tenure, or those that that have a relatively low wage at t as well as low employment, low hiring, and high average firm tenure. The existence of a time-varying wage component that is at once common to all a firm's workers but co-moves with its employment serves to bias estimates of the return to tenure because of the negative feedback from so-called "equal-treatment shocks" to tenure. The authors claim that the correction of the bias can be controlled for by using firm-year interaction fixed effects in panel wage regressions that add match fixed effects to the estimation process (but see below). Using data for Germany and Portugal, the authors report that the returns to tenure corrected for wage shocks that impact all workers in the firm are substantially higher than reported using the methodology of all three studies considered earlier, each of which uses the PSID.

In a paper that considers the endogeneity of job changes and its effects on estimated returns to tenure, again using the PSID, Buchinsky et al. (2010) offer a structural treatment of the endogenous decisions of participation and mobility while incorporating features of the above studies. Individuals in the model make key decisions on employment and participation and inter-firm mobility, which decisions duly influence wages. Through these reduced-form decision equations the model accounts for the potential selection biases that stem from such endogenous decisions and permits the estimation of the parameters associated with the wage function, including the returns to tenure and experience. The approach offers a unified framework allowing the authors to address and reexamine results previously reported in the literature. Individual unobserved heterogeneity is tackled via person-specific random correlated effects, while past labor market history is captured by an individual-job specific function that summarizes the changes in wages that correspond to an individual's particular career wage path.

Estimation of the model thus involves a three-equation system: a participation (employment) equation; an interfirm mobility equation; and a wage equation. As noted, unobserved heterogeneity is controlled for by introducing person-specific random correlated effects in each equation. Also, each equation contains the individual's returns to seniority on a specific career path. It is reported that the returns to seniority are large and statistically significant.[1] With respect to specific career paths, the timing of a move in a worker's career matters. For example, the net effect for a college-educated worker changing jobs after a decade of seniority and a decade of experience is an 8 percent reduction in the wage whereas the corresponding value for a college-educated worker at the beginning of a career with just 2 years' seniority and experience is a 12 percent net gain.

The bottom line is that wage growth comes about through a combination of wage increases within a firm and mobility across firms, the former being more important for high school dropouts because of their lower returns to experience and larger for college graduates because there is no penalty from job-to-job transitions and because the returns to seniority are larger during the first few years on a given job. As for the indirect effects

[1] Although the estimated returns to experience are also larger than previously obtained in the literature, they are differentiated by education group (being greater for college graduates).

on experience and seniority that depend on a worker's career wage path, it is firmly established that these play an important role in explaining wage growth.

A second equilibrium job search model deployed by Bagger et al. (2014) identifies only one reason why wages increase with firm tenure. Firms are said to confront a moral hazard problem - workers being unable to commit to not accepting attractive outside offers - and therefore have an incentive to backload pay to retain their workforces. Rather than having wages increase smoothly with tenure as under the standard deferred compensation argument, however, it is argued that firms will revisit wages each time the worker receives an attractive offer. Accordingly, wages will increase with tenure in discrete steps in response to these poaching attempts. There is no explicit distinction in this "offer matching" treatment between general and firm-specific capital; rather, it is a combination of search frictions and moral hazard that explains upward sloping wage-tenure profiles.

The authors (otherwise) offer a structural wage model in the spirit of Mincer with worker and firm fixed effects, human capital effects, and stochastic dynamics resulting from between-firm competition for labor (activated by on-the-job search) and individual productivity shocks (that can account for cuts in earnings). As its main contribution, the model provides a decomposition of earnings growth into the contributions of human capital accumulation and job search (both within and between job spells).

Using Danish matched employer-employee data, it is reported that human capital accumulation and job search contribute to the concavity of the wage-experience profiles. For its part, the contribution of job search declines within the first ten years of a career, identified with a "job-shopping phase" of a working life. In a second stage, workers settle into high-quality jobs and use outside offers to generate gradual wage increases, thereby benefiting from the competition between employers. This within-job component dominates the between-job component, especially after the first ten years of labor marker experience.

Finally, the study reveals considerable heterogeneity in the returns to tenure or within-job growth. They are firm specific in that more productive employers offer steeper profiles. They are not constant, depending upon the firm-specific salary scale at which they are evaluated. Thus, for example, a worker hired out of unemployment is likely to receive a low wage rate with considerable scope for future increase whereas another worker in the same firm may have already negotiated a wage rate close to the maximum and have little chance of benefiting from further increases. That is, the structural model implies much greater heterogeneity in the returns to tenure than indicated in conventional wage regression-based measures.

Buhai et al. (2014) seek to tackle the identification problem arising from the perfect correlation of the within-job variation in tenure and in experience. By defining seniority as the worker's tenure relative to that of all his or her co-workers, the identification problem attaching to the estimation of the linear term in the return to tenure is avoided. In turn, this rank ordering measure preempts the need to resort to between-spell variation after Topel (1991), *inter al.* Since seniority as defined is not a deterministic function of tenure it is possible to identify a return to seniority separately from the return to tenure, while the return to seniority is independent of a firm-size wage effect because retirements and other exogenous shocks provide a source of variation in the number of workers with longer tenure.

Buhai et al. (2014) motivate their treatment by asking why workers with the same abilities are differentially separated when an employer must reduce employment and why they are also paid differently by the same firm. Building on a model of layoff ordering (Kuhn and Robert, 1989), the authors offer strong empirical support for these stylized facts.[2] Using matched employer-employee data for Denmark and Portugal, they demonstrate that a worker who is last to be hired is first to be fired and, moreover, that there is a return to seniority in wages on top of the return to tenure. The weaker negative (positive) effects of increased seniority on the separation hazard (wages) estimated for Denmark are attributed to that nation's more flexible labor market and more proactive labor market policy.

The three preceding studies examine different samples of workers by education. Arellano-Bover and Saltiel (ABS) (2021) instead draw a distinction between types of firms. The authors group firms into skill learning classes using a clustering methodology. The ar-

[2] The specific rationale for a LIFO layoff rule that yields a wage return to seniority offered by the authors is that it provides a solution to the inefficiency of a standard monopoly union/employer right to manage model where gains from trade remain unexploited.

gument is that there are heterogeneous learning opportunities across firms. Firms are first classified into classes according to similar distributions of earnings growth, and then returns to heterogeneous experiences acquired across these firm class intervals are estimated. The authors use administrative datasets for regions in Brazil and Italy, focusing on cohorts of workers observed from labor market entry to their mid-thirties.

ABS use a split-sample approach with one half of the workers in the sample being used to assign firms into classes and the other half to estimate returns to heterogenous experiences. The number of firm classes is set at ten. Log earnings regressions are estimated that allow for different returns in each of the ten types of experience while including worker and firm fixed effects. Pronounced disparities in the returns to experience are detected across the different firm classes. Workers with higher unobserved skills display higher returns across each of the ten firm classes, but there are no meaningful differences in relative returns across classes vis-à-vis workers with lower skills. Having already controlled for worker fixed effects, ABS thus rule out a sorting on unobserved ability explanation.[3]

In their consideration of heterogeneous learning across firms, ABS range beyond earnings to consider for one of their datasets a proxy for workers skills in the form of the task content of jobs derived from the O*NET. The result is that experience acquired in top learning firm classes is also associated with subsequent increases in workers' non-routine analytic and non-routine interpersonal task content.

We conclude by noting that although ABS report that firm's observable characteristics play only a limited role in predicting on-the-job learning opportunities (and the assignment of firms into classes), companion research has identified observable characteristics as important to this learning process and earnings growth. Perhaps the best example is work by Jarosch et al. (2020) emphasizing the importance of coworker education and skills to heterogeneity in on-the-job learning and human capital accumulation.

[3]Interestingly, similarly heterogeneous returns to experience acquired in different firm classes are found for displaced workers on their next job, offering support for the authors' argument that their estimates capture returns to the acquisition of general rather than firm-specific training.

3 Extending the Mincerian wage model

We begin by considering the extension of the canonical Mincer wage equation in three important dimensions. First, we allow for distinct returns to job tenure over the sequence of jobs during the worker career. Second, we also accommodate distinct returns to previous labor market experience over the worker history of jobs held. Third, we incorporate the possibility of a varying wage hike on each occasion that the worker changes a job.

Our benchmark wage regression model can be written as:

$$w_{(i,t)} = \alpha_{1j} T_{j(i,t)} + \alpha_{2j} T^2_{j(i,t)} + \textstyle\sum_{s=1}^{j-1} (\delta_{1s} T_s + \delta_{2s} T^2_s) + \phi_{j(i,t)} + \boldsymbol{X}_{(i,t)} \beta + u_{(i,t)}, \qquad (1)$$

where $w_{(i,t)}$ denotes the (log) wage of worker i at year t. $T_{j(i,t)}$ is current tenure at time t on the j^{th} job. T_s represents the completed job duration at job s. $\phi_{j(i,t)}$ identifies a fixed effect associated with the order of the job, where $\phi_{1(i,t)}$ is normalized to be 0. $\boldsymbol{X}_{(i,t)}$ represents a vector of other explanatory variables (a set of schooling dummies, a gender dummy, firm size, and a time trend); and $u_{(i,t)}$ is an error term, assumed to be orthogonal to the explanatory variables.

It should be clear that in this model we are accounting for the work history of the individuals in a number of ways. First, $\phi_{j(i,t)}$ gives the accumulated returns to job mobility at the j^{th} job, that is, the wage changes when a worker moves from the first to the second job, from the second to the third, and so on until the current j^{th} job. Second, at each stage, we take into account the accumulated returns to experience from each of the previous jobs. Those accumulated returns are given by the expression $\sum_{s=1}^{j-1} (\delta_{1s} T_s + \delta_{2s} T^2_s)$. Third, the j subscript in the $\alpha_{1j} T_{j(i,t)} + \alpha_{2j} T^2_{j(i,t)}$ expression means that returns to current tenure, which of course also include returns to experience in the current job, may vary in the sequence of jobs over the career.

We will also consider, in the long and rich tradition of papers that aim to properly estimate the returns to tenure, initiated by Topel (1991), a specification that includes a job match fixed effect:

$$w_{(i,t)} = \alpha^1_{1j} T_{j(i,t)} + \alpha^1_{2j} T^2_{j(i,t)} + \boldsymbol{X}_{(i,t)} \beta^1 + \psi_{i \times f} + u^1_{(i,t)}, \tag{2}$$

where $\psi_{i \times f}$ denotes the job match fixed effect, identifying each pair of worker (i) and firm (f) combinations. The inclusion of the job match fixed effect leads inevitably to the collapse of the job mobility and previous experience coefficients because there is no within-variation of these variables. The main reason why, in this literature, researchers care about the job match fixed effect is because they suspect that better job matches tend to lead to longer jobs and, in the absence of any control for job match quality, the estimated returns to tenure would be upward biased. However, it is clear that the job match fixed effect, while incorporating the job match quality effect, also includes the worker fixed effect and the firm fixed effect. In this paper, therefore, we will aim (under certain orthogonality assumptions) to disentangle the role of worker, firm, and match quality heterogeneity in driving the returns to experience, tenure, and job mobility.

To obtain a better insight from our decomposition exercise it is useful to present the benchmark wage regression equation in a matrix formulation, singling out the regression coefficients of particular interest:

$$\boldsymbol{Y} = \mathbf{X}\boldsymbol{\beta_0} + \mathbf{J}\boldsymbol{\gamma_0} + \boldsymbol{\epsilon_0}, \tag{3}$$

where $\mathbf{Y}$ stands for the vector of wages; $\mathbf{X}$ denotes the matrix of control variables (the gender dummy, education dummies, firm size, and the time trend); $\boldsymbol{\beta_0}$ is a vector of regression coefficients; $\mathbf{J}$ is a matrix that represents the variables that we use to compute the returns to job mobility, experience, and tenure, $\boldsymbol{\gamma_0}$ representing the corresponding coefficients; and $\boldsymbol{\epsilon_0}$ gives the error term.

Making use of the Frisch-Waugh-Lovell theorem, we can express the OLS estimate of $\boldsymbol{\gamma_0}$ by running a regression of $\boldsymbol{Y}$ on $\mathbf{J}$ after partialling out the effect of $\mathbf{X}$ on both variables. That is,

$$\widehat{\boldsymbol{\gamma_0}} = (\mathbf{J}'\mathbf{P_X}\mathbf{J})^{-1}\mathbf{J}'\mathbf{P_X}\mathbf{Y}, \tag{4}$$

where $\mathbf{P_X}$ is the familiar residual-maker matrix, $\mathbf{P_X} = (\mathbf{I} - \mathbf{X}(\mathbf{X'X})^{-1}\mathbf{X'})$.

More compactly, we can write:

$$\widehat{\gamma_0} = \mathbf{A_X Y}, \tag{5}$$

where it useful to retain the meaning of the matrix $\mathbf{A_X} = (\mathbf{J'P_XJ})^{-1}\mathbf{J'P_X}$ which, for any given dependent variable, always gives the regression coefficient estimates of $\mathbf{J}$ from an OLS regression that also includes $\mathbf{X}$.

We now incorporate in the wage regression the set of dummy indicators that, for each worker, identify each job-match, $\mathbf{M}$. The job-match corresponds, as usually defined, to each worker/firm combination. Thus,

$$\boldsymbol{Y} = \mathbf{X}\widehat{\boldsymbol{\beta_1}} + \mathbf{J}\widehat{\boldsymbol{\gamma_1}} + \mathbf{M}\widehat{\boldsymbol{\psi_1}} + \widehat{\boldsymbol{\epsilon_1}}, \tag{6}$$

where $\widehat{\boldsymbol{\psi_1}}$ denote the job match fixed effects.

In order to obtain the impact of introducing the job match fixed effect on the returns to job mobility, experience, and tenure, all that needs to be done is to run an auxiliary regression taking the estimated match fixed effects as the dependent variable and the variables in $\mathbf{X}$ and $\mathbf{J}$ as the covariates. That is,

$$\mathbf{M}\widehat{\psi_1} = \mathbf{X}\widehat{\boldsymbol{\eta}} + \mathbf{J}\widehat{\boldsymbol{\theta}} + \widehat{\boldsymbol{\upsilon}}. \tag{7}$$

In identical fashion, we can apply the omitted variable bias formula to obtain the change in the coefficient estimates due to the inclusion of the job match fixed effect. We simply multiply both terms of equation (7) by $\mathbf{A_X}$, to obtain

$$\widehat{\gamma_0} - \widehat{\gamma_1} = \mathbf{A_X M}\widehat{\psi_1} = \widehat{\boldsymbol{\theta}}, \tag{8}$$

since, by construction, $\mathbf{A_X X}\widehat{\boldsymbol{\eta}} = \mathbf{0}$ and $\boldsymbol{A_X}\widehat{\boldsymbol{\upsilon}} = \mathbf{0}$.

These estimates can of course be more straightforwardly obtained directly from the base and the full model. Proceeding in the former manner will prove instructive once we move to the three components of the match fixed effect: worker, firm, and match quality heterogeneity.

To further disentangle the impact of worker self-selection, sorting among firms with different wage policies, and the allocation into job matches with distinct match quality, some strong assumptions will be necessary. A workable assumption, and in this framework a natural one, is to treat the match quality fixed effect as orthogonal to the worker and firm fixed effects. This approach has been used by Raposo et al. (2021) and Woodcock (2022) to study the wage losses of displaced workers. In assuming that the match quality fixed effects are uncorrelated with the worker and firm fixed effects, the match quality component of the wage gap is best seen as a lower bound.

To grasp the impact of worker, firm and match quality heterogeneity we expand equation (7) by including a matrix of worker identifying dummies ($\mathbf{W}$) and a matrix of firm identifying dummies ($\mathbf{F}$):

$$\mathbf{M}\widehat{\psi_1} = \mathbf{X}\widehat{\boldsymbol{\eta}_1} + \mathbf{J}\widehat{\boldsymbol{\Omega}} + \mathbf{W}\widehat{\boldsymbol{\Phi}} + \mathbf{F}\widehat{\boldsymbol{\Sigma}} + \widehat{\boldsymbol{\upsilon}_1}, \tag{9}$$

where $\widehat{\boldsymbol{\Phi}}$ denotes the worker fixed effects, $\widehat{\boldsymbol{\Sigma}}$ embodies the firm fixed effects, $\widehat{\boldsymbol{\Omega}}$ identifies the impact of match quality, and $\widehat{\boldsymbol{\upsilon}_1}$ represents the residual term.

Multiplying both terms of equation (9) by $\mathbf{A_X}$ we can finally split the match component into three parts (Gelbach, 2016):[4]

$$\widehat{\boldsymbol{\theta}} = \widehat{\boldsymbol{\delta}_{\boldsymbol{\Phi}}} + \widehat{\boldsymbol{\delta}_{\boldsymbol{\Sigma}}} + \widehat{\boldsymbol{\Omega}}, \tag{10}$$

where $\widehat{\boldsymbol{\delta}_{\boldsymbol{\Phi}}}$ represents the worker component and $\widehat{\boldsymbol{\delta}_{\boldsymbol{\Sigma}}}$ represents the firm component.

4 Data

Our data are taken from the Quadros de Pessoal (QP), or Personnel Records, a longitudinal matched employer-employee dataset covering the period 1986-2020. The QP is an annual mandatory employment survey conducted by the Portuguese Ministry of of Employment that covers all establishments with at least one employee. Under Portuguese

[4]Note that, by construction, $\mathbf{A_X}\mathbf{X}\widehat{\boldsymbol{\eta}_1} = \mathbf{0}$, $\mathbf{A_X}\mathbf{J}\widehat{\boldsymbol{\Omega}} = \widehat{\boldsymbol{\Omega}}$ and $\boldsymbol{A_X}\widehat{\boldsymbol{\upsilon}_1} = \mathbf{0}$.

law, each such establishment with wage earners has an obligation to complete the survey. The detailed information contained in the survey is not only supplied by the employer but also has to be published in a public space at the establishment itself. Both facets of information provision flag the reliability of the information provided. The data on workers cover gender, age, education, skill, occupation, tenure, and earnings. The hallmark of these data is their precision. Thus, for example, we observe the worker's date of admission to the establishment, which is crucial in attributing tenure and experience over a career, while the wage data include gross pay for normal hours of work, regular benefits, and overtime pay.

The following broad restrictions were imposed on the raw dataset. Workers had to be employed full time, employed in the private sector, and earning at least 80 percent of the minimum wage (which corresponds to the lowest permissible wage for apprentices). In addition, workers from agriculture and fisheries were excluded.

Workers are for the first time observed in the database. They must be on their first job in the year that they enter the sample, have less than one year's tenure on that job, and be aged less than 30 years. In other words, we retain in our sample wage earners born after 1956 if they are observed in their first year in their first job in our survey. Having set these initial conditions, we proceed to follow workers up to a maximum sequence of 10 jobs.

By way of summary, our definition of the key career variables is as follows. First, tenure is obtained from the worker's date of admission to the firm. Second, previous experience is the summation of all previous tenures. Third, job spell is obtained from a combination of worker-firm identifiers. Each firm in the QP is assigned a unique identification number, considerable care being taken by the administering agency to ensure that previous reportees are not assigned a different number; while the worker's identification number is based on his/her social security number. Firm-worker matching combinations are duly ordered by job sequence, namely 1 through 10. Fourth, both tenure and previous experience are provided for each job spell, that is, for each job spell we identify current tenure and the previous completed experience. Observe that some late spells are necessarily incomplete as our sample period ends in 2020.

Our flow sample comprises some 2,089,087 workers, 4,334,946 worker-job spell combinations, and 15,573,251 worker-job spell-year observations. Some information on the job mobility of these 2,089,087 workers is given in Table 1. Some 42.5 percent of workers record only 1 job while 27.2 percent have 2 jobs. Thereafter, the proportions are sharply lower. Turning to worker histories, those who have only 1 job have a completed tenure of 4.17 years as compared with 4.16 years in the case of workers with 2 jobs. Completed tenure decreases naturally albeit fairly modestly with an increasing number of jobs held. Finally, 57.5 percent of workers move on to a second job, and 52.8 percent proceed to a third job. This decline in the proportion of worker movers with the number of jobs held is monotonic.

Table 1: Job mobility over the worker's history

Job	Maximum no. jobs %	Completed tenure in years	Job moves %
1st	42.49	4.17	
2nd	27.18	4.16	57.51
3rd	15.33	4.39	52.75
4th	7.88	4.11	49.47
5th	3.86	3.96	47.50
6th	1.80	3.76	45.84
7th	0.82	3.58	44.99
8th	0.36	3.45	44.34
9th	0.17	3.42	44.40
10th	0.12	3.18	42.71

Notes: These statistics are obtained at the worker level (2,089,087 workers).

Descriptive statistics on workers (by earnings, age, tenure, and gender), firms (firm size) and sector (6 industries) across all observations are provided in Table A.1, while Table A.2 charts the evolution of first jobs over each year of the sample period. The basis of the former is all worker-job spell-year observations, while the sum of the number of first jobs gives the number of workers in the sample.

5 Empirical results

Table 2 presents the regression results for our extended wage model given in equation (1). The first column provides estimates for the accumulated wage changes after a given number of job changes. The wage uplift when a worker moves from the first to the second job is estimated to be 12.2 percent (corresponding to the 0.1155 coefficient estimate). When the worker moves to the third job he/she will benefit from two wage changes, that is, the previous wage boost and then that accompanying the move from the second to the third job. The combined effect of those two job changes is estimated to be 17.5 percent (corresponding to the 0.1616 coefficient estimate). The interpretation of the remaining estimates in the first column can be explained in similar fashion. It is noteworthy that the returns to job mobility are sizable and larger at the beginning of the job career. The suggestion seems to be that the returns to job search decline over time with the accumulation of jobs.

Table 2: Wage regression based on work histories (base model)

Job sequence	Accumulated	Previous experience		Current tenure	
	job changes	Linear term	Quadratic term	Linear term	Quadratic term
1st		0.0133	-0.0002	0.0426	-0.0008
		(0.0003)	(0.0000)	(0.0001)	(0.0000)
2nd	0.1155	0.0149	-0.0004	0.0322	-0.0006
	(0.0008)	(0.0004)	(0.0000)	(0.0002)	(0.0000)
3rd	0.1616	0.0128	-0.0005	0.0250	-0.0005
	(0.0012)	(0.0005)	(0.0000)	(0.0003)	(0.0000)
4th	0.1870	0.0107	-0.0004	0.0227	-0.0005
	(0.0018)	(0.0008)	(0.0000)	(0.0004)	(0.0000)
5th	0.2089	0.0091	-0.0004	0.0191	-0.0005
	(0.0026)	(0.0012)	(0.0001)	(0.0007)	(0.0000)
6th	0.2350	0.0077	-0.0003	0.0159	-0.0004
	(0.004)	(0.0019)	(0.0001)	(0.0011)	(0.0001)
7th	0.2590	0.0086	-0.0005	0.0159	-0.0005
	(0.006)	(0.0026)	(0.0001)	(0.0017)	(0.0001)
8th	0.2788	-0.0080	0.0002	0.0135	-0.0006
	(0.0088)	(0.0039)	(0.0002)	(0.0025)	(0.0001)
9th	0.3262	-0.0088	-0.0001	0.0141	-0.0007
	(0.0127)	(0.0072)	(0.0003)	(0.0037)	(0.0002)
10th	0.4022			0.0058	-0.0001
	(0.0206)			(0.0060)	(0.0003)

Notes: Robust standard errors, clustered by job match,are given in parenthesis. The regression also includes 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend.

The returns to previous job experience are provided in the second and third columns of the table. Because we are allowing for different returns in each job, we need to consider the accumulated returns. For example, a worker in his/her third job receives returns from the previous completed tenure in the first job, namely 0.0133 for the linear term and -0.0002 for the quadratic term (given by the coefficient estimates in the first line). The same reasoning applies to other job sequences. Whereas the returns to experience increase from the first to the second job, there is every indication that the returns decline thereafter. This would seem to suggest that investments in general training are more significant in early jobs of the career.

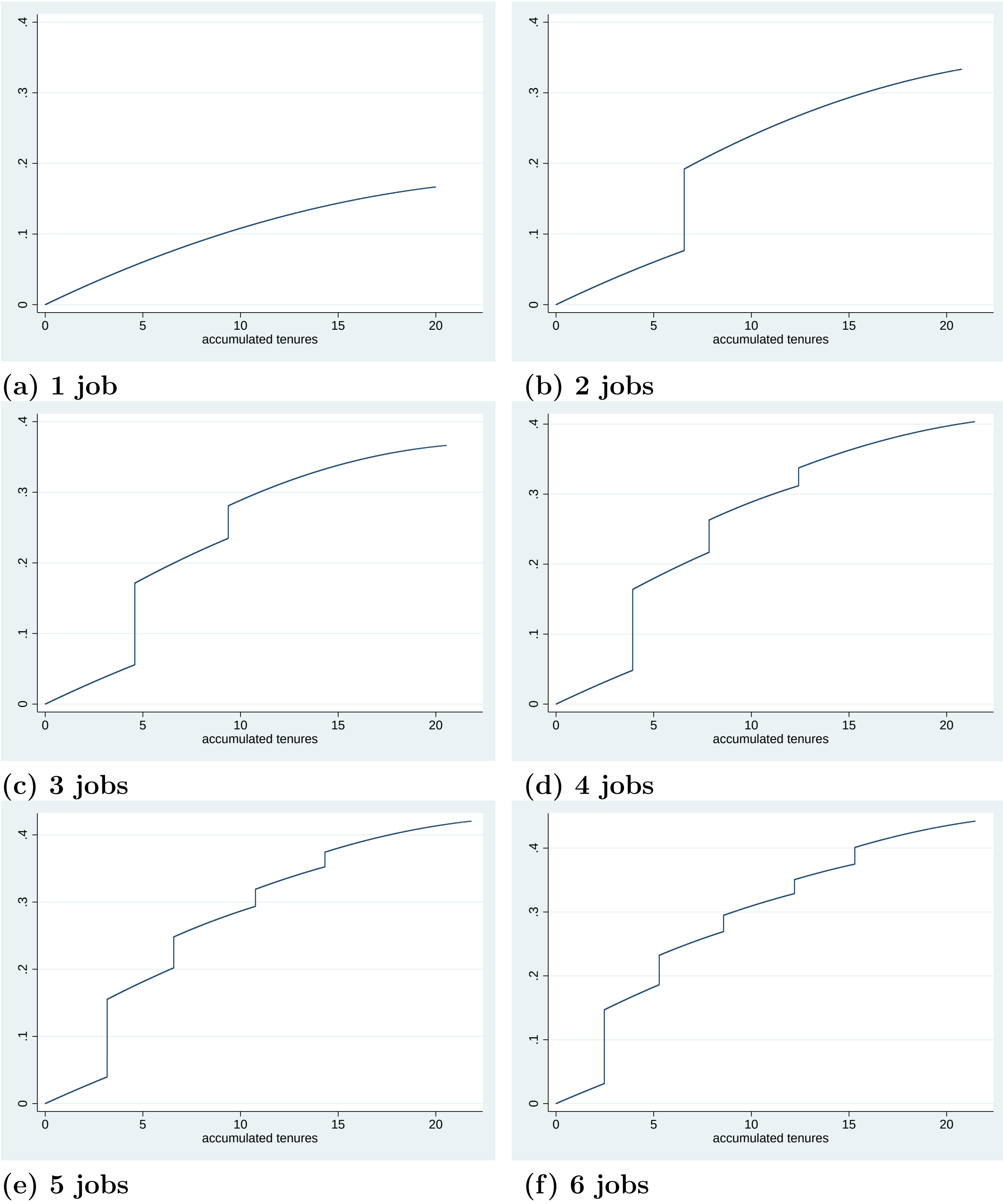
The interpretation of the last two columns is perhaps more straightforward. At each job, the coefficient estimates give the combined returns to tenure *and* experience in the current job. For example, for a worker in his/her third job, the returns to current tenure and experience are given by the end values in the third row (0.025 for the linear term and -0.0005 for the quadratic term). Again, there is evidence that the returns to current tenure and experience decline smoothly over the job career.

In order to retrieve the return to current tenure purged of the return to experience, all that needs to be done is simply to subtract, for each job, the returns to previous experience from the corresponding combined returns to current tenure and experience. For example, for a worker in his/her third current job, the return to tenure will be 0.012 (0.025-0.013) for the linear term and -0.00001 (-0.00051-(-0.00050)) for the quadratic term.

Figures 1, 2 and 3 illustrate the impact of job histories on wages. Figure 1 depicts the returns to job mobility and experience for 6 simulated job sequences. The first panel shows the returns to experience for a worker who never changes jobs. In the second panel it is shown that an important source of wage growth stems from job mobility. At 10 years of experience around one half of the wage growth comes from job mobility and the other half from returns to experience. This is prima facie evidence that failure to model job mobility is likely to considerably overstate the returns to experience. More generally, the wage hikes due to job mobility underpin the notion that the curvature of the earnings profile is more acutely quadratic as a result.

Figure 2 shows the returns to experience and tenure in the current job. It is clear that

Figure 1: Returns to job mobility and returns to experience in previous jobs (base model)



(a) 1 job

(b) 2 jobs

(c) 3 jobs

(d) 4 jobs

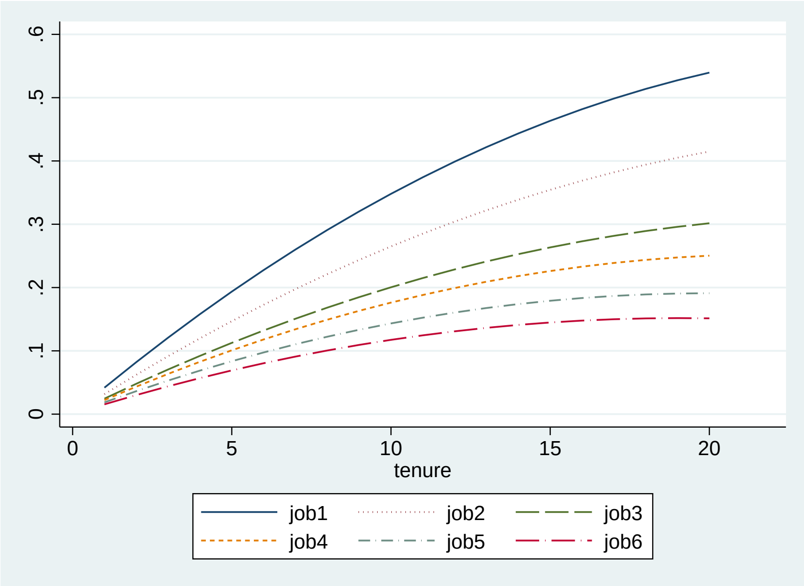
(e) 5 jobs

(f) 6 jobs

Notes: The figures are computed from the regression estimates in Table 2. Spikes in earnings are located at the end of each (average) job duration.

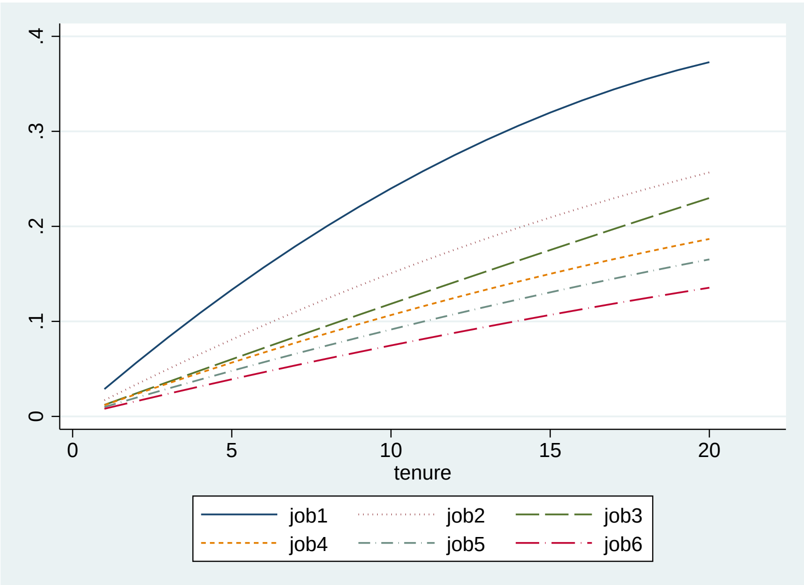
the highest returns occur during the first job and that the returns decline sharply during subsequent jobs. In Figure 3 we show the returns to tenure on the current job (purged of the returns to experience). The returns to tenure are heterogenous across the sequence of jobs. They are highest during the first job but decline substantially in subsequent jobs,

Figure 2: Returns to experience and tenure in the current job (base model)



Notes: The curves depict the returns to experience and tenure in the current job given in Table 2.

Figure 3: Returns to tenure in the current job (base model)



Notes: The curves correspond to the difference between the returns to experience and tenure in the current job and the returns to previous experience in that job.

suggesting that the profile of the returns to tenure largely shape the returns to tenure and experience.

As discussed above, our model has the conventional Mincerian model as a special case. By restricting the returns to job mobility to be zero, the returns to previous experience to be the same irrespective of the job sequence in the worker's career, and the returns to experience and tenure in the current job to be the same across jobs, we arrive at the standard Mincer model specification. Table 3 provides the regression coefficient estimates of the restricted model and the corresponding statistical tests for each set of linear restrictions as well as those for the overall set of joint restrictions. As is clear, we soundly reject these restrictions in favor of our extended model. The restricted coefficient estimates for previous experience are presumably too high, most likely because they are capturing the effects of job mobility. Conversely, the estimated returns to tenure appear to be downwardly biased due to the upward bias in the return to previous experience. Be that as it may, it is clear that we can no longer entertain the notion that the returns to experience and to tenure are homogeneous over the job career of the worker.

Table 3: Testing the restrictions of the Mincerian wage equation

Job sequence	Accumulated job changes	Previous experience Linear term	Previous experience Quadratic term	Current tenure Linear term	Current tenure Quadratic term
1st		0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
2nd	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
3rd	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
4th	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
5h	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
6th	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
7th	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
8th	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
9th	0.0000	0.0234	-0.0008	0.0341	-0.0006
		(0.0001)	(0.0000)	(0.0001)	(0.0000)
10th	0.0000			0.0341	-0.0006
				(0.0001)	(0.0000)
H_0: Returns to job mobility equal zero	F-stat: 11943.30				
H_0: Returns to experience are the same		F-stat: 1275.36			
H_0: Returns to tenure are the same				F-stat: 5343.64	

Notes: The F-statistic corresponding to all the linear restrictions is equal to 3828.87.

In Table 4 we expand our model to include a job match fixed effect. In this full model we are implicitly accounting for worker heterogeneity, firm heterogeneity, and match quality heterogeneity (see section 3). In this setup, the returns to current tenure which, as before, represent the sum of the returns to previous experience and tenure, are somewhat smaller compared with the base model. This illustrates the upward bias in the returns to tenure in the models that do not account for match heterogeneity. At this stage, we can not yet disentangle whether this bias arises from the estimated returns to previous experience or job tenure. However, in the following section, we will decompose the sources of this bias.

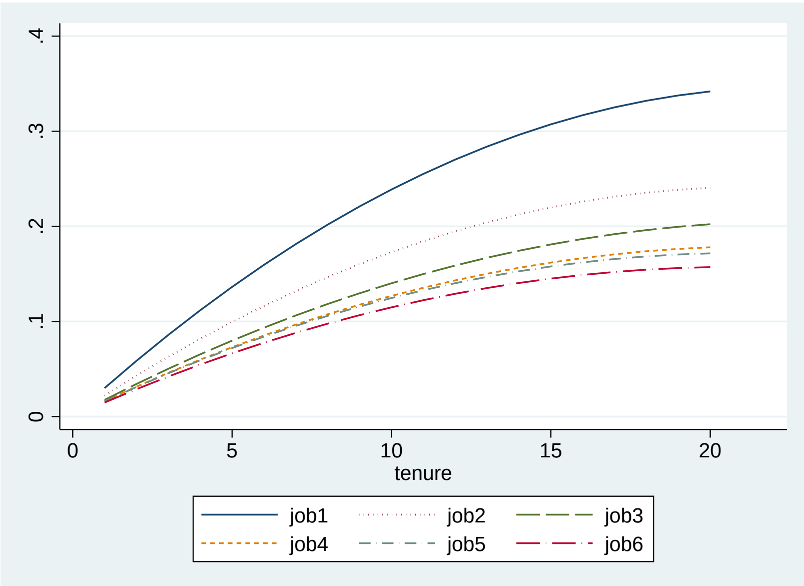
Table 4: Job match fixed effects wage regression based on work histories (full model)

	Current tenure	
	Linear term	Quadratic term
1st	0.0307	-0.0007
	(0.0001)	(0.0000)
2nd	0.0225	-0.0005
	(0.0001)	(0.0000)
3rd	0.0179	-0.0004
	(0.0002)	(0.0000)
4th	0.0165	-0.0004
	(0.0003)	(0.0000)
5th	0.0163	-0.0004
	(0.0004)	(0.0000)
6th	0.0151	-0.0004
	(0.0006)	(0.0000)
7th	0.0176	-0.0004
	(0.0012)	(0.0001)
8th	0.0189	-0.0005
	(0.0019)	(0.0001)
9th	0.0276	-0.0009
	(0.0032)	(0.0002)
10th	0.0240	-0.0004
	(0.0052)	(0.0003)

Notes: Robust standard errors, clustered by job match, are given in parenthesis. The regression also includes 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend. The coefficients on job mobility and previous experience are not identified in the presence of a job match fixed effect.

Figure 4 exhibits the simulated returns to tenure in the current job (not purged of the returns to experience), based on the full model presented in Table 4. After 10 years in the first job it shown that wages increase by 23.7 percent, which compares with a wage increase of 37.4 percent using the base model. Returns to tenure decline in subsequent jobs; reaching, after ten years of job duration, 17.5 percent in the second job and 12.5 percent in the third job.

Figure 4: Returns to experience and tenure in the current job (full model)



Notes: The curves correspond to the returns to experience and tenure in the current job in the full model.

6 Decomposing the sources of heterogeneity

Tables 5A, 5B, and 5C show the changes in the regression coefficient estimates associated with the inclusion of worker, firm, and match quality fixed effects. A useful property of the Gelbach decomposition is that the changes in the coefficients associated with each fixed effect exactly sum to the difference between the base model estimates and the full model estimates.

From Table 5A it can seen that the returns to job mobility (given in the first column) are largely driven by improvements in match quality over a worker's career. There is also some evidence that job match heterogeneity biases upwards the returns to previous experience. Furthermore, the impact of match quality on the estimated returns to current tenure and experience is rather small, meaning that the absence of match quality does not contaminate the returns to current tenure and experience.

Table 5A: Gelbach decomposition, the impact of match quality

Job sequence	Accumulated	Previous experience		Current tenure	
	job changes	Linear term	Quadratic term	Linear term	Quadratic term
1st		0.0041	-0.0001	-0.0008	0.0000
		(0.0002)	(0.0000)	(0.0000)	(0.0000)
2nd	0.0940	0.0070	-0.0002	0.0012	0.0000
	(0.0006)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
3rd	0.1288	0.0063	-0.0003	0.0003	-0.0001
	(0.0008)	(0.0003)	(0.0000)	(0.0001)	(0.0000)
4th	0.1412	0.0053	-0.0002	0.0004	-0.0001
	(0.0011)	(0.0005)	(0.0000)	(0.0001)	(0.0000)
5th	0.1485	0.0046	-0.0002	-0.0014	0.0000
	(0.0016)	(0.0007)	(0.0000)	(0.0002)	(0.0000)
6th	0.1561	0.0061	-0.0003	-0.0022	0.0000
	(0.0023)	(0.001)	(0.0001)	(0.0004)	(0.0000)
7th	0.1496	0.0037	-0.0002	-0.0036	0.0000
	(0.0034)	(0.0015)	(0.0001)	(0.0007)	(0.0000)
8th	0.1496	0.0051	-0.0002	-0.0056	0.0000
	(0.0052)	(0.0023)	(0.0001)	(0.0011)	(0.0001)
9th	0.1433	-0.0024	-0.0001	-0.0117	0.0002
	(0.0077)	(0.004)	(0.0002)	(0.0019)	(0.0001)
10th	0.1818			-0.0096	-0.0001
	(0.0123)			(0.0031)	(0.0002)

Notes: The dependent variable is the match fixed effect computed in the full model. The regression also includes 9 education dummies, a gender dummy, (log of) firm size, (the log of) a linear time trend, and worker and firm fixed effects. Robust standard errors, clustered by job match, are given in parenthesis.

In Table 5B we show how the contribution of worker heterogeneity determines the returns to experience, tenure, and job mobility. Including a worker fixed effect significantly reduces the returns to previous experience, implying that higher returns to previous experience were hiding the fact that more experienced workers tend to be disproportionally more productive. Accordingly, the returns to experience and tenure are reduced by around the same magnitude, as can be seen by comparing the returns to current tenure and the returns to previous experience. The benefits from job mobility, at least early in the job career, do not seem to be significantly influenced by worker heterogeneity.

Table 5B: Gelbach decomposition, the impact of worker heterogeneity

Job sequence	Accumulated job changes	Previous experience Linear term	Previous experience Quadratic term	Current tenure Linear term	Current tenure Quadratic term
1st		0.0087	-0.0002	0.0093	-0.0001
		(0.0002)	(0.0000)	(0.0001)	(0.0000)
2nd	-0.0061	0.0071	-0.0001	0.0062	0.0000
	(0.0005)	(0.0003)	(0.0000)	(0.0001)	(0.0000)
3rd	-0.0086	0.0054	-0.0002	0.0055	0.0000
	(0.0008)	(0.0003)	(0.0000)	(0.0002)	(0.0000)
4th	-0.0071	0.0039	-0.0001	0.0054	0.0000
	(0.0011)	(0.0005)	(0.0000)	(0.0003)	(0.0000)
5th	-0.0016	0.0029	-0.0001	0.0042	0.0000
	(0.0015)	(0.0007)	(0.0000)	(0.0004)	(0.0000)
6th	0.0072	0.0021	0.0000	0.0035	0.0000
	(0.0022)	(0.001)	(0.0001)	(0.0006)	(0.0000)
7th	0.0178	0.0028	-0.0001	0.0039	-0.0001
	(0.0032)	(0.0013)	(0.0001)	(0.001)	(0.0001)
8th	0.0268	-0.0052	0.0002	0.0033	-0.0001
	(0.0045)	(0.0024)	(0.0002)	(0.0013)	(0.0001)
9th	0.0451	-0.0024	0.0001	0.0022	-0.0001
	(0.0064)	(0.0037)	(0.0002)	(0.0018)	(0.0001)
10th	0.0688			-0.0066	0.0003
	(0.0094)			(0.0027)	(0.0002)

Notes: The dependent variable is the worker fixed effect obtained from the match fixed effect regression (Table 5A). The regression also includes 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend. Robust standard errors, clustered by job match, are given in parenthesis.

For its part, Table 5C shows that sorting into better paying firms is a modest but significant component of the returns to mobility over the job career of worker. There is no evidence that firm heterogeneity plays a role in driving either the returns to experience or those to tenure.

Figure 5 exhibits a graphical representation of the contributions of worker, firm, and match quality heterogeneity to the gap in the regression coefficient estimates between the two models (Tables 5A to 5C). The usefulness of the Gelbach procedure is that is provides an unambiguous decomposition of the regression coefficient estimates, in terms of worker, firm, and match quality fixed effects. Expressed differently, the vertical sum of these three curves corresponds exactly to the base model. As suggested earlier, the most important component driving down the returns to job mobility and previous experience is match quality heterogeneity. The second most important component is worker heterogeneity,

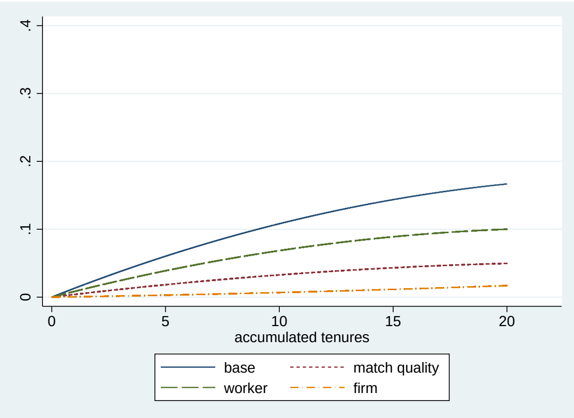
Table 5C: Gelbach decomposition, the impact of firm heterogeneity

Job sequence	Accumulated job changes	Previous experience Linear term	Previous experience Quadratic term	Current tenure Linear term	Current tenure Quadratic term
1st		0.0005	0.0000	0.0035	0.0000
		(0.0002)	(0.0000)	(0.0001)	(0.0000)
2nd	0.0276	0.0009	0.0000	0.0023	0.0000
	(0.0005)	(0.0002)	(0.0000)	(0.0001)	(0.0000)
3rd	0.0414	0.0011	0.0000	0.0013	0.0000
	(0.0007)	(0.0003)	(0.0000)	(0.0001)	(0.0000)
4th	0.0529	0.0015	-0.0001	0.0005	0.0000
	(0.001)	(0.0005)	(0.0000)	(0.0002)	(0.0000)
5th	0.0620	0.0016	-0.0001	-0.0001	0.0000
	(0.0015)	(0.0007)	(0.0000)	(0.0003)	(0.0000)
6th	0.0717	-0.0005	0.0000	-0.0005	0.0000
	(0.0024)	(0.0011)	(0.0001)	(0.0005)	(0.0000)
7th	0.0916	0.0021	-0.0002	-0.0020	0.0000
	(0.0036)	(0.0017)	(0.0001)	(0.0009)	(0.0000)
8th	0.1025	-0.0079	0.0002	-0.0032	0.0000
	(0.0055)	(0.0028)	(0.0002)	(0.0014)	(0.0001)
9th	0.1378	-0.0040	-0.0001	-0.0041	0.0000
	(0.0083)	(0.0047)	(0.0002)	(0.0022)	(0.0001)
10th	0.1516			-0.0020	0.0001
	(0.0130)			(0.0037)	(0.0002)

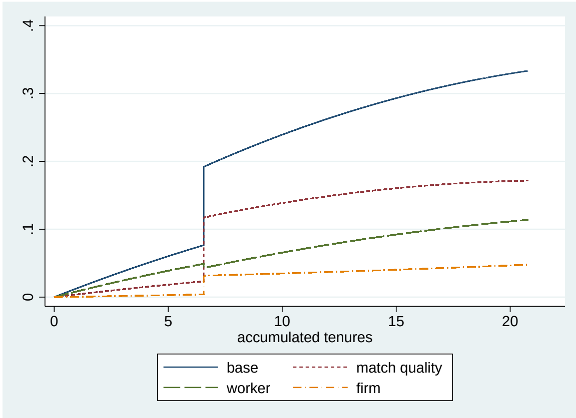
Notes: The dependent variable is the firm fixed effect obtained from the match fixed effect regression (Table 5A). The regression also includes 9 education dummies, a gender dummy, (log of) firm size and (the log of) a linear time trend. All the coefficient estimates are statistically significant at 1% level or better. Robust standard errors, clustered by job match, are given in parenthesis.

which is evidence of worker quality compositional bias.

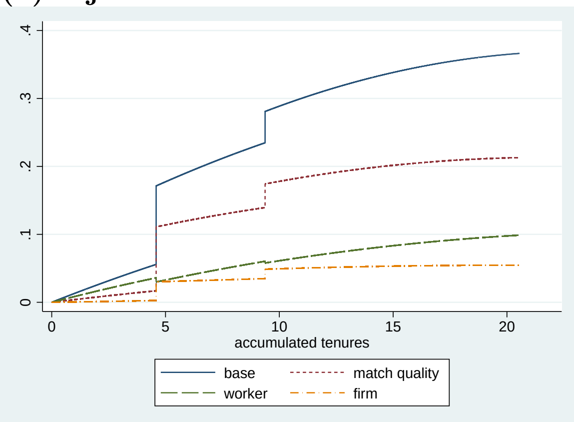
Figure 5: Gelbach decomposition of the returns to job mobility and returns to experience in previous jobs



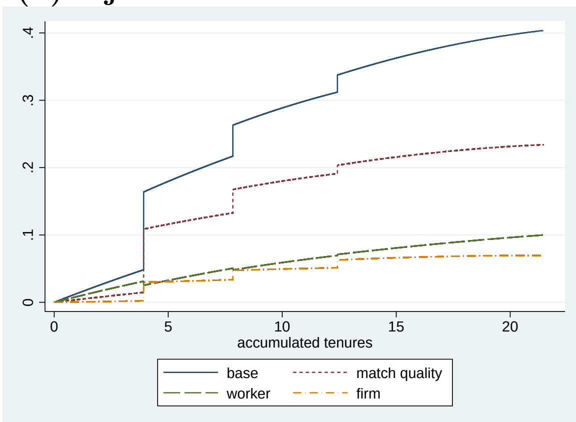
(a) 1 job



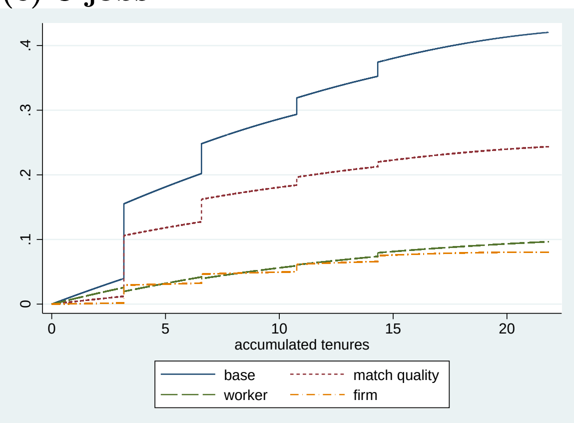
(b) 2 jobs



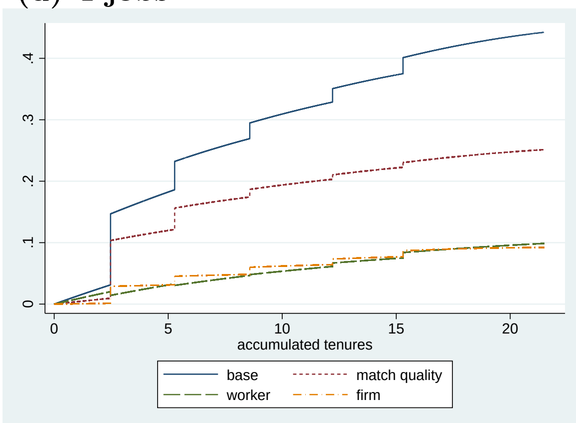
(c) 3 jobs



(d) 4 jobs



(e) 5 jobs



(f) 6 jobs

Notes: The panels show how the difference between the returns to experience and job mobility in previous jobs between the full and the base model are decomposed into worker heterogeneity, firm heterogeneity and match quality heterogeneity. Spikes in earnings are located at the end of each (average) job duration.

Finally, Figure 6 depicts our estimates of the returns to tenure (purged of the returns to previous experience). We obtain these estimates by subtracting from the returns to current tenure in the full model (Table 4) the bias-corrected returns to previous experience. In the latter we filter the returns to previous experience in the base model (Table 2) by removing the impacts of match quality (Table 5A) and worker heterogeneity (Table 5B).[5] For example, we compute the estimate of the linear term of the return to tenure in the first job (0.0302) by subtracting 0.0005 from 0.0307. To obtain the subtrahend we filter the returns to previous experience in the base model (0.0133) by removing the impacts of match quality (0.0041) and worker heterogeneity (0.0087). Now this approach, depends critically on our orthogonality assumption, but in our view provides a useful approximation to Equation (5) in Topel (1991). A general implication of this methodology is that the returns to previous experience are very small, leading to higher returns to job tenure.

In this study, we have identified a number of important sources of upward bias in the returns to previous experience: the role of job mobility; the presence of unobserved worker heterogeneity; and the sorting across jobs with distinct match quality.

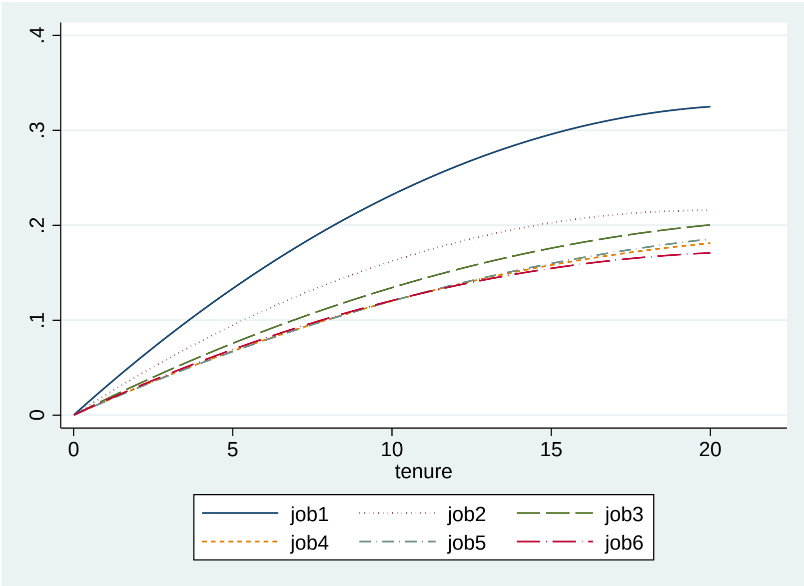
After 10 years in the first job, it is shown that wages increase by 22.8 percent. This compares with a wage increase of 23.3 percent using the base model. For their part, returns to tenure decline in subsequent jobs; reaching, after ten years of job duration, 16.6 percent in the second job and 12.8 percent in the third job.

7 Alternative regression model specifications

In a final application, we offer two robustness checks. The first is based on a comparison of the wage effects of direct transitions between jobs, that are more likely to be associated with employer poaching, with those from job moves intermediated by a spell of joblessness. The second, more conventional robustness check, centers on the experience and tenure-earnings profiles generated by our own model versus those of the four dominant methodologies deployed in the literature.

[5] Under our running assumptions, the Gelbach decomposition implies that this estimate is equivalent to substracting the firm component in the return to previous experience from the return to current tenure in the full model.

Figure 6: Bias-corrected returns to tenure in the current job



Notes: The curves correspond to the bias-corrected returns to tenure in a sequence of jobs. The returns to tenure are obtained by subtracting from the returns to experience and tenure in the full model the bias-corrected returns to previous experience.

7.1 On the role of job-to-job transitions

Table 6 provides for distinct wage effects of the two different types of job transition. It is comparable with our base model presented in Table 2, the difference residing in the use of job mobility interaction terms. A specific result is that moving into a second job leads to a wage increase of 11.5 percent (or 10.88 log points) where there is an intervening spell of joblessness but to an increase of 13.9 percent (13.04 log points) in the case of direct transitions. More generally, the findings of Table 6 are threefold. Firstly, irrespective of the type of job move, there is always a wage gain whenever the worker changes his/her job. Secondly, that wage gain is always greater for direct job-to-job transitions. Finally, a comparison with Table 2 reveals that the regression coefficient estimates for previous experience and current tenure are not materially disturbed by the inclusion of the job mobility interaction terms.

Table 6: Wage regression based on work histories (additional gain from job-to-job)

Job sequence	Accumulated job changes		Previous experience		Current tenure	
	from joblessness	additional gain from job to job	Linear term	Quadratic term	Linear term	Quadratic term
1st			0.0125	-0.0002	0.0425	-0.0008
			(0.0003)	(0.0000)	(0.0001)	(0.0000)
2nd	0.1088	0.0216	0.0147	-0.0004	0.0322	-0.0006
	(0.0008)	(0.0008)	(0.0004)	(0.0000)	(0.0002)	(0.0000)
3rd	0.1466	0.0494	0.0117	-0.0004	0.0245	-0.0005
	(0.0013)	(0.0014)	(0.0005)	(0.0000)	(0.0003)	(0.0000)
4th	0.1628	0.0808	0.0092	-0.0003	0.0218	-0.0005
	(0.0019)	(0.0024)	(0.0008)	(0.0000)	(0.0004)	(0.0000)
5h	0.1744	0.1068	0.0070	-0.0003	0.0176	-0.0004
	(0.0028)	(0.004)	(0.0012)	(0.0001)	(0.0007)	(0.0000)
6th	0.1893	0.1320	0.0055	-0.0003	0.0139	-0.0004
	(0.0041)	(0.007)	(0.0018)	(0.0001)	(0.001)	(0.0001)
7th	0.2008	0.1388	0.0062	-0.0004	0.0136	-0.0005
	(0.0062)	(0.0117)	(0.0026)	(0.0001)	(0.0017)	(0.0001)
8th	0.2076	0.1971	-0.0101	0.0003	0.0108	-0.0005
	(0.009)	(0.0214)	(0.0039)	(0.0002)	(0.0025)	(0.0001)
9th	0.2406	0.1941	-0.0106	0.0000	0.0120	-0.0007
	(0.0129)	(0.043)	(0.0072)	(0.0003)	(0.0037)	(0.0002)
10th	0.2997	0.1383			0.0039	-0.0001
	(0.0208)	(0.0972)			(0.0060)	(0.0003)

Notes: Robust standard errors, clustered by job match, are given in parenthesis. The regression also includes 9 education dummies, a gender dummy, (log of) firm size and (the log of) a linear time trend.

7.2 Alternative methods of obtaining the tenure and experience wage profiles

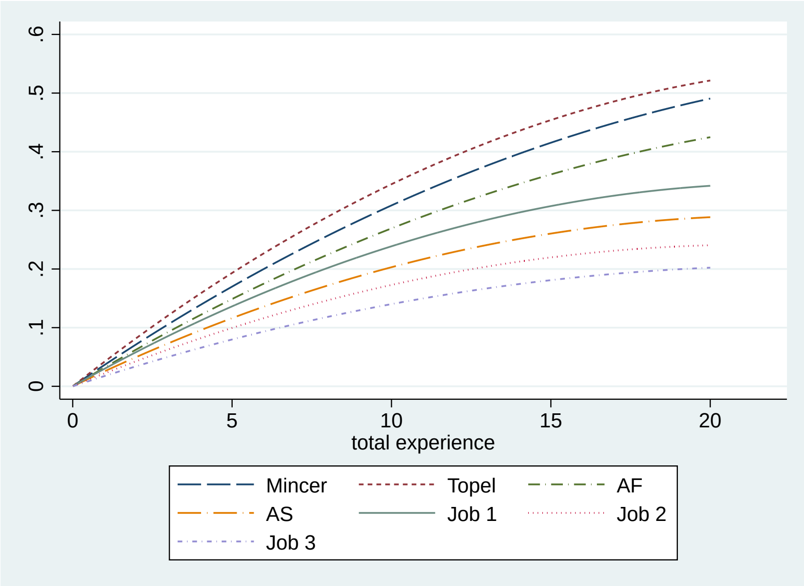
We next compare the tenure-earnings and experience earnings profiles generated by our own approach with four of the research methodologies identified in Section 2; namely, the conventional Mincerian approach and those of Topel (1991), Altonji and Shakotko [AS] (1987), and Abraham and Farber [AF] (1987).[6]

In all regressions we use previous experience and its square, tenure and its square, 9 education dummies, a gender dummy, (log of) firm size, and (log of) a linear time trend. In the case of the benchmark Mincer wage regression, there are no fixed effects (match, worker, or firm) to account for unobserved heterogeneity. In the case of the Topel specification, the joint return to tenure and experience arises from a regression model that includes a job match fixed effect, whereas the estimate of the returns to previous experience is obtained from an OLS estimator with no controls for unobserved heterogeneity. In the case of Abraham and Farber (1987), we use completed tenure for completed job spells; and, for incomplete job spells, we predict completed tenure using a truncated exponential mean. As before, there are no controls for unobserved heterogeneity to obtain the estimates of the returns to tenure and experience. Finally, in the case of Altonji and Shakotko (1987), we use the deviation of a worker's tenure from average tenure at the firm as an instrument for tenure. In this approach, worker fixed effects are included in the instrumental variable regression. In our case, we control for job match heterogeneity in the estimation of the joint returns to tenure and experience (as in Topel, 1991) and we obtain a bias-corrected estimate of the returns to previous experience by removing the effects of worker and match quality heterogeneity.[7]

[6]Note that in this exercise we do not employ the methodology of Snell et al. (2018) because in a wage regression that includes a match fixed effect and a firm/year fixed effect the joint return to experience and tenure cannot, by construction, be identified. Specifically, there is no within (job match) variation that would enable the observer to disentangle this effect from the time effects that are present in the firm/year fixed effects. This lack of identification can be demonstrated by simply noting that, within a job match, the tenure and the experience variables (which corresponds to linear time trends) can be defined as a linear combination of firm/year dummies.

[7]Alternatively, we also estimated the returns to previous experience using a worker fixed effect wage regression model. In order to obtain the corresponding alternative measure of the returns to tenure, we subtracted these new estimates from the returns to experience and tenure. In the Appendix, we provide a graphical representation of the returns to tenure (Figure A.1). As can be seen, the two methodologies provide comparable wage tenure profiles, suggesting that match quality heterogeneity does not severely

Figure 7: Returns to experience and tenure using different established methodologies



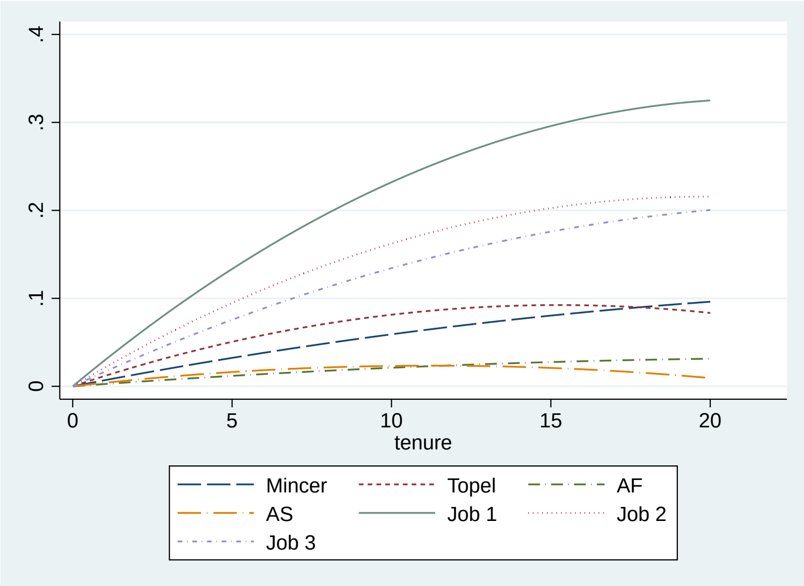
Notes: The figure gives a comparison of the returns to tenure and experience according to 5 different methodologies. Job 1 (Job 2 and Job 3) represents the returns to tenure and experience in the 1st job (2nd and 3rd jobs) from Figure 4. *Mincer* refers to the returns to tenure using a Mincerian specification. *Topel* refers to the returns to tenure and experience using Topel (1991), *AF* refers to the returns to tenure using Abraham and Farber (1987), and *AS* to the returns to tenure using Altonji and Shakotko (1987). All specifications include 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend.

Figure 7 illustrates the tenure and experience earnings profiles associated with each of the alternative methodologies. The approaches of *Topel* and *AF* produce high returns to tenure and experience (close to the canonical *Mincer* regression). On the other hand, our own estimates of the returns to experience are much lower than those implied by the *Mincer* wage regression. The main driver of our lower returns arise from the fact that we are controlling for job mobility.

Figure 8 gives the corresponding tenure earnings profiles; comparing our own depiction of the returns to tenure in jobs 1 through 3 (taken from Figure 4) with those generated from the *Mincerian*, *Topel*, *AF*, and *AS* specifications. It is apparent that the approaches of *AS* and *AF* provide very low estimates of the returns to tenure. This finding is in sharp contrast with our own estimates, which in turn imply that the returns to tenure exceed those being reported by the *Mincerian* benchmark. Furthermore, as we have seen, the returns to tenure start high on the first job and subsequently decline in later jobs.

bias the returns to previous experience.

Figure 8: Returns to tenure using different established methodologies



Notes: The figure gives a comparison of the returns to tenure according to 5 different methodologies. Job 1 (Job 2 and Job 3) represents the returns to tenure in the 1st job (2nd and 3rd jobs) from Figure 4. *Mincer* refers to the returns to tenure using a Mincerian specification. *Topel* refers to the returns to tenure using Topel (1991), *AF* refers to the returns to tenure using Abraham and Farber (1987), and *AS* to the returns to tenure using Altonji and Shakotko (1987). All specifications include 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend.

The main reason why our returns to job tenure are high is, of course, because our returns to previous experience are low. There are three reasons for the latter result. Firstly, as hinted above, the returns to experience no longer incorporate the benefits of job mobility. Secondly, they are not biased by the fact that over the life-cycle workers tend to sort themselves into better-paying job matches. Finally, they are not biased by the presence of worker unobserved heterogeneity.

8 Conclusions

In this paper we have expanded the canonical Mincer regression model to allow for heterogeneous returns to job mobility, labor market experience, and firm tenure across the sequence of jobs held over the worker's career. To this end, we employ an unusually rich matched employer-employee dataset that allows us to track all private-sector wage earners born after 1956 if they are observed in their first year in their first job in our longitudinal survey. We then followed workers from their first job up to, possibly, their tenth job.

Consistent with Topel and Ward (1992) and Murphy and Welch (1992), we report that job changes are important drivers of wage growth, particularly during the early career stage of the worker. We also show that the returns to job mobility tend to decline over the sequence of jobs, suggesting that the opportunity to improve the quality of the job becomes narrower whenever a worker finds a better job. Similarly, and probably for the same reason, the returns to tenure decline over the sequence of jobs.

In our approach, returns to experience are conspicuously low once we account for job mobility, worker heterogeneity, and match quality. Consequently, the returns to job tenure (those purged of the returns to experience) are high, and indeed significantly higher than those obtained by alternative methodologies. These returns may reflect investment in specific training or, in line with search theory, by reason of discrete wage changes in response to outside wage offers. It should, however, be borne in mind that our results rely crucially on the assumption of conditional orthogonality between the match quality fixed effects and the worker and firm fixed effects. An important implication of this identification strategy was that that we were able unambiguously to determine whether sorting into good matches spuriously contaminates the return to current tenure. Our evidence is that the inclusion of a job match fixed effect reduces trivially the return to 10 years of tenure in the first job from 23.3 to 22.8 percent.

The decomposition exercise gave information on how worker, firm, and match quality heterogeneity influence the returns to job mobility, experience, and tenure. We learned that the returns to job mobility largely reflect sorting into better job matches and only partially reflect sorting into firms offering more generous wage policies. We also found that the estimated returns to experience are upwardly biased because more productive workers (with higher worker fixed effects) tend to be more experienced. However, none of the three components of the job match fixed effect evinced any clear impact on the returns to tenure.

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Appendix

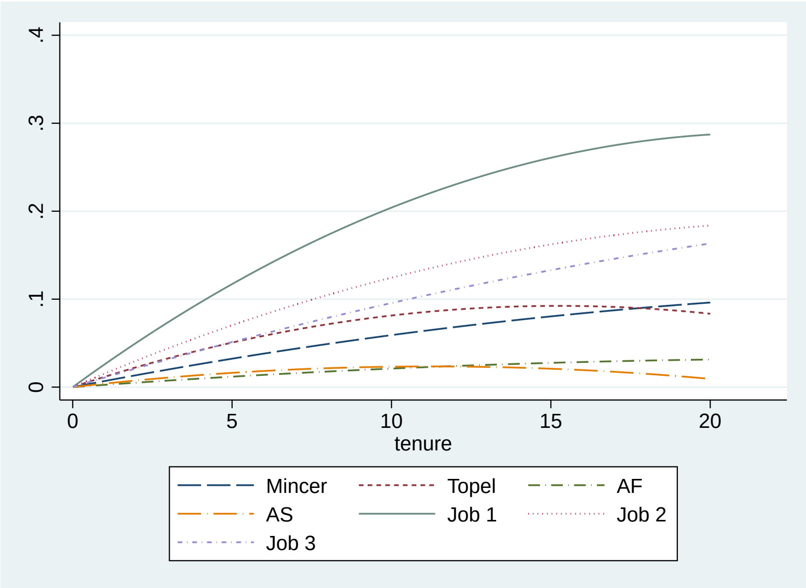
Table A.1: Descriptive statistics

Variables	Means
Total monthly wages (2020 euros)	1071.52
Job to job (%)	20.39
Age (in years)	32.64
Tenure (in years)	5.77
Female (%)	43.22
Education (%)	
Less than basic school	0.61
Basic school	13.73
Preparatory	19.28
Lower secondary	25.48
Upper secondary	27.2
Pos-Secondary non bachelor	0.37
Bachelor - 3 years	1.71
Bachelor - 3 years	10.54
Master	1.02
PhD	0.05
Firm size (no. coworkers)	363.28
Industry (%)	
Manufacturing	28.87
Construction	10.6
Wholesale and retail trade	32.92
Transports	6.13
Financial services	12.11
Education/health	9.36
Observations	15,573,251

Table A.2: First job for each worker by year

Year	N	%
1986	71660	3.43
1987	74539	3.57
1988	80888	3.87
1989	89194	4.27
1991	70418	3.37
1992	62419	2.99
1993	52967	2.54
1994	51446	2.46
1995	53909	2.58
1996	53045	2.54
1997	57337	2.74
1998	61506	2.94
1999	58587	2.80
2000	58983	2.82
2002	65069	3.11
2003	55280	2.65
2004	58613	2.81
2005	74198	3.55
2006	69709	3.34
2007	76945	3.68
2008	78325	3.75
2009	57947	2.77
2010	64837	3.10
2011	56729	2.72
2012	41787	2.00
2013	44609	2.14
2014	49573	2.37
2015	63791	3.05
2016	61758	2.96
2017	68889	3.30
2018	74070	3.55
2019	82245	3.94
2020	47815	2.29
Observations	2,089,087	

Figure A.1: Alternative estimates of the returns to tenure



Notes: The figure gives a comparison of the returns to tenure according to 5 different methodologies. Job 1 (Job 2 and Job 3) represents the returns to tenure in the 1st job (2nd and 3rd jobs) using the methodology described in footnote 7. *Mincer* refers to the returns to tenure using a Mincerian specification. *Topel* refers to the returns to tenure using Topel (1991), *AF* refers to the returns to tenure using Abraham and Farber (1987), and *AS* to the returns to tenure using Altonji and Shakotko (1987). All specifications include 9 education dummies, a gender dummy, (log of) firm size, and (the log of) a linear time trend.