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WAGE RETURNS TO EXPERIENCE AND TENURE FOR YOUNG MEN IN ITALY

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WORKING PAPERS

2009/03

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Titolo: WAGE RETURNS TO EXPERIENCE AND TENURE FOR YOUNG MEN IN ITALY

ISBN: 978-88-8467-514-9

Prima Edizione: Maggio 2009
Seconda Edizione: Novembre 2012
Terza Edizione: Dicembre 2013

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www.cuec.it

Wage Returns to Experience and Tenure for Young Men in Italy*

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Abstract

This paper provides estimates of wage returns to experience, firm, sector and occupation specific tenure for a sample of young Italian male workers. By comparing returns obtained using different estimators, I evaluate the importance of endogeneity and selection problems generated by specific unobserved components and individual fixed effects. After controlling for the role of collective bargaining agreements and occupation categories, results indicate that general labour market experience is the fundamental source of wage growth for blue and white collars, while returns to firm tenure are insignificant. There is some evidence of positive returns to sector and occupational tenure for white collars. Estimates from different sectors suggest that union coverage can be relevant in offsetting the role of search and matching in wage determination.

Keywords: Wages, Skills, Search, Endogeneity, Unions, Italy.

JEL Classification: J24, J31, J62.

*This paper is based on Chapter 3 of my PhD dissertation at the University of Essex, UK. I would like to thank my supervisors Melvyn Coles and Amanda Gosling for help and guidance, and Michele Belot and Barbara Petrongolo for suggestions and comments. Thanks to Francesco Devicienti, Emanuela Marrocu, Fabiano Schivardi and two anonymous referees for further suggestions that substantially improved the paper, and to Emiliano Rustichelli for data explanations. I also thank Alessia Matano and Paolo Naticchioni for giving me access to data on national bargaining agreements and occupational categories. Thanks to participants at the VIII Brucchi Luchino Workshop, at the Conference of the Italian Association of Labour Economists, at the Annual Conference of the Society of Italian Economists. Part of this paper has been revised while I was visiting the Department of Economics at the University of Edinburgh, I wish to thank that institution for its hospitality. I am solely responsible for all errors and misinterpretations.

I. Introduction

The analysis of labour market transitions, employment duration and wage growth has received renewed attention in recent years. In particular, this line of research investigates the effect of labour market experience and specific tenure on wages. This is not surprising, as correctly estimating true returns to skills accumulated in the labour market is fundamental for the analysis of wage dispersion and its evolution over time.[1] Furthermore, different theoretical models answer the question of why wages grow as experience and tenure accumulate, resulting in the concave profile observed in the data. Human capital accumulation as individual investment in job specific skills (Becker, 1964), theories of deferred compensation as incentive mechanism (Lazear, 1981), and search and matching models (Burdett, 1978; Jovanovic, 1979) are all able to explain these empirical stylised facts.

Studying the returns to general and specific skills in the labour market therefore turns out to be important for a number of reasons. Firstly, it gives a picture of the overall individual wage growth over the life-cycle, with implications for individual well-being and for the wage distribution (Farber, 1999). It is also a good discriminating test of human capital and search models and their implications in terms of accumulation (and loss) of human and search capital. Finally, the slope of wage profiles varies across countries with different institutional and wage bargaining environments, and this has various implications for labour mobility and rent sharing (Teulings and Hartog, 1998).

However, correctly estimating wage returns to skills is not an easy task. Standard OLS estimates are biased due to endogeneity and omitted variable problems, and the direction of such bias is *ex ante* ambiguous. Hence, a large literature has developed proposing different estimators to solve such endogeneity problems and/or including in the analysis previously omitted variables.[2]

[1]The first wave of studies were focused on the US, see Mincer and Jovanovic (1981), Abraham and Farber (1987), Altonji and Shakotko (1987), and Topel (1991). Nowadays, recent contributions propose methodological advances (Buchinsky et al., 2010) or offer evidence on European countries, or both: see Altonji and Williams (2005), Dustmann and Meghir (2005) and Beffy et al. (2006).

[2]Needless to say, no estimator is completely unbiased, hence most of this literature focuses on comparison of different

Altonji and Shakotko (1987) instrument firm tenure using deviations of tenure from the job-match mean, thus controlling for both unobserved individual and match specific effects which are correlated with tenure and experience. In turn, the two-step estimation methodology proposed by Topel (1991) uses an identification strategy partially based on job changes, as movers have zero tenure and different levels of experience. This technique is not beyond criticism, as job movers are selected in new jobs on the basis of their past choices, thus not entirely solving the endogeneity concern. To overcome that problem, Dustmann and Meghir (2005) identify returns to experience and tenure using a sample of displaced workers. The intuition behind their identification strategy is that displaced workers can be considered as a random sample of the population, as their status is not conditioned by their past choices, but it is assumed to be substantially exogenous.

Neal (1995) also uses a sample of displaced workers as a source of identification in the estimation of returns to industry-specific tenure, a variable that was previously omitted in standard wage equations. In his paper, exogenous displacement allows him to compare workers with the same level of firm tenure but different levels of sector-specific skills. Similarly, by using deviations from the individual and job means as instruments for experience, firm- and sector-tenure, Parent (2000) confirms that considering skills that are neither firm specific nor completely general strongly reduces wage returns to experience and tenure.

More recently, a new strand of literature includes occupational tenure in wage regressions, thus explicitly considering the skills needed to perform tasks in a particular occupation, which are transferable across jobs and sectors. Kambourov and Manovskii (2009) and Zangelidis (2008a) convincingly show that, after including occupational tenure, wage returns to firm and sector tenure lose their capacity to explain wage growth. These results hold in decentralised labour markets, characterised by high labour mobility and large returns to specific skills, such as the US and the UK.

In this paper, I estimate the average returns to experience, firm, sector and occupation

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estimators or comparison of the same estimator in different contexts, or both.

specific tenure on a sample of young Italian male workers. In this context, I explicitly take into account the role of unions and national bargaining agreements on wage growth.[3] Wage returns to skills are identified using the instrumental variables methods proposed by Altonji and Shakotko (1987) and subsequently used in various other studies in this field. I also combine that estimator with additional information on displaced workers in the spirit of Dustmann and Meghir (2005). In fact, exogenous displacement is a further source of exogenous variation that may help to correct the potential bias present in the instrumental variable estimator.

The paper contributes to the literature in two main directions. First, by using Italian data, I illustrate how the institutional features of the labour market can influence accumulation of human capital and search behaviour, and consequently wages. In fact, most of this literature focuses on the US, with only recent evidence for the UK or few other countries in Europe.[4] Hence, Italy can be an interesting case to study, as the labour market is characterised by persistent heterogeneity in union coverage across sectors and by high Employment Protection Legislation (EPL). Moreover, to the best of my knowledge, this is the first paper that studies the role of occupational tenure in a highly unionised labour market.[5] Second, I compare results obtained with IV and panel methodologies to analyse the relative importance of omitted variable bias and reverse causality on the bias present in

[3]Card et al (2013) and Matano and Naticchioni (2013) use information from national contractual agreements in the same dataset used in this study to analyse the importance of rent sharing in Italy. Torres et al (2013) include in their regression model dummies for national contractual agreements and detailed occupation categories within each national contract to study the sources of wage variability in Portugal.

[4]Dustmann and Pereira (2008) find that returns to experience are substantially lower in countries in which firing restrictions are more stringent (Germany) and where labour market institutions reduce the importance of search for wage growth. In the UK, where firing and hiring restrictions are less stringent, the presence of unions reduces returns to experience and increases returns to tenure (see Zangelidis, 2008b and Williams, 2009). Beffy et al (2006) show that returns to firm tenure are very small and insignificant in France.

[5]Cingano (2003) conducts a similar exercise on two Northern Italian provinces, although the focus of his paper is on the returns to district-specific skills.

OLS estimates and analyse in detail the quality of instruments, which is something substantially neglected in this literature.

I use a rich panel data set extracted from the Italian Administrative Social Security Archive (INPS) for the period 1985-2003. The data provides detailed information about the labour market histories of workers employed in the private sector and also information about their employers. I extract a subsample of very young workers (younger than 25 at entry) to study wage growth in the early stages of their careers, as it is in this period that most of the lifetime wage increases take place, limiting my attention to male workers and separating the analysis for blue and white collars.

Results indicate that general labour market experience is the fundamental source of wage growth for both blue and white collars, with a large degree of heterogeneity in returns across sectors. However, returns to experience are substantially reduced after controlling for national bargaining agreements and occupations. In fact, part of returns for white collars can be attributed to sector and occupation specific skills, especially in less unionised sectors. Positive returns to firm tenure are found only for a small group of blue collars in highly unionised sectors. A series of tests for identification confirms the quality of the instruments, and suggests that unobserved components and search behaviour play an important role in explaining wage growth. However, such role is partially offset by centralised bargaining, which reduces mobility and compresses the wage distribution, with less incentives for firms to offer steep wage-tenure profiles.

The rest of the paper is organised as follows. In Section 2 I discuss the econometric framework, focusing on identification and estimation issues. Section 3 presents the data with a short descriptive analysis of mobility. The main results are illustrated in Section 4, while Section 5 concludes.

II. Econometric Framework

II.1 Wage Equation

An intuitive interpretation of the coefficients of experience and firm tenure in wage regressions is that the former proxies the accumulation of skills that are perfectly transferable across jobs, while

the latter proxies the accumulation of skills that are rewarded on the job but are not transferable across different jobs.

However, standard OLS estimates of wage equations which include experience and tenure among regressors provide biased estimates of returns to general and specific skills. In fact, comparing workers with different levels of accumulated skills results in biased estimates for several reasons. As Altonji and Williams (2005) discuss, differences in levels of experience and tenure can be determined by the fact that workers who have been in the labour market for longer are located in better matches and have accumulated more skills. On the other hand, the underlying heterogeneity in the population of workers generates an additional source of endogeneity: high ability workers are likely to have a stronger labour market attachment and hence more experience and tenure.[6] Similar arguments apply when sector and occupational tenure are included in wage regressions as additional sources of skill accumulation on wage growth.

To identify the sources of bias, I briefly present the econometric framework discussed by Altonji and Williams (2005), and subsequently extended by Parent (2000) to consider sector tenure and by Kambourov and Manovskii (2009) to take into account occupational tenure. I consider the following wage equation:

$$\ln w_{ijsot} = \beta_0 + \beta_1 Exp_{it} + \beta_2 Ten_{ijt} + \beta_3 Ind_{ist} + \beta_4 Occ_{iot} + \varepsilon_{it},$$

where $\ln w_{ijsot}$ is the natural logarithm of real wage for worker i, working at firm j, in sector s, in occupation o in period t. Exp, Ten, Ind and Occ denote total labour market experience, firm, sector and occupation specific tenure respectively, and ε_{it} is the error term.[7] The latter can be decomposed as

$$\varepsilon_{it} = \mu_i + \phi_{ij} + \vartheta_{is} + \omega_{io} + u_{it}.$$

[6]An additional source of bias in returns to experience is that workers with higher returns to experience are likely to spend less time out of the market because the opportunity cost of not working is higher (Dustmann and Meghir, 2005).

[7]To ease exposition, I do not include other control variables or nonlinear terms for experience and specific tenure terms.

The first component (μ_i) is an individual specific fixed effect, ϕ_{ij} is a unobserved job-match specific error component, ϑ_{is} is a sector-match specific component, ω_{io} is an occupation-match component, while u_{it} represents measurement error in wages.

The key parameters to be estimated are β_1, β_2, β_3, and β_4, respectively the effect of an additional year of experience, firm, sector and occupation tenure on wages. However, as the individual and the other unobserved components in the error term are correlated with experience and other measures of specific tenure, endogeneity is likely to be an issue and OLS estimates are biased and inconsistent.

Essentially, job match-specific heterogeneity ϕ_{ij} is positively correlated with experience, due to job shopping effects induced by search and matching behaviour of workers. Moreover, the correlation of the job match-specific component with tenure is ambiguous. If workers and firms share the rents from the match, then there is a positive correlation between tenure and the job match-specific component, as the latter is inversely correlated to the probability of a layoff . In turn, if there is selection due to voluntary quits, the correlation of the match-specific component with tenure is negative (Topel, 1991).

On the other hand, the individual specific component μ_i is likely to be positively related to tenure as high productivity workers have lower quit and layoff propensities and then higher tenure, which determines an upward bias in returns to tenure.[8] However, as Williams (2009) notes, in strongly unionised markets, the correlation between individual and job match components and tenure can be small or negative, as high ability workers have no incentive to work in sectors with a very compressed wage distribution resulting in a smaller relative ability bias for workers employed in such sectors.

[8]Altonji and Williams (2005) argue that, conditioning on observables, worker quality is independent from year of birth and low and high wage workers have similar labour market attachment, hence the correlation between individual fixed effects and experience is negative.

A similar argument applies to the correlation of sector and occupation match-specific components and the respective tenure variables. In fact, a worker in a good sectoral or occupational match is more likely to be earning high wages and to accumulate more tenure in that sector or occupation. Moreover, when including sector and occupational tenure in the analysis, an additional bias arises. In fact, both sector and occupational tenure are correlated with the specific job-match component. As long as sector and occupational tenure are correlated with firm tenure due to job shopping effects (more sector/occupational tenure helps to find a better match in that sector/occupation), the estimates of sector and occupational tenure are upward biased and wage returns to firm tenure are biased down.

The discussion above suggests that the bias in OLS estimates depends on search behaviour of workers and their allocation across sectors and occupations of the economy. Still, the direction of the bias for experience is ambiguous, because the correlation of experience with the job match component and with individual heterogeneity go in opposite directions (Altonji and Williams, 2005). For tenure, the bias deriving from individual heterogeneity can be positive or negative, and the effect of job match heterogeneity can reinforce or offset the previous one. What is more, if the labour market is characterised by strong union coverage, with predetermined wage policies, the correlation between individual ability and tenure can be zero or negative, resulting in a downward bias for OLS estimates. Finally, the correlations of individual and job match components with sector and occupational tenure will also bias the coefficients of interest.

II.2 Identification Strategy

As I further discuss below, there are two sources of endogeneity: one is reverse causality between experience and various measures of tenure and wages, the second is an omitted variable problem. To identify returns to experience and different measures of specific tenure I use an instrumental variable approach, by making use of two sets of excluded instruments. The first set of instruments is constructed using deviations of experience, firm, sector and occupational tenure from their specific means, while the second set comprises a dummy that equals one if the worker has been previously

displaced due to firm closure.[9] Squared terms are also instrumented using the same method.[10]

As the instrument for firm tenure has zero mean within each job, it is not correlated with the individual and job match components. However, this instrument doesn't take into account the correlation between the job match component and labour market experience: if such correlation is positive, returns to tenure are downward biased while returns to experience are upward biased. The problem is not solved when instrumenting experience using deviations from the individual means, as this instrument takes into account only the correlation of experience with the individual fixed effect. Hence, the bias in returns to experience and the downward bias in returns to tenure persist. Similarly, instruments for sector and occupational tenure do not take into account the possible correlation between such tenure variables and the other non-own match specific components.[11]

In this framework, separately identifying returns to general and specific skills requires mobility across jobs, sectors and occupations. Conditional on experience, changes of job, sector and occupation allow me to compare workers with different levels of experience and with the same level of specific tenure.[12] If job mobility is random, then assignment of workers to jobs doesn't generate any additional selection problems and the sample of job movers could be used to jointly estimate returns to specific skills and experience. However, if mobility is not a random process, but rather the result of previous optimal matching decisions of workers, then mobility can be correlated with the idiosyncratic components of the error term. Hence, conditional on observables, some exogenous variation for identification is needed. The problem can be addressed by making

[9]The first set of instruments was proposed by Altonji and Shakotko (1987) and used by Dustmann and Pereira (2008), Zangelidis (2008a, 2008b), Kambourov and Manovskii (2009) and Williams (2009). The use of displaced workers as identification strategy can be found in Neal (1995), Dustmann and Meghir (2005) and Cingano (2003).

[10]For example, the instrument for tenure is defined as $\widetilde{T}_{ijt} = T_{ijt} - \overline{T}_{ij}$ where $\overline{T}_{ij}$ is average tenure over the duration of the job. When squared terms are added, instruments are $(\widetilde{T}_{ijt})^2 = T_{ijt}^2 - \overline{(T_{ij})^2}$.

[11]Kambourov and Manovskii (2009) discuss in detail such correlations and conclude they should be not very relevant.

[12]This identification strategy partially based on job changes is proposed by Topel (1991).

distributional assumptions on the error term and by finding exclusion restrictions. Exogenous displacement following plant closure can satisfy both conditions for identification. First, the instrument should be related to the endogenous variables: as long as mobility is correlated with experience and specific tenure variables, this is a relevant instrument. Second, it should not be correlated with the idiosyncratic part of the error term, thus being a valid exclusion restriction. The identification assumption is that, conditional on observables, exogenous displacement doesn't affect wages directly and workers accept the first job they are offered.[13]

II.3 Estimation Method

There are different strategies to deal with endogeneity. The availability of panel data allows me to deal with individual fixed effects and solve the ability bias problem, while instrumental variables regressions help to deal with the covariance of experience and specific tenure variables with other components of the error term and solve the reverse causality problem. Finally, the Hausman-Taylor (1981) estimator can help to obtain estimates of the parameters of interest.

I use five different estimators to obtain estimates of wage returns to experience and specific tenure and to identify the role of endogeneity bias. As a benchmark comparison I report OLS estimates, then I estimate models with individual fixed effects by using panel data (FE). Instrumental variables 2SLS regressions in the cross section (IV) are then followed by within 2SLS regressions with individual fixed effects (FE IV), finally I report estimates for the Hausman-Taylor (HT) estimator.[14]

III. Data

III.1 Description of the Sample

I use a 1:90 random sample of workers obtained from the Italian Social Security Institute (INPS)

[13]I conduct some tests on this excluded instrument and test if the displacement dummy is significant in OLS regressions. It turns out that it is not significant, while it is strongly significant in reduced forms of IV regressions.

[14]Note that both the between and the random effects IV estimators are inconsistent when the covariance between the instruments and individual fixed effects is different from zero.

and representative of the population of employed workers in the private sector (self-employed and public sector workers are registered in different social security archives). Data are available from 1985 to 2003. As in other matched employer-employee data sets, each worker and each firm are identified by their own specific codes during the permanence in the administrative files. When a worker-firm match is created, a new string is generated resulting from the firm and worker's codes. If the match is destroyed, the worker and the firm continue to maintain their previous codes. Hence, this data allows me to construct labour market histories of workers, with detailed information on transitions across jobs. Each wage observation relates to a single firm, hence for job changers who move directly to a new job, two records are available in the same year.

Information on demographic characteristics is limited to gender, age, nationality and broad skill category (i.e., blue and white collars).[15] On the firm side, information on the sector of activity (1 and 2 digits), number of employees and area of work is available. Moreover, detailed information is available for a large number of national collective agreements and professional categories, which allow me to define precise tasks performed by workers and thus specific occupations.[16]

For each observation in the sample, the exact date of the beginning and termination of the employment spell is recorded. Hence, using information on the number of weeks worked during the

[15]No information on the education levels is provided. Hence, broad skill categories are defined on the basis of the job performed: blue collars are essentially manual workers while white ones mostly perform administrative work.

[16]However, the coding of occupational categories varies across national contracts. For example, the national collective agreement "*CCNL Metalmeccanici*" identifies 7 large occupational categories with detailed descriptions of tasks performed within each category (*categorie professionali*) ranking from 1 to 7, and 8 levels in the wage scale (*livello di inquadramento*), for a total of 56 occupation-level cells. In turn, the collective contract for "*CCNL Commercio*" ranks 6 occupational categories in reverse order, 1 being the highest. Note also that workers can be employed under the same contract in different firms and sectors. For example, under the contract "*CCNL Metalmeccanici*", 86% work in manufacturing, 8% in construction and 4% in commerce. Although it is virtually impossible to assign exact labels to different occupations, using information on changes in the national contract and occupation it is possible to construct a measure of occupational tenure.

year, and controlling for possible transitions to other jobs, sectors or contracts and occupations, I can construct the variables with minimal measurement error. Total labour market experience is calculated as the total sum of weeks worked since entry in the labour market; while firm tenure is the sum of weeks worked at a particular firm; sector tenure is the sum of weeks spent in a particular industry, and, finally, occupational tenure is calculated as the sum of weeks worked under a specific bargaining agreement in a particular professional category (occupation).[17] To construct a measure of monthly wages directly comparable across workers, I divide the real yearly wage (expressed in 2002 Euros) by the number of weeks paid during the year and by multiplying this measure by 4, which is the number of weeks paid during the month. Finally, as information on firm closure is also available, I identify as displaced those workers who lost their jobs upon firm closure.

The sample is composed by male workers under 25, who entered the labour market between 1985 and 2003 and were continuously observed for at least two years.[18] The youngest worker in the sample is 15 years old, while the oldest one is 43 at the end of the period. This allows me to study wage growth in the first stages of their careers, when most the lifetime wage growth takes place.

I have access to two versions of the *same* dataset, on which I impose the same sample selection criteria, with almost perfect overlapping in terms of variables and observations.[19] The first

[17]I consider only 1 digit occupational categories, thus discarding very noisy information on the position in the wage scale within each occupational category. This choice results in 39 different national contracts and 30 occupations. However note that the most 5 most "popular" national contracts include about 60% of total observations, and that more than 85% of observations are in the 6 most "popular" occupation categories.

[18]This means that workers that exit the sample for more than one year are not considered in the analysis. In Appendix A I provide detailed explanations for this choice. The procedure for the selection of the sample is reported in Table 9.

[19]The first version of the dataset contains information on displacement and citizenship but not on national bargaining agreements and occupations, while the second version contains information on national agreements and occupations, but not on displacement and citizenship. Unfortunately, the algorithm used to obtain identification codes of workers and firms in the INPS dataset assigns such codes differently at each version, hence it is impossible to merge the two (virtually identical) samples of the same dataset.

(second) sample consists of 203,365 (183,364) observations for 23,940 (22,349) blue collar workers and 62,901 (56,389) observations for 7,376 (6,907) white collars observed on average for 8.5 (8.1) years. Reassuringly, descriptive statistics in Table 1 show that the two samples are virtually identical and that differences between blue and white collars are statistically significant.

III.2 Descriptive Evidence

In Figure 1, I report mobility patterns for blue and white collars.[20] The share of workers who change their job is quite high during the first 5 years of experience, and is around 20% for both groups. Such percentage decreases to about 10% after 20 years. Similarly, the dynamics of job-to-job moves, defined as transitions with an intervening period of non-employment less or equal to one month, show that about 10% of the total number of changes is directed to a new job, with slightly higher levels for white collars. The pattern of sectoral mobility is quite different in the two groups.

As firm closure has important implications in terms of loss of specific capital (see Neal, 1995), in Table 2 I investigate the patterns of job displacement by considering workers on the basis of the tenure accumulated on the previous job (as in Topel, 1991). The probability of losing a job decreases as tenure accumulates, at least for blue collars, while the pattern is not monotonic for white collars. In the Table, I report both the last change in wages within the firm before displacement and the wage drop after displacement.[21] All workers that end up being displaced suffer some wage losses before firm closure. Greater losses are expected as tenure increases. Inspection of the Table reveals that blue collars reduce their wages by about 10% upon displacement, while for white collars firm closure after 10 years of tenure can cost as much as 50% of the previous wage, suggesting that specific skills are more important for this group of workers.

The average growth of wages in Figure 2 indicates that stayers have a somewhat flatter

[20]This part of the analysis is based on the first version of the dataset, results for the second are very similar and available upon request.

[21]Note that observations with a period of unemployment greater than one year have been dropped, hence this sample is made of individuals continuously participating in the labour market during the period.

profile. In turn, wage growth of movers is higher for both groups in the first 5 years, and decreases afterwards. Wage gains for white collars at the beginning of their careers can be substantial. This can be related to higher variance of wages accepted by those that move in early stages of their careers: if ability is not immediately revealed, higher variance of external offers is most likely if workers have not sorted themselves in their preferred matches.

IV. Results

IV.1 Returns to Experience, Firm and Sector Tenure

I begin with a parsimonious specification in which the dependent variable is the natural logarithm of monthly wages. On the right hand side, I include experience, firm tenure and sector specific tenure, with relative squared terms; further controls are dummies for year, firm size, area of work, Italian nationality and sector of activity at 1 digit level.[22]

In Tables 3 and 4, I report estimates of the coefficients obtained with different estimation methods. In the first column of each Table, I report OLS estimates of regressions in which all variables are treated as exogenous. These estimates are biased and inconsistent, still they represent the natural benchmark comparison. The coefficients indicate that returns to experience are about 2.5% and 5.5% per year for blue and white collars respectively. Interestingly, both groups enjoy more than 1% returns to sector tenure, while only blue collars benefit from staying at the same firm for one additional year, with a return of about 1.4%.

In column (2) I report fixed effects estimates of the same wage model. This estimate eliminates individual effects, hence takes into account the ability bias problem, but doesn't solve the two-way causation problem that generates an additional source of endogeneity. Moreover, the within group estimator doesn't allow to separately identify the effects of experience, firm and sector tenure as they increase by the same amount for workers that don't change job: as a result, the coefficient for experience is identified for those who change job (it turns out to be negative in the

[22]This part of the analysis is based on the first version of the INPS dataset, with no information on national agreements and occupations. Subsection IV.2 uses the second version of the dataset. See Table 1 for a comparisons of the versions.

case of white collars). In this case, returns to sector tenure are less than 1% per year for both blue and white collars. The reduction in coefficients for tenure and experience indicates that part of the wage growth is attributable to the ability bias due to the correlation of such variables with unobserved fixed effects.

In column (3), I report the instrumental variables estimates.[23] As mentioned in previous sections, I instrument endogenous variables with deviations from individual and job means, with the addition of the dummy for displaced workers.[24] When considering endogeneity and reverse causality using IV, returns to experience slightly decrease to 5.0% for white collars while they increase from 2.5 to 4% for blue collars. Moreover, blue collars don't get any return from staying in the same sector, while white collars enjoy less than 1% increase in returns to sector tenure.[25] The fact that IV estimates for blue collars are higher than OLS may suggest that less able workers are selected into jobs, while the selection mechanism works in the opposite direction for white collars. In column (4) I report estimates of fixed effects models with instrumental variables.[26]

Finally, I report estimates on panel data obtained using the Hausman and Taylor (1981) estimator: the latter allows to specify which regressors are correlated with the individual fixed effect, while it assumes no correlation with the idiosyncratic part of the error term. Again, deviations of variables from the individual mean are used as instruments.[27] Results presented in column (5) indicate that returns to experience and sector tenure are somewhat similar for blue and

[23]The p value of Durbin-Wu-Hausman tests strongly rejects the null hypothesis of exogeneity of experience and tenure, indicating OLS methods are inappropriate and IV methods must be used.

[24]First stage estimates of reduced forms and a complete set of tests for identification are reported in Tables 10, 11 and 12 in Appendix B.

[25]Actually, blue collars get negative returns. However, obtaining marginally negative returns to specific tenure is not uncommon in this literature. Possible explanations are related to the business cycle or to rent sharing effects.

[26]In this case, year dummies are not included as they generate a multicollinearity problem with the instrument for experience. Hence comparison with results obtained in other columns must be cautious.

[27]Instruments are generated within the model, in this case I don't use information on displaced workers.

white collars (around 2-3% and 1% respectively). In addition, blue collars enjoy 1% increase in returns to firm tenure, very close to the values obtained in OLS and presented in column (1), thus confirming that the selection mechanism is relatively less important for this group of workers.[28]

IV.2 Returns to Occupational Tenure and Sector Heterogeneity

In their contributions, Kambourov and Manovskii (2009) and Zangelidis (2008a) show that occupational experience is a fundamental component of wage growth in the US and the UK, and that including such variable in wage regressions strongly reduces the effect of firm and sector specific tenure. In order to analyse this issue, I extend the above analysis by explicitly considering the role of national collective agreements and occupational experience as potential factors affecting specific human capital and wage growth. I only report results for OLS, IV and HT estimators.

Since in this set of regressions I use the second version of the INPS dataset, I begin in column (1) of Tables 5 and 6 replicating OLS regressions contained in column (1) of Tables 3 and 4.[29] Reassuringly, results confirm previous findings. In order to control for the role of national bargaining agreements and occupations, in column (2) I add dummies for 39 national contracts and 30 occupational categories. As expected, returns to experience, firm and sector tenure remain positive and statistically significant but are significantly reduced in magnitude.

In column (3) of both Tables, I include a measure of occupational tenure and drop dummies for national contracts and occupations. Interestingly, for both groups, returns to firm and sector tenure are further reduced, while returns to experience increase to their previous levels (2.2% and 5.5% for blue and white collars, respectively), suggesting that experience captures part of the effect

[28]I also conduct further robustness checks. First, following Williams (2009), I instrument experience with potential experience, obtaining somewhat higher returns than those obtained in above Tables, with similar results for firm and sector tenure. Second, I consider accumulation of sector tenure at 2 digit level, confirming previous results. A complete battery of results is available from the author upon request.

[29]Note that apart from the number of observations, due to one year difference in data availability, the only difference between the two OLS regressions is that in Tables 5 and 6 there is no dummy for Italian nationality.

of national contracts. What is more, occupational tenure shows a positive and statistically significant effect: one additional year of occupational tenure increases wages by about 2% for blue collars and 1.4% for white collars. In column (4) I run a regression that includes both a measure of occupational tenure and dummies for national contracts and occupations: results substantially confirm that in OLS regressions all components of general and specific capital have a positive impact on wage growth, apart from firm tenure for white collars.

In columns (5) and (6) I take into account endogeneity problems by estimating IV regressions and using the Hausman and Taylor (1981) estimator for panel data. In the IV regressions, blue collars enjoy positive returns to experience (about 2.5%), while there is no evidence of returns to the other specific factors. Conversely, white collars enjoy large returns to experience (about 3.9%), and positive returns to sector (about 1%) and occupational tenure (0.9%). Comparing these results with those found in column (3) of Tables 3 and 4, it is clear that, not considering the role of national bargaining agreement and occupational tenure, the estimated returns to experience are upward biased.[30] Results in column (6) substantially confirm previous findings.

Previous results suggest that occupational tenure is an important component of wage growth, at least for less unionised white collars. Interestingly, Zangelidis (2008b) shows that such returns are statistically significant only for non-unionised workers in the UK, while Zangelidis (2008a) looks at sectoral and occupational heterogeneity in wage returns to specific skills.

In Tables 7 and 8 I shed some light on these issues using Italian data: I report results for OLS, IV and HT estimators for different sectors. As Boeri et al. (2001) report, there is a large degree of heterogeneity in union power across sectors. For example, in 1980, union density in Italy

[30]To ease comparison, I also run IV regressions identical to the ones presented in column (5) of Tables 5 and 6 using the first version of the dataset and dropping the displacement dummy from the set of instruments and the dummy for Italian nationality from the set of regressors. Results are virtually unaltered, suggesting that using displaced workers for identification doesn't change the main results. However, such variable provides additional source of exogenous variation and it is necessary to run overidentification tests discussed in Appendix B.

was reported to be 56% in manufacturing, 77% in transport, 22% in commerce and 33% in the financial sector. In 1997 the corresponding figures were 39%, 57%, 23% and 17% suggesting an overall downward trend in unionisation rates.[31] For each group of workers, I report estimates for two representative sectors. The Tables show an interesting pattern. In manufacturing, where unions are historically strong, but product market competition imposes some degree of decentralisation in wage bargaining, both groups enjoy only positive returns to experience, with very small and marginally significant returns to occupation tenure (the IV estimate is 0.3% for blue collars and not significant at conventional levels for white collars). In turn, blue collar workers enjoy large and statistically significant returns to firm tenure in highly unionised sectors as transport (about 2% in columns (5) and (6) in Table 7), while white collars benefit from large returns to sector (4.2%) and occupational tenure (1.7%) in less unionised sectors as finance (see column (5) of Table 8). Interestingly, for this group of workers, returns to experience and firm tenure are not very relevant.

IV.3 Discussion and Comparison

Overall, these results indicate that returns to general labour market experience are the fundamental source of wage growth for both blue and white collars in Italy. However, such returns are reduced after controlling for national bargaining agreements and occupation levels. Returns to firm tenure are nil and insignificant for both groups, while white collars enjoy positive returns to sector and occupation tenure, especially in less unionised sectors. Some evidence of large positive returns to firm tenure are found only for a small number of blue collars in highly unionised sectors.

Interestingly, returns to experience estimated with OLS are downward biased for blue collars, while they are upward biased for white collars, suggesting that the two groups of workers select themselves into jobs in a different way. This also confirms the importance of using IV techniques for obtaining unbiased estimates of returns to skills. Moreover, returns to sector and

[31] Although union density is a good measure of union power, a more appropriate measure would be excess union coverage, i.e. the difference between the share of employees covered by collective agreements and union density. In Italy union coverage is almost 80%, and virtually extends *erga omnes*. See Boeri et al (2001) for a thorough analysis.

occupational tenure are somewhat higher for white collars, suggesting that the role of search and matching is relatively more important for this group, that has greater incentives to move and choose a good occupation and sector match.

In fact, as Williams (2009) and Zangelidis (2008b) discuss for the UK, wage policies in strongly unionised labour markets (as blue collars in Italy), characterised by strong wage compression, can neutralise endogenous selection effects. In other words, as the incentives to move and find a better match are reduced by extensive union coverage and wage compression, the search and matching behaviour is less important in wage determination for unionised workers and there is negative selection into jobs.

Further evidence on this mechanism is also found in studies obtained by other authors using similar methodologies. Cingano (2003) finds that OLS estimates are downward biased and that returns to experience are the main source of wage growth for workers in two Italian northern provinces. Dustmann and Pereira (2008) find that after controlling for endogeneity and selection, returns to firm tenure for both unskilled and medium skilled workers drop to zero. On the other hand, returns to experience obtained instrumenting tenure and experience are higher in Britain than in Germany, suggesting that returns to skills are higher in more competitive labour markets. Results obtained in this paper are also in line with those presented by Williams (2009) for union jobs in the UK. In fact, he finds that returns to tenure drop substantially to zero when controlling for selection and endogeneity, while returns to experience estimated with instrumental variable methods are higher than OLS and higher for non-union workers, confirming that the presence of strong labour market institutions tends to depress returns to skills.

Interestingly, results are also in line with those reported by Zangelidis (2008b) who finds statistically significant positive returns to occupational tenure for non-unionised workers and by Zangelidis (2008a) who finds high returns to occupational tenure for managerial and administrative positions, with positive returns to sectoral tenure in the banking and finance sectors in the UK.

V. Concluding Remarks

In this paper, I provide different estimates for the average returns to experience and firm, sector and occupational specific tenure for a sample of young Italian male workers in the private sector. I also consider the role of national bargaining agreements and occupational categories, with new evidence on wage profiles in highly unionised labour markets.

To overcome standard selection and endogeneity problems that arise because of optimal mobility decisions of workers, I estimate wage equations using instrumental variables techniques on cross section and panel data. In particular, I use deviations of experience, firm, sector and occupation tenure from their means over the observation period as instruments for endogenous variables. Identification is enriched by considering a dummy for displacement as further excluded instrument.

Results indicate that both white and blue collars enjoy substantial returns to general labour market experience, and that both groups benefit from very small or insignificant returns to firm tenure. There is some evidence of positive returns to sector and occupational tenure for white collars, especially in less unionised sectors. Positive large returns to firm tenure are found only in highly unionised sectors for a small number of blue collars.

I argue that individual and specific match components are important in shaping the wage profile of young workers. In particular, more skilled white collars have more incentives to move and find a good sector and/or occupation match. On the other hand, national collective agreement, union power and high centralisation of bargaining have a role in reducing the incentives to mobility for less skilled blue collars.

The paper leaves open some avenues for future research. The interaction between endogenous job mobility and heterogeneous wage profiles across firms and is one example in this direction. Moreover, the empirical literature on structural estimation of search models substantially neglects the importance of tenure and experience on wage growth.

Appendix A. The Selection of the Sample

In this Appendix, I discuss the selection of the sample, which is reported in detail for convenience in the first column of Table 9.[32] I begin with 1712535 observations and drop observations for workers which are not in working age (younger than 15 or older than 65), or for which some relevant information (such as the yearly wage or the number of weeks and days paid during the year is missing). To avoid misreporting, I drop observations where the number of weeks (days) worked during the year is greater than 53 (365) or equal to 0. Observations for part-time jobs - around 50,000 - are also excluded. Similarly, fixed term positions and seasonal jobs are not considered as their dynamics of labour market participation and job mobility can be very different from those in permanent jobs; this reduces the sample by more than 80,000 observations. Managers and apprentices are not considered in the analysis, and this results in the cut of around 100,000 further observations.

The two subsequent rows in the Table deserve some comments: workers older than 43 are dropped as the oldest individual at the beginning of the observation period in 1985 is 25, and consequently 43 at the end of the observation period. This reduces the number of observations by around 460,000 units. Similarly, about 470,000 observations for workers who were older than 25 when first entered the panel are dropped.

The last three operations need some further accurate clarifications. As reported in the Table, I decide to drop all *workers* who exit the sample for more than one year (about 230,000 observations). In fact, when the worker-firm match is interrupted, and the worker doesn't find a job

[32]As explained above, I have access to two versions of the same dataset and conduct the same sample selection procedure on the two versions. To save on space, here I just discuss the procedure for the selection of sample referring to the first version, while for the second version I just report corresponding figures in Table 9. One important difference between the two versions concerns yearly wages and weeks paid, that in the second version have already been trimmed and expressed in 2002 prices from the original source.

within one year, the worker exits the sample. However, the destination of such transitions cannot be precisely identified. In fact, workers can exit to be unemployed, to work in the public sector, to work as self-employed, to retire or move to non-participation. Although one can conjecture on the destinations on the basis of the duration of the absence, the age at exit, and looking at transition rates available from other data sources, including these individuals would create a serious problem for the purposes of this study. In particular, it would be impossible to correctly construct the experience and different tenure variables.

The second important issue concerns workers having more than one observation at the same firm in the same year. In this case, the spell with longest weeks worked during the year is kept, while the others are dropped from the sample. Finally, workers who had more than 20 jobs over the observation period are dropped. The final number of observations is equal to 266266.

Appendix B. First Step Estimates and Additional Tests for IV Regressions

The use of instrumental variables is known to generate additional bias if the instruments are weakly correlated with the endogenous variables. The estimated models could be also unidentified. However, such problems are substantially neglected in this literature, hence in this part of the Appendix, I report different batteries of tests for overidentification, rank condition and weak identification concerning IV estimates.

In Tables 10 and 11, I report coefficient estimates of excluded instruments in first stage regressions for instrumental variables regressions reported in column (3) of Tables 3 and 4 respectively. First note that the F statistic for excluded instruments are well above the rule of thumb of 10, indicating a strong correlation between them and the endogenous regressors. Using displaced workers helps in identifying returns to firm and sector tenure but doesn't have any explanatory power for experience.[33]

[33]To further investigate this issue, I conduct a redundancy test on this single instrument. The latter is a LM test

Including the dummy for displacement following firm closure in the set of instruments helps to identify returns to skills, it also allows me to conduct some overidentification tests. In Table 12, I report three batteries of tests for the most relevant regressions estimated in the paper, they essentially refer to the IV estimates and to some FE-IV estimators. The Hansen J statistic suggests that the excluded instruments are correctly excluded from the wage equation, and that these variables are orthogonal to the error term. This is particularly true for IV regressions, in which p values are very high, suggesting I cannot reject the null that exclusion restrictions are not valid. As far as FE-IV estimates there is some evidence that the overidentifying restrictions are not valid, at least for blue collars.

In the second column of the Table, I report the Kleibergen-Paap test of underidentification, which are essentially tests of relevance of instruments. The null hypothesis is that the equation is underidentified and has not full rank. In this case, p values are always zero for all estimated models, they strongly reject the null indicating the matrix is of full column rank and the model is identified.

Finally, in the last column, I check the possibility the instruments used are "weak". In fact, if instruments are only weakly correlated with the endogenous regressors, they can cause serious problems also when models are identified. The null hypothesis of the Anderson-Rubin Wald test that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero is always rejected in this case, suggesting that the overidentifying restrictions are valid.[34]

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distributed as χ^2. The statistic is equal to 884.971 and 321.939 for blue and white collars respectively, with p values equal to 0 and rejects the null of redundancy.

[34]Results for the Wald F statistic based on Kleibergen-Paap rk statistic confirm previous results. What is more, the Angrist-Pischke F tests indicate that no endogenous regressor is "weakly identified".

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TABLE 1

Descriptive statistics

	First Version					Second Version				
	Blue Collars		White Collars		Difference	Blue Collars		White Collars		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	T test	Mean	Std. Dev.	Mean	Std. Dev.	T test
Monthly wage	1,347.6	806.7	1,916.4	862.85	-1.5e+02	1,351.1	387.13	1,879.1	702.08	-2.3e+02
Age	26.38	5.15	28.70	5.08	-99.19	26.14	4.93	28.33	4.83	-92.91
Experience	5.53	4.63	7.07	4.88	-71.96	5.24	4.39	6.68	4.62	-67.04
Firm tenure	4.00	3.87	4.56	3.99	-24.18	3.33	3.43	4.09	3.7	-44.72
Sector tenure (1 digit)	4.75	4.33	5.85	4.60	-54.61	4.52	4.12	5.54	4.36	-50.83
Sector tenure (2 digits)	4.13	3.86	4.93	4.21	-51.66	3.84	3.7	4.72	4.03	-48.35
Occupation tenure	N.A.		N.A.		N.A.	3.46	3.26	4.62	3.71	-70.91
Change job	0.16	0.37	0.14	0.35	13.63	0.16	0.37	0.14	0.35	12.08
Change sector (1 digit)	0.07	0.25	0.07	0.26	-5.61	0.07	0.26	0.07	0.26	-3.70
Change sector (2 digit)	0.11	0.32	0.12	0.32	-2.09	0.12	0.32	0.12	0.33	-2.54
Displaced	0.01	0.10	0.01	0.11	-2.22	N. A.		N.A.		N.A.
Agriculture and fishing	0.001	0.038	0.000	0.010	N. A	0	0.03	0	0.02	N. A
Mining and gas	0.005	0.070	0.001	0.039	N. A	0	0.07	0	0.04	N. A
Manufacturing	0.582	0.493	0.362	0.480	98.64	0.59	0.49	0.37	0.48	94.14
Energy	0.008	0.088	0.016	0.127	N. A	0.01	0.09	0.02	0.13	N. A
Construction	0.148	0.355	0.044	0.206	69.51	0.14	0.35	0.04	0.21	63.14
Commerce	0.115	0.319	0.226	0.418	-70.66	0.11	0.32	0.23	0.42	-68.89
Hotels and restaurants	0.036	0.186	0.008	0.088	36.67	0.04	0.19	0.01	0.09	34.92
Transport and comun.	0.054	0.228	0.055	0.229	-1.11	0.05	0.22	0.05	0.22	-1.39
Financial activities	0.000	0.024	0.133	0.340	-1.7e+02	0	0.02	0.13	0.34	-1.6e+02
Real estate and R&D	0.030	0.170	0.120	0.324	-90.50	0.03	0.17	0.11	0.32	-81.43
Public administration	0.000	0.018	0.000	0.023	N. A	0	0.04	0.01	0.08	N. A
Education	0.001	0.035	0.006	0.079	N. A	0	0.05	0.01	0.11	N. A
Health and assistance	0.002	0.050	0.012	0.109	N. A	0.01	0.1	0.01	0.1	N. A
Household services	0.012	0.111	0.012	0.109	N. A	0.01	0.11	0.01	0.1	N. A
Other	0.003	0.058	0.003	0.059	N. A	N.A.		N.A.		N. A
North-west	0.38	0.49	0.44	0.50	-23.89	0.38	0.49	0.44	0.5	-23.23
North-east	0.30	0.46	0.26	0.44	18.66	0.3	0.46	0.26	0.44	18.11
Centre	0.16	0.37	0.18	0.38	-8.12	0.17	0.37	0.18	0.38	-6.18
South	0.11	0.31	0.09	0.28	14.60	0.1	0.31	0.09	0.28	12.50
Islands	0.04	0.20	0.03	0.18	9.13	0.04	0.2	0.04	0.19	8.34
Less than 20 empl.	0.50	0.50	0.28	0.45	98.09	0.49	0.5	0.28	0.45	88.68
From 20 to 200 empl.	0.31	0.46	0.31	0.46	3.94	0.31	0.46	0.3	0.46	5.02
More than 200 empl.	0.19	0.39	0.42	0.49	-1.2e+02	0.19	0.39	0.41	0.49	-1.1e+02
Italian nationality	0.95	0.23	0.98	0.14	-34.77	N.A.		N.A.		N.A.
National contracts	N.A.		N.A.		N.A.	39 #		38 #		N.A.
Occupations	N.A.		N.A.		N.A.	30 #		28 #		N.A.
Observations	203,365		62,901			183,364		56,389		

Notes: Wages are measured in 2002 Euros while durations are in years. Number of national contracts and occupations are reported. N.A. indicates the variable is not available in the version of the dataset. First version period 1985-2003, second version 1985-2002. T test are performed under the null hypothesis of equal means between blue and white collars.

TABLE 2

Displacement, wages, and firm tenure

Years of firm tenure before displacement	Blue collars		White collars	
	% displaced	Δ wage	% displaced	Δ wage
Less than 1	1.39	t-1 -0.04	0.98	t-1 -0.01
		t -0.04		t -0.25
Between 1 and 3	1.27	t-1 -0.03	1.13	t-1 -0.03
		t -0.10		t -0.28
Between 3 and 5	1.20	t-1 -0.02	1.49	t-1 -0.00
		t -0.09		t -0.29
Between 5 and 10	1.08	t-1 -0.03	1.75	t-1 -0.01
		t -0.10		t -0.49
More than 10	0.43	t-1 -0.06	0.41	t-1 -0.09
		t -0.02		t -0.50
Total	1.18	t-1 -0.04	1.24	t-1 -0.02
		t -0.08		t -0.35

Notes: Δ wage is the difference in ln of monthly wages; t-1 refers to the last change of wage within the firm before displacement, while t refers to the first change of wage between firms after displacement.

TABLE 3

Returns to experience, firm and sector tenure, blue collars

	(1) OLS	(2) FE	(3) IV	(4) FE IV	(5) HT
Experience	0.0254***	0.0210***	0.0404***	0.0477***	0.0255***
	(0.0016)	(0.0031)	(0.0020)	(0.0035)	(0.00093)
Experiencesq	-0.000492***	-0.000412***	-0.00129***	-0.00135***	-0.000473***
	(0.000092)	(0.000084)	(0.000099)	(0.000096)	(0.000050)
Tenure	0.0143***	0.00978***	-0.000263	-0.00114	0.00982***
	(0.00087)	(0.00077)	(0.00081)	(0.00078)	(0.00056)
Tenuresq	-0.000821***	-0.000596***	-0.0000872*	-0.0000814*	-0.000599***
	(0.000060)	(0.000049)	(0.000048)	(0.000045)	(0.000037)
Sector tenure	0.0124***	0.00904***	-0.00882***	-0.0108***	0.00854***
	(0.0017)	(0.0015)	(0.0020)	(0.0020)	(0.00091)
Sector tenuresq	-0.000561***	-0.000385***	0.000410***	0.000471***	-0.000361***
	(0.000099)	(0.000089)	(0.00010)	(0.000099)	(0.000056)
Controls					
Sector	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Italian citizenship	Yes	Yes	Yes	Yes	Yes
Observations	203,329	203,329	203,329	202,642	203,329
R^2	0.23	0.14	0.08	0.00	.

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, FE indicates fixed effects, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 3-5, instruments for experience and specific tenure variables are deviations from the specific mean and a dummy for displaced workers. In column 6 no displacement dummy is used.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE 4

Returns to experience, firm and sector tenure, white collars

	(1) OLS	(2) FE	(3) IV	(4) FE IV	(5) HT
Experience	0.0546***	-0.0491***	0.0501***	-0.0362***	0.0311***
	(0.0028)	(0.013)	(0.0028)	(0.013)	(0.0022)
Experiencesq	-0.00120***	-0.000851***	-0.00110***	-0.00132***	-0.00107***
	(0.00016)	(0.00014)	(0.00014)	(0.00014)	(0.000070)
Tenure	-0.00406**	-0.00181	0.00131	-0.00506***	-0.00123
	(0.0019)	(0.0016)	(0.0014)	(0.0014)	(0.00088)
Tenuresq	-0.0000293	-0.000204*	-0.000291***	-0.0000649	-0.000220***
	(0.00014)	(0.00011)	(0.000097)	(0.000098)	(0.000059)
Sector tenure	0.0133***	0.0100***	0.00720***	-0.00153	0.00886***
	(0.0028)	(0.0024)	(0.0026)	(0.0026)	(0.0012)
Sector tenuresq	-0.000665***	-0.000573***	-0.000286*	-0.0000769	-0.000541***
	(0.00019)	(0.00015)	(0.00015)	(0.00015)	(0.000075)
Controls					
Sector	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Italian citizenship	Yes	Yes	Yes	Yes	Yes
Observations	62,897	62,897	62,897	62,156	62,897
R^2	0.39	0.40	0.16	0.03	.

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, FE indicates fixed effects, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 3-5, instruments for experience and specific tenure variables are deviations from the specific mean and a dummy for displaced workers. In column 6 no displacement dummy is used.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE 5

Returns to experience, firm, sector and occupational tenure, blue collars

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) HT
Experience	0.0246***	0.0180***	0.0222***	0.0157***	0.0254***	0.0197***
	(0.00164)	(0.00158)	(0.00171)	(0.00159)	(0.00183)	(0.000914)
Experience sq	-0.000443***	-0.000262***	-0.000334***	-0.000183*	-0.000665***	-0.000224***
	(0.000101)	(9.87e-05)	(0.000105)	(9.93e-05)	(9.96e-05)	(5.16e-05)
Firm tenure	0.0111***	0.00821***	0.00383***	0.00251**	-0.00211*	0.00192***
	(0.00113)	(0.00111)	(0.00126)	(0.00121)	(0.00114)	(0.000665)
Firm tenure sq	-0.000609***	-0.000384***	-0.000215**	-8.63e-05	0.000252***	-4.56e-05
	(8.31e-05)	(8.36e-05)	(9.31e-05)	(8.98e-05)	(7.81e-05)	(4.71e-05)
Sector tenure	0.0138***	0.00733***	0.00410**	0.00365**	-0.00272	0.00548***
	(0.00173)	(0.00167)	(0.00177)	(0.00166)	(0.00190)	(0.000904)
Sector tenure sq	-0.000719***	-0.000333***	-0.000251**	-0.000156	0.000171	-0.000246***
	(0.000110)	(0.000110)	(0.000116)	(0.000110)	(0.000109)	(5.78e-05)
Occupation tenure			0.0203***	0.0169***	0.00215	0.00999***
			(0.00146)	(0.00142)	(0.00149)	(0.000856)
Occupationtenuresq			-0.00122***	-0.000983***	-0.000271***	-0.000640***
			(0.000120)	(0.000116)	(0.000105)	(6.69e-05)
Controls						
National contracts	No	Yes	No	Yes	Yes	Yes
Occupations	No	Yes	No	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Italian citizenship	No	No	No	No	No	No
Observations	183,364	140,817	140,817	140,817	140,817	140,817
R-squared	0.269	0.327	0.261	0.329	0.081	

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 5 and 6, instruments for experience and specific tenure variables are deviations from the specific mean. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6

Returns to experience, firm, sector and occupational tenure, white collars

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) HT
Experience	0.0570***	0.0468***	0.0555***	0.0447***	0.0387***	0.0235***
	(0.00283)	(0.00241)	(0.00290)	(0.00245)	(0.00276)	(0.00227)
Experience sq	-0.00136***	-0.00139***	-0.00125***	-0.00126***	-0.00101***	-0.000976***
	(0.000174)	(0.000146)	(0.000188)	(0.000148)	(0.000144)	(7.30e-05)
Firm tenure	-0.00433**	-0.00328*	-0.00998***	-0.00534***	-0.00105	-0.00240***
	(0.00190)	(0.00182)	(0.00216)	(0.00188)	(0.00177)	(0.000927)
Firm tenure sq	-8.25e-05	3.84e-05	0.000239	0.000186	-8.55e-06	-7.03e-05
	(0.000147)	(0.000137)	(0.000166)	(0.000140)	(0.000120)	(6.58e-05)
Sector tenure	0.0113***	0.00953***	0.00521*	0.00717***	0.00994***	0.00888***
	(0.00276)	(0.00247)	(0.00299)	(0.00255)	(0.00266)	(0.00125)
Sector tenure sq	-0.000560***	-0.000497***	-0.000211	-0.000340**	-0.000471***	-0.000475***
	(0.000189)	(0.000165)	(0.000208)	(0.000170)	(0.000157)	(7.96e-05)
Occupation tenure			0.0143***	0.0108***	0.00886***	0.00885***
			(0.00283)	(0.00252)	(0.00263)	(0.00129)
Occupation tenure sq			-0.00107***	-0.000877***	-0.000683***	-0.000796***
			(0.000226)	(0.000189)	(0.000172)	(9.28e-05)
Controls						
National contracts	No	Yes	No	Yes	Yes	Yes
Occupations	No	Yes	No	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Italian citizenship	No	No	No	No	No	No
Observations	56,389	42,103	42,103	42,103	42,103	42,103
R-squared	0.434	0.542	0.417	0.543	0.146	

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 5 and 6, instruments for experience and specific tenure variables are deviations from the specific mean. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 7

Sectoral heterogeneity, blue collars

	(1) OLS	(2) IV	(3) HT	(4) OLS	(5) IV	(6) HT
		Manufacturing			Transport	
Experience	0.0143***	0.0304***	0.0266***	0.0246***	0.0242***	0.0373***
	(0.00217)	(0.00285)	(0.00206)	(0.00616)	(0.00719)	(0.00811)
Experience sq	-0.000272**	-0.000875***	-0.000497***	-0.000522	-0.000432	-0.000551**
	(0.000135)	(0.000148)	(8.34e-05)	(0.000407)	(0.000426)	(0.000254)
Firm tenure	0.00114	-0.00476***	-0.000567	0.0242***	0.0218**	0.0329***
	(0.00137)	(0.00132)	(0.000709)	(0.00829)	(0.00901)	(0.00439)
Firm tenure sq	1.86e-05	0.000379***	6.05e-05	-0.00169**	-0.000787	-0.00136***
	(0.000102)	(9.13e-05)	(4.86e-05)	(0.000697)	(0.000683)	(0.000388)
Sector tenure	0.00342	-0.00849***	-0.000925	0.0153	0.0181	-0.00211
	(0.00236)	(0.00300)	(0.00202)	(0.0103)	(0.0115)	(0.00841)
Sector tenure sq	2.55e-05	0.000396**	2.70e-05	-0.00115	-0.00165**	-0.000737*
	(0.000149)	(0.000161)	(8.80e-05)	(0.000842)	(0.000801)	(0.000391)
Occupation tenure	0.0142***	0.00332*	0.0100***	-0.0118	-0.0297**	-0.0298***
	(0.00164)	(0.00171)	(0.000930)	(0.0113)	(0.0137)	(0.00760)
Occupat. tenure sq	-0.000916***	-0.000443***	-0.000684***	0.00184*	0.00277***	0.00168***
	(0.000135)	(0.000123)	(7.05e-05)	(0.000951)	(0.000966)	(0.000507)
Controls						
National contracts	Yes	Yes	Yes	Yes	Yes	Yes
Occupations	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	No	No	No	No	No	No
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Italian citizenship	No	No	No	No	No	No
Observations	87,528	87,528	87,528	4,263	4,263	4,263
R-squared	0.369	0.077		0.444	0.101	

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 2, 3, 5 and 6, instruments for experience and specific tenure variables are deviations from the specific mean. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 8

Sectoral heterogeneity, white collars

	(1) OLS	(2) IV	(3) HT	(4) OLS	(5) IV	(6) HT
		Manufacturing			Finance	
Experience	0.0537***	0.0567***	0.0506***	0.0102	0.00510	0.0279***
	(0.00459)	(0.00600)	(0.00464)	(0.00679)	(0.00712)	(0.00833)
Experience sq	-0.00161***	-0.00169***	-0.00125***	4.07e-05	0.000238	-0.000514***
	(0.000256)	(0.000286)	(0.000157)	(0.000391)	(0.000382)	(0.000197)
Firm tenure	-0.00865***	-0.00443*	-0.00552***	-0.00839**	-0.0114***	-0.00912***
	(0.00278)	(0.00260)	(0.00133)	(0.00412)	(0.00393)	(0.00192)
Firm tenure sq	0.000219	6.02e-05	-0.000104	0.000395	0.000508*	0.000292**
	(0.000205)	(0.000174)	(9.37e-05)	(0.000279)	(0.000259)	(0.000126)
Sector tenure	-0.00350	-0.00924	-0.00221	0.0391***	0.0422***	0.0255***
	(0.00485)	(0.00582)	(0.00385)	(0.00814)	(0.00781)	(0.00675)
Sector tenure sq	0.000186	0.000390	-1.97e-05	-0.00131***	-0.00155***	-0.000582***
	(0.000290)	(0.000303)	(0.000159)	(0.000428)	(0.000407)	(0.000212)
Occupation tenure	0.00739**	0.00337	0.00906***	0.0117*	0.0173***	0.00769**
	(0.00371)	(0.00402)	(0.00193)	(0.00675)	(0.00665)	(0.00306)
Occupat. tenure sq	-0.000470*	-0.000282	-0.000621***	-0.00113**	-0.00114***	-0.00105***
	(0.000280)	(0.000261)	(0.000139)	(0.000506)	(0.000441)	(0.000189)
Controls						
National contracts	Yes	Yes	Yes	Yes	Yes	Yes
Occupations	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	No	No	No	No	No	No
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Area of work	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Italian citizenship	No	No	No	No	No	No
Observations	17,334	17,334	17,334	5,362	5,362	5,362
R-squared	0.543	0.126		0.515	0.217	

Notes: Dependent variable is ln of monthly wage. OLS indicates ordinary least squares, IV indicates instrumental variables, HT indicates Hausman and Taylor estimator. In columns 2, 3, 5 and 6, instruments for experience and specific tenure variables are deviations from the specific mean. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 9

Selection of the sample

	First version	Second version
Initial observations	1,712,535	1,555,699
Dropped if		
age > 65 and age < 15	2,338	2,558
yearly wage = 0 or missing	12,726	0
weeks paid > 53	10,581	102
weeks paid = 0	3,287	41
days paid > 365	131	125
days paid = 0	39	0
part time = 1	50,570	46,593
contract is missing	18	0
fixed term or seasonal position	82,053	65,721
occupation manager or apprentice	107,467	91,690
age > 43	462,803	429,974
first observation age > 25	470,581	452,851
exits from panel 1 year or more	231,352	215,517
multiple spells same employer same year	11,196	9,984
more than 20 jobs	1,127	789
Final observations	266,266	239,753

Notes: First version of the dataset refers to the period 1985-2003, in the second version the period is 1985-2002. In the second version, wage and weeks data are already trimmed and reported to 2002 prices from the original source.

TABLE 10

First stage regressions, Table 3, blue collars

	(1) experience	(2) experiencesq	(3) tenure	(4) tenuresq	(5) sectenure	(6) sectenuresq
Displaced	-0.0371	-0.791	-1.778***	-20.31***	-0.278***	-3.271***
	(0.064)	(0.95)	(0.058)	(0.73)	(0.065)	(0.90)
Devexp	1.119***	2.719***	0.371***	4.204***	0.628***	7.275***
	(0.0094)	(0.14)	(0.013)	(0.15)	(0.014)	(0.17)
Devexpsq	0.00155***	0.981***	-0.0122***	-0.118***	-0.0202***	-0.206***
	(0.00041)	(0.0062)	(0.00074)	(0.0086)	(0.00076)	(0.0093)
Devten	0.0234***	0.299***	0.779***	-2.160***	0.0239***	0.254***
	(0.0029)	(0.043)	(0.0064)	(0.078)	(0.0040)	(0.054)
Devtensq	-0.0000229	-0.00247	0.00962***	1.080***	-0.00161***	-0.0188***
	(0.00020)	(0.0033)	(0.00042)	(0.0057)	(0.00030)	(0.0043)
Devsect	0.0415***	0.531***	-0.0600***	-0.515***	0.526***	-4.560***
	(0.0063)	(0.094)	(0.013)	(0.14)	(0.011)	(0.13)
Devsectsq	-0.00171***	-0.0182***	-0.000908	-0.0139	0.0199***	1.174***
	(0.00040)	(0.0063)	(0.00083)	(0.0100)	(0.00074)	(0.0094)
Observations	203,329	203,329	203,329	203,329	203,329	203,329
F test	6939.19	25508.10	18722.89	21120.32	9710.17	23813.52
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.68	0.72	0.48	0.55	0.63	0.68

Notes: Regressions include year, firm size, area of work, sector and nation at birth dummies.

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 11

First stage regressions, Table 4, white collars

	(1) experience	(2) experiencesq	(3) tenure	(4) tenuresq	(5) sectenure	(6) sectenuresq
Displaced	0.0611	0.526	-1.775***	-21.66***	-0.355***	-5.046***
	(0.090)	(1.50)	(0.093)	(1.24)	(0.10)	(1.54)
Devexp	1.048***	1.701***	0.360***	3.856***	0.434***	5.199***
	(0.019)	(0.29)	(0.021)	(0.26)	(0.023)	(0.29)
Devexpsq	0.0115***	1.152***	-0.0108***	-0.0909***	-0.0147***	-0.150***
	(0.00072)	(0.011)	(0.0011)	(0.013)	(0.0011)	(0.013)
Devten	0.0356***	0.473***	0.792***	-2.479***	-0.0168*	-0.0970
	(0.0066)	(0.11)	(0.013)	(0.17)	(0.0089)	(0.13)
Devtensq	-0.00155***	-0.0207***	0.0200***	1.257***	-0.000272	-0.00798
	(0.00046)	(0.0078)	(0.00092)	(0.014)	(0.00065)	(0.0098)
Devsect	0.00612	0.0402	-0.0286	0.0702	0.691***	-3.243***
	(0.012)	(0.19)	(0.021)	(0.25)	(0.019)	(0.23)
Devsectsq	-0.000802	-0.00620	-0.00467***	-0.0751***	0.0224***	1.266***
	(0.00067)	(0.011)	(0.0013)	(0.016)	(0.0010)	(0.014)
Observations	62,897	62,897	62,897	62,897	62,897	62,897
F test	2389.88	7944.30	6059.72	5514.35	3492.02	6996.03
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.77	0.81	0.59	0.65	0.71	0.76

Notes: Regressions include year, firm size, area of work, sector and nation at birth dummies.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE 12

Tests for instrumental variables regressions

Table (Column)	Overidentification Hansen J statistic Chi-sq (Excluded-Endogenous)	Underidentification/Rank Kleibergen-Paap rk LM statistic Chi-sq (Included-Regressors+1)	Weak Instruments Anderson-Rubin Wald test Chi-sq (Excluded)
3 (3)	0.194 (0.6593)	6024.24 (0.0000)	2311.86 (0.0000)
3 (4)	9.867 (0.0017)	2814.88 (0.0000)	1828.60 (0.0000)
4 (3)	0.349 (0.5548)	1864.67 (0.0000)	1602.28 (0.0000)
4 (4)	3.050 (0.0808)	1143.35 (0.0000)	858.38 (0.0000)

Note: Tests refer to regressions in columns 3 and 4 of Tables 3 and 4. Chi-sq (Degrees of Freedom); p values in parentheses. All tests use robust standard errors.

Figure 1. Transition dynamics by experience

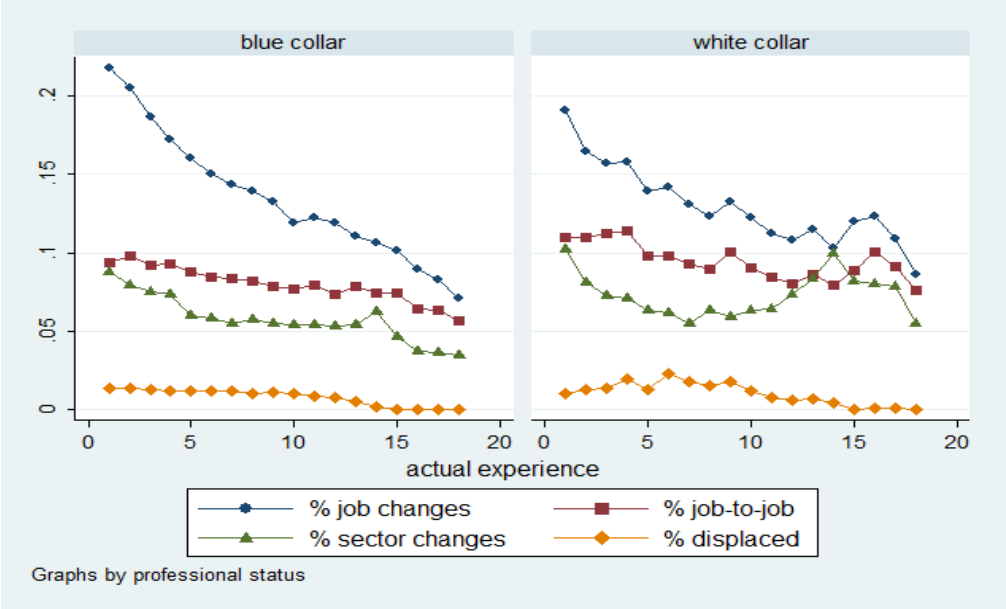
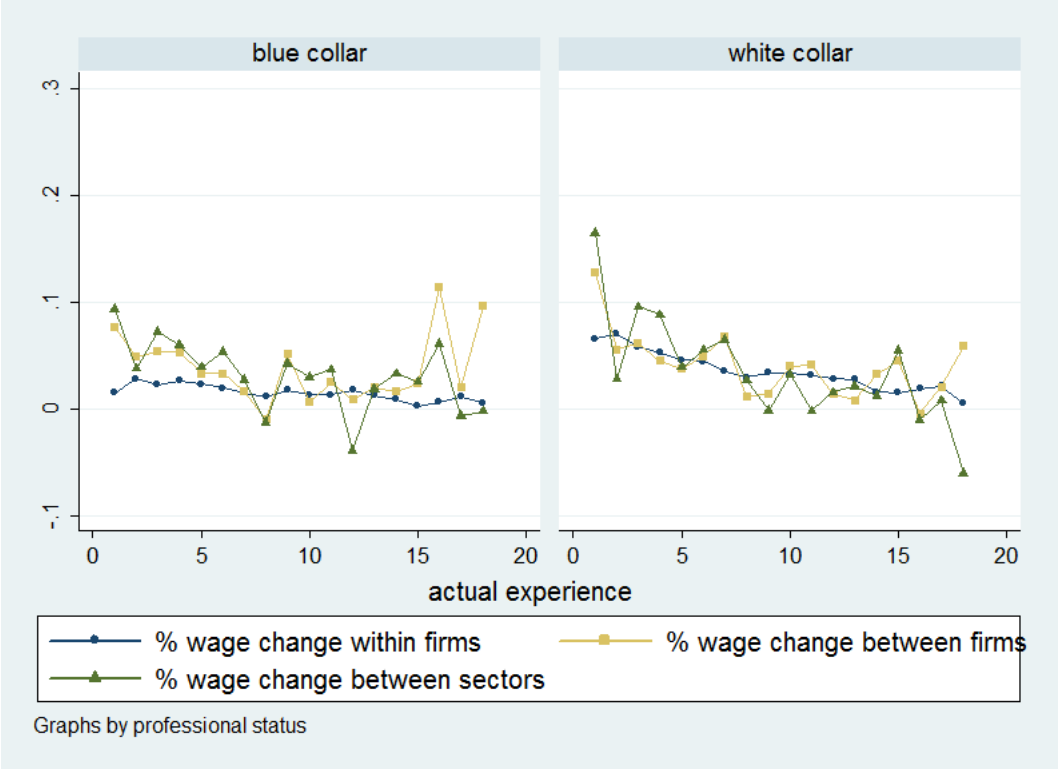


Figure 2. Average wage growth by experience



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ISBN 978- 88-8467-514-9