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

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Abstract

This paper provides estimates of the average returns to labour market experience and firm-specific tenure for a sample of young Italian male workers. Using instrumental variables, I take into account endogeneity and selection problems generated by job matching and individual fixed effects. Results indicate that OLS estimates for experience and tenure are downward biased and that white collars workers enjoy higher returns to general and specific skills than blue collars.

Keywords: Wages, Experience, Tenure, Search, Endogeneity, Italy.
JEL Classification: J24, J31, J62.

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1 Introduction

During recent years, there has been a renewed considerable attention towards the analysis of labour market transitions, employment duration and wage growth, in particular its relation with labour market experience and firm tenure. This is not surprisingly, as correctly estimating true returns to general and specific skills accumulated in the labour market is fundamental to study wage dispersion and its evolution over time.[1]

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 turns out to be important for a couple of reasons. Firstly, it gives a picture of the overall individual wage growth over the life-cycle, with important implications for individual well-being and for the overall wage distribution (Farber, 1999). It is also a good discriminating test of human capital and search models and their main implications in terms of accumulation (and loss) of human and search capital. In this respect, it is essential to the definition and evaluation of active labour market programs directed at employing different workers and for the evaluation of such programs in terms of transferability of skills. Consequently, it has important implications for the recent debate regarding the segmentation of labour markets into permanent and fixed-term positions (Dustmann and Meghir, 2005). Finally, the slope of wage-experience and tenure profiles is found to be different between countries with different institutional and wage setting bargaining environments, revealing different structural characteristics of labour markets (Teulings and Hartog, 1998).

[1] The first wawe of these studies, mainly published in the 80s, were exclusively focused on the US labour market with papers by Mincer and Jovanovic (1981), Abraham and Farber (1987), Altonji and Shakotko (1987), and Topel (1991). After almost 20 years, the debate is still open and important recent contributions have been published proposing new methodological advances or offering evidence on European labour markets, or both. In this direction, Altonji and Williams (2005), Dustmann and Meghir (2005) and Beffy et al (2006) represent the most important papers. On the other hand, there has been a recent growing interest of empirical researchers for applications of such methods: Dustmann and Pereira (2008), Munasinghe et al (2008), Zangelidis (2008), Kambourov and Manovskii (2009) and Williams (2009) are very recent examples of studies that use similar methods to analyse the relationship between wages, experience and firm tenure, mostly referring to European labour markets.

However, correctly estimating wage returns to experience and tenure is not an easy task, as accurate empirical investigations show that OLS estimates can be biased due to endogeneity and omitted variable problems; most importantly, the direction of the bias is *ex ante* ambiguous. This paper uses and compares different estimators to identify the true average returns to experience, calculated as the total number of months worked since entry in the labour market, and firm-specific tenure, obtained as the sum of months worked by the same employer, on a sample of young Italian male workers. Identification of returns to experience and firm tenure is obtained by using instrumental variables methods. To control for endogeneity of general and specific skills accumulation, I use age and deviations of tenure from its own mean over the duration of a job as excluded instruments; I also use information on displaced workers as suggested, by Dustmann and Meghir (2005) as a further source of exogenous variation. As long as displacement is exogenous (conditional on observables) and is not correlated with unobserved components in the error term, this strategy allows to disentangle wage growth generated by pure skill accumulation to wage growth due to worker's matching behaviour.[2]

The data used is from the Italian Administrative Social Security Archive (INPS), in which detailed information about labour market histories of workers employed in the private sector is available and matched with relevant information about the current firm. From the dataset, I extract a subsample of very young workers (younger than 25 at entry) to study wage growth in early stages of the careers, as in this period most of wage increase takes place. I limit my attention to male workers and separate the analysis for blue and white collars.

The rest of the paper is organised as follows. Section 2 briefly reviews the literature and discusses the econometric framework for estimation of average returns to experience and tenure. Section 3 is dedicated to the descriptive analysis of job and wage mobility and to the estimation of wage equations with various econometric methods. After discussing my results, in Section 4 I conclude.

[2] In a recent paper, Cingano (2003) studies returns to industrial districts in Italy using data for two Northern provinces with similar methods. There are some differences between the two papers. Firstly I focus on returns to experience and firm tenure using different instruments and using panel data methods, whereas he is more focused on returns to district tenure and estimates only cross section equations. What is more, my paper extends his analysis to the whole country, being Italy an important example to strong heterogeneity in labour market outcomes. I further discuss some other differences between the two papers in the next sections.

2 Literature and Framework

2.1 Related Studies

Empirical studies interpret experience as accumulation of general labour market skills, while firm tenure is a proxy for accumulation of firm specific skills. However, OLS estimates of standard wage equations including these two variables gives biased results; comparing workers with different levels of these skills can bias results for a couple of reasons. As Altonji and Williams (2005) discuss in their recent reassessment of the literature, differences in levels of experience and tenure can be determined by the fact that workers who are longer in the labour market are in better matches and have accumulated more skills. The second reason is the underlying heterogeneity in the population of workers: high ability workers are likely to have a stronger labour market attachment and hence more experience.[3]

Early studies for the US labour market based on simple OLS regressions indicate very large returns to tenure and experience when no control for individual heterogeneity is taken into account. However, controlling for previous labour market history can substantially reduce the effect of experience and seniority on earnings (Mincer and Jovanovic, 1981). Recognising the bias deriving form individual and firm heterogeneity, other authors have proposed different estimators to take into account the problems of selection and endogeneity of tenure and experience. Altonji and Shakotko (1987) use deviations of tenure from the average sample observation on job match as instrument for tenure, while Abraham and Farber (1987) present IV estimates using a residual from a regression of tenure on completed job duration as instrument for tenure. Both studies provide estimates of returns to tenure are far less than the standard OLS. However, using information on workers that start a new job, Topel (1991) finds there are substantial returns to job seniority (similar to the OLS results).

In a very recent and relevant paper, Dustmann and Meghir (2005) solve above problems identifying returns to experience and tenure using a sample of German displaced workers. The intuition behind their identification strategy is that of assuming displaced workers can be considered as a random sample of the population, as the current status is not conditioned by their past choices, but is substantially exogenous. The problem of ability bias still remains

[3] An additional source of bias encountered when estimating the average returns to experience is that workers with higher returns to experience are likely to spend less time out of the labour market because the opportunity cost of not working is higher. This determines that experience and returns to experience are positively correlated (Dustmann and Meghir, 2005).

because experience is correlated with the error term: in fact more productive workers tend to stay longer in the labour market and/or have higher returns to experience. In their paper, age effects as exclusion restrictions combined with a control function estimator on displaced workers are used to estimate unbiased returns to experience, firm- and sector-tenure.[4]

Finally, Cingano (2003) uses data for two northern Italian provinces to look at returns that are neither firm-specific nor general but derive from accumulation of district tenure (time spent in industrial districts). In his paper, age and firm closure are used as instruments for experience and tenure, while district tenure is instrumented with the proportion of employed workers in district industries or the distance between residence and workplace for a worker. Interestingly, he finds that returns to firm tenure and experience are substantially higher when using IV methods (although barely significant, at least for tenure), while no returns to district tenure is detected.[5]

2.2 Econometric Framework

In this section, I briefly discuss the econometric framework used in this paper by following the notation proposed by Altonji and Williams (2005).

Consider the following wage equation:

$$\ln w_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 T_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where $\ln w_{ijt}$ is the log of real wage for worker i, working at firm j in period t, X and T denote total labour market experience and firm tenure respectively, and ε_{ijt} is the error term.[6]

The latter can be decomposed as

$$\varepsilon_{ijt} = \mu_i + \phi_{ij} + u_{ijt}. \tag{2}$$

The first one (μ_i) is an individual specific fixed effect, ϕ_{ij} is a fixed job match specific error component, while u_{ijt} represents measurement error in

[4]Neal (1995) and Parent (2000) show that once sector tenure is instrumented with deviations from its own mean, estimated returns to firm tenure are substantially reduced.

[5]Various applications of above methodologies have been recently proposed in the literature. Williams (2009) and Zangelidis (2008) propose a set of different IV estimators to compare experience and tenure profiles of union and non-union workers in the UK; Dustmann and Pereira (2008) compare returns to general and specific skills of workers in the UK and Germany; Munasinghe et al. (2008) consider the role of these returns in shaping the gender differential in the US; Kamborouv and Manovskii (2009) analyse the importance of occupational tenure.

[6]For expositional reasons I do not include any other control variable or non linear terms in experience and tenure.

wages.[7] The key parameters to be estimated are β_1 and β_2, the effect of an additional year of experience and tenure on wages respectively; estimates with OLS methods are usually quite high for both variables. However, the method is inappropriate because both experience and tenure are correlated with the unobserved individual and job match components mentioned above. Essentially, job match-specific heterogeneity is positively correlated with experience due to job shopping effects, while the correlation with tenure is ambiguous: if workers and firms share the rents from the match, then there is a positive correlation, while the correlation is negative if there is selection due to voluntary quits (Topel, 1991). On the other hand, the individual specific component μ_i is likely to be positively related to tenure with low productivity workers having high quit and layoff propensities and then lower tenure.

To better explain the source of bias, some auxiliary regressions for the unobserved components on experience and tenure are specified. Consider first the unobserved fixed job match error component ϕ_{ij}. The auxiliary regression is the following

$$\phi_{ij} = b_1 X_{ijt} + b_2 T_{ijt} + \xi_{ijt}. \tag{3}$$

In this context, it is necessary to sign the two coefficient, $b_1$and b_2. Firstly, search and matching models imply that job shopping over a career induces a positive correlation between X_{ijt} and ϕ_{ij}, suggesting a positive value for b_1. Secondly, workers will quit more frequently from low wage jobs than from high wage jobs; if firms share returns from a good match, ϕ_{ij} will be negatively correlated with the layoff probability; this suggests that tenure is positively related to ϕ_{ij} and b_2 is positive. However, Topel (1991) points out that selection due to voluntary quits will lead to low tenure associated with high ϕ_{ij}, so b_2 can be negative. In general, the sign of the tenure b_2 parameter in the auxiliary regression is ambiguous.

Consider now the problem of individual heterogeneity. The auxiliary regression is given by

$$\mu_i = c_1 X_{ijt} + c_2 T_{ijt} + \omega_{ijt}. \tag{4}$$

Again, signing these parameters is not an easy task. Altonji and Williams (2005) show that c_1 is negative and c_2 is positive. The latter is likely to be positive as less able workers are more likely to quit or be laid off, which leads to an upward biased estimate of the effect of tenure. In fact, if ability

[7]It is also possible to include in this decomposition another variable referring to the time-varying match-specific component, however, I don't consider additional difficulties in this setting.

is revealed over the duration of a match, then there is positive correlation between individual ability and tenure. However, as Williams (2009) notes, in strongly unionised markets, c_2 can be negative, as high ability workers have no incentive to work in sectors with a very compressed wage distribution.[8]

As a result, the biases in the OLS are given by

$$\begin{aligned} \beta_1^{OLS} - \beta_1 &= b_1 + c_1, \\ \beta_2^{OLS} - \beta_2 &= b_2 + c_2. \end{aligned}$$

As far as experience is concerned, the direction of the bias is ambiguous, because the job match component b_1 and individual heterogeneity c_1 go in opposite directions. For tenure, the bias of c_2 deriving form individual heterogeneity can be positive or negative, and the effect of job match heterogeneity b_2 can reinforce or offset the previous one. If unions are very strong, c_2 can zero or negative, and OLS estimates are downward bias.

3 Empirical Analysis

3.1 Data and Descriptive Statistics

The data is a 1 : 90 random sample of workers obtained from the Italian Social Security Institute (INPS) representative of the population of employed workers in the private sector observed from 1985 to 1996. This is the most important source of data for studying labour market dynamics in Italy. As in other matched employer-employee data sets, each worker and each firm are identified by a specific code during their permanence in the administrative files; for every match, a new code, generated as a string from the firm and worker's codes, is created. As the match is destroyed, the worker and the firm still continue maintaining their previous codes.[9]

Demographic characteristics of workers are matched with relevant information regarding the firm, as sector of activity, number of employees, geographical area and type of contract. Given the longitudinal structure of the data, it is possible to track the entire career of workers and easily construct the variables object of study: total labour market experience is obtained as the total sum of months worked since entry in the labour market; firm tenure is the sum of months worked at a particular firm, while sector tenure is the sum of months spent in a particular industry. As information regarding firm

[8] He also argues that the job match heterogeneity component should be very small for heavily unionised workers.

[9] See Contini (2002) for more accurate description of the dataset.

Table 1: Descriptive Statistics

	blue collars	white collars
monthly wage	2529 (662)	3042 (930)
age	24.58 (3.79)	25.96 (3.50)
experience	3.92 (2.89)	4.15 (2.97)
tenure	2.23 (2.33)	2.68 (2.51)
sector tenure	3.14 (2.71)	3.43 (2.80)
1-20 employees	0.54 (0.49)	0.34 (0.47)
20-200 employees	0.30 (0.46)	0.29 (0.45)
200 + employees	0.16 (0.36)	0.37 (0.48)
energy	0.62	0.95
mining	7.21	5.61
metal	25.06	18.08
textile	20.58	10.36
construction	18.20	5.33
commerce	16.89	24.22
transport	4.94	4.64
credit	6.52	30.81
observations	214,563	57,107

Note: Standard deviation in parentheses.
Wages in thousands of Italian Lira.
Durations in months.

closure is also available, I can identify displaced workers as those that lost their jobs upon firm closure. I construct a measure of monthly wage directly comparable across workers.[10]

From the dataset, I extract a subsample of workers that entered the labour market between 1985 and 1995; I use this sample of very young workers (younger than 25 at entry) to study wage growth in early stages of the careers, as in this period most of wage increase takes place. I limit my attention to male workers and separate the analysis for blue and white collars.[11] The main descriptive statistics are in Table 1.

[10] Following Contini (2002), yearly wages are deflated with the CPI at 1996 prices. Then, to make them comparable across workers with different number of days worked during the year, the following adjustment is adopted: realwage=(yearly wage/days paid)*26 where 26 is the average number of days worked during the month. From the sample I also trim wages below 700 and above 7200 thousands lira that correspond to the 0.025% of the wage monthly distributions. The overall sample selection procedure is available upon request.

[11] In this data, as in other administrative archives, no information regarding education level is provided.

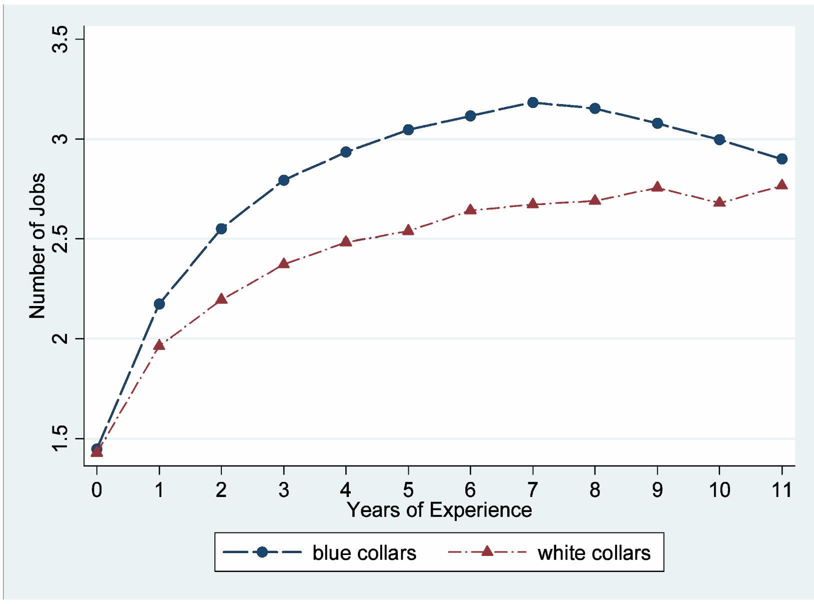

Figure 1: Average Number of Jobs by Experience

Before analysing returns to experience and tenure using econometric techniques, I offer some evidence regarding the mobility process in the sample; in particular I focus on job mobility and wage growth. This is an important step before considering endogeneity and selection effects discussed above. In Figure 1, I report the average number of jobs held for each year of experience dividing between blue and white collars. For blue collars, the average number of jobs increases quite rapidly at the beginning of the career, at least until the sixth year, afterwards I can observe a little decrease in the slope. White collars workers hold fewer jobs, after 5 years in the market they have less than 2.5 jobs against 3 for blue collars.[12]

As job changes can be motivated by many reasons, in Table 2 I tabulate mobility patterns and average re-entry wages for stayers and movers, dividing them by the number of months in unemployment.[13] White collars are less

[12]These numbers are quite close to those reported by Dustmann and Meghir (2005) for Germany, while are certainly quite lower from those found by Topel and Ward (1992) for the US.

[13]Although the dataset is well suited to study labour force dynamics, some clarifications regarding the characteristics of the data have to be provided in advance. First, precisely defining the unemployment status is not immediate. When the worker-firm match is interrupted, workers can exit to unemployment, to work in the public sector, as self-employed or retire. As a consequence, although in the paper I refer to unemployment for exposition reasons, it is important to remember that this state has to be interpreted as

Table 2: Job Mobility and Average Wages

	blue collars	white collars
job mobility		
stayers	76.76	82.36
job to job	9.08	8.91
6 mths	2.86	1.60
12 mths	1.96	1.12
18 mths	1.21	0.75
24 mths	0.78	0.56
average wages		
stayers	2545	3083
job to job	2582	3081
6 mths	2435	2617
12 mths	2393	2576
18 mths	2397	2552
24 mths	2410	2591

Note: Wages in thousands of Italian Lira.

mobile, and job changes are characterised by quite short periods of unemployment. Most of total job changers move directly to a new job, the figure for blues collars is slightly higher, with almost 50% of transitions directed to a new employer. The pattern for average wages indicates the expected negative relationship with unemployment duration; both blue and white collars enjoy higher entry wages upon re-employment in case of a quit. White collar stayers have higher wages than movers, the opposite is true for blue collars.

Till now, the analysis has been conducted on simple patterns of job mobility and average wages, however job changing behaviour can be determined by wage growth differentials in the current and future job. Some workers could move and accept lower wages in exchange for higher expected wage growth in the new job (Postel-Vinay and Robin, 2002). To further investigate this issue, Table 3 shows the distribution of wage changes both for stayers and movers, distinguishing between sector changers and stayers. Average wage growth is higher for movers than for stayers, and surprisingly higher for sector movers, at least for blue collars. Stayers increase their wages by about 5-6% per year, while wage growth is about 12% when moving.[14] Interest-

"out of sample." Secondly, identification of job-to-job transitions versus layoffs is based on the duration of subsequent periods of unemployment.

[14]About half of job changes involve a sector change, both for blue and white collars, while average wages of movers are higher for those that don't change sector of activity,

Table 3: Distribution of Wage Growth

	blue collars			white collars		
	within firms	between firms	between sectors	within firms	between firms	between sectors
10 percentile	-0.111	-0.331	-0.371	-0.081	-0.335	-0.341
median	0.016	0.018	0.024	0.032	0.024	0.021
90 percentile	0.213	0.666	0.810	0.228	0.655	0.727
mean	0.050	0.123	0.160	0.066	0.126	0.138
variance	0.069	0.334	0.424	0.050	0.314	0.300

ingly, sector switchers have lower wage levels upon moving, buy benefit from higher wage growth afterwards. As expected, the distribution of wage growth is much more dispersed for movers than for stayers; looking at percentiles of the distribution, it is immediately clear that there is much more variability in wage offers for movers.

Wage dynamics for stayers, movers and sector movers as experience accumulates are also considered in Figure 2 for the overall sample. The average growth of monthly wages by years of experience indicates that stayers have a somewhat flatter profile. Interestingly, between jobs average wage growth is higher in the first years, as the average growth for those that change sector. However, after 3 years of experience average wage growth is very similar for all groups of workers. The difference in wage growth between movers and stayers clearly declines as experience increases. In previous Table, I showed this fact can be related to higher variance of wages accepted by those that move in early stages of their careers. Search and matching models have clear predictions regarding this job shopping effect: as jobs are experience goods, and ability is not immediately revealed, higher variance of external offers is most likely if workers have not sorted themselves in their preferred matches.

Very high mobility rates can signal low ability levels; gains from moving can decline with the number of jobs held, indicating that the incentive for improving matches declines with experience. To verify this conjecture, in Table 4 I report results for regressions of the log of monthly wage on the number of jobs held including age and year dummies. Results indicate that workers having more jobs earn on average higher wages, at least blue collars, even if the pattern is not monotonic. Quite surprisingly, white collars movers don't get much upon moving. The same regression is presented in

this is true for blue and white collars. This fact indicates that probably some skills are specific to sectors and neither completely general nor firm specific.

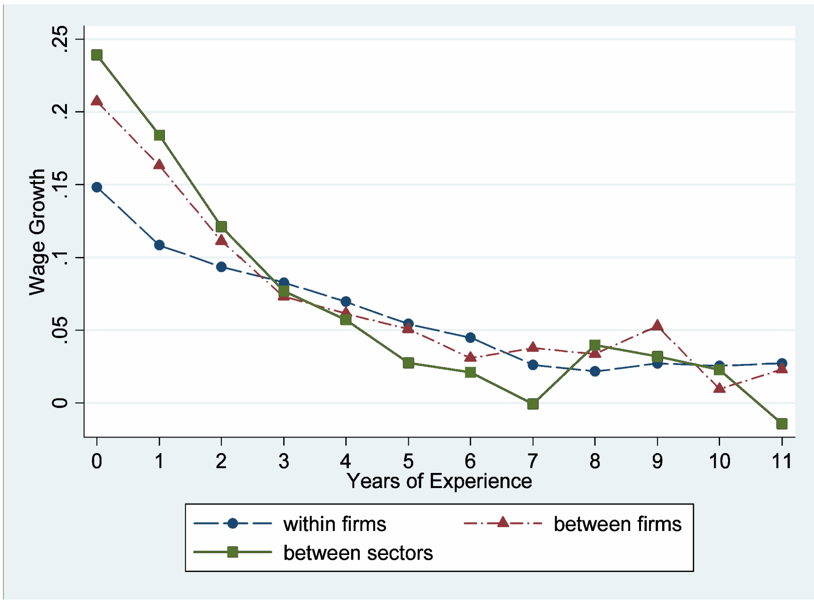

Figure 2: Average Wage Growth By Experience

the bottom panel of the Table including individual fixed effects. As long as these estimates control for individual heterogeneity, this can shed some preliminary light on the selection process discussed in the previous sections. Interestingly, now the association between the number of jobs and wages is reversed. Blue collars seem to be negatively selected, while more productive white collars seem to be those that move more to get some wage gains, at least up to 4 jobs. This indicates heterogeneity in individual ability is very important in modelling transitions and wage gains.

Previous descriptive evidence shows search and matching considerations play an important role in interpreting the mobility patterns of young Italian male workers. In what follows I try to shed some light on returns to experience and tenure using more appropriate econometric techniques dealing with endogeneity and selection problems.

3.2 Returns to Experience and Tenure

In previous sections I discussed in detail the sources of bias for OLS estimates of returns to experience and tenure: as long as job search and matching effects play a role, the unobserved match and individual components of the error term are correlated with accumulation of general and specific skills. However, the direction of the bias cannot be signed a priori, hence the empirical analysis

Table 4: Wages and Number of Jobs

	blue collars	white collars
OLS		
2nd Job	0.0100*	-0.0113*
3rd Job	0.0130*	-0.0206*
4th Job	0.0086*	-0.0363*
5th Job	0.0082*	-0.0464*
FE		
2nd Job	-0.0039*	0.0071*
3rd Job	-0.0130*	0.0191*
4th Job	-0.0233*	0.0063
5th Job	-0.0345*	-0.0088

Note: * denotes significance at 1% levels.

is an instrument to quantify the importance of above components.

To overcome endogeneity and selection problems, and provide unbiased estimates of returns to tenure and experience, I use an instrumental variable approach. First, I estimate four reduced forms, for experience, tenure and relative squared terms. Experience is defined as the number of years (including fraction of years) worked until the date of observation; tenure is defined as the total number of years worked at the same firm. I use age (and age squared) and deviations of tenure from its mean over the duration of a job as instrument for experience and tenure (and their squared terms); the latter instrument is defined as $\widetilde{T_{ijt}} = T_{ijt} - \overline{T_{ij}}$ where $\overline{T_{ij}}$ is average tenure over the duration of the job.[15]

Using deviations of tenure from the mean as instrument has been first proposed by Altonji and Shakotko (1987) and recently used, among others, by Dustmann and Pereira (2008); using age as instrument for experience has been proposed by Dustmann and Meghir (2005) and used by Cingano (2003). Following the latter two papers, I also include a dummy for displacement for those workers that loose their jobs upon firm closure. This excluded instrument is correlated with tenure and experience as is clearly related to mobility. In this case, if firm closure is exogenous, conditional on observables, the identifying assumption is that displaced represent a random sample of the population of workers and their past labour history doesn't affect the next wage they accept. Age is correlated with experience because older workers have on average more experience; on the other hand, individual deviations of

[15]When squared terms are added, instruments are $(\widetilde{T_{ijt}})^2 = T_{ijt}^2 - (\overline{T_{ij}})^2$.

tenure from their own means are uncorrelated by construction with both the individual fixed effect component and the permanent job match component and should satisfy the exogenous variation condition. Reduced forms also include dummies for year, sector, area of work, firm size, type of contract and sector tenure.[16]

Formally, the estimated equation is the following

$$\ln w_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 T_{ijt} + \delta_1 \widehat{\mathrm{exp}}_{it} + \delta_2 \widehat{\mathrm{ten}}_{ijt} + \xi_{ijt}, \tag{5}$$

where X_{ijt} is experience, T_{ijt} is tenure, and $\widehat{\mathrm{exp}}_{it}$ and $\widehat{\mathrm{ten}}_{ijt}$ are residuals from previous reduced forms for tenure, experience and relative squared terms.[17]

Results are in Tables 5 and 6 for blue and white collars respectively. In the first column of each Table, for comparison purposes, I report OLS estimates of standard wage regressions in which all variables are treated as exogenous.[18] Estimates of coefficients indicate there are some differences between the two groups: white collars enjoy persistently higher returns to experience (3% against 0.5% per year), while both of them do not get any return from tenure (actually, these are negative and barely significant).[19] When controlling for selection and endogeneity in the second column of the Tables, things change quite a lot. Both groups enjoy substantially higher returns to experience (about 13% and 11% per year for white and blue collars), while returns to tenure also increase to 1.5% per year for white collars and 0.7% for blue collars. These results clearly indicate OLS estimates are downward biased and that controlling for selection and search is important to obtain reliable estimates of the effects of tenure and experience on individual wage growth.

Columns from 3 to 5 of Tables 5 and 6 report panel data estimates for three different models. Firstly, fixed effects estimates indicate that blue collars have higher returns to experience (13% against 7%), while returns

[16]In what follows, sector tenure is included in the regressions and treated as exogenous; in the next subsection I deal with endogeneity problems related to the sector-specific match components.

[17]Higher order terms are not reported but included in the regression and appropriately instrumented. In next Tables I don't even report coefficients estimates for reduced forms, results are available upon request.

[18]A previous regression without sector tenure (not reported) gives the following results: one year of experience increases wages by about 2% for blue collars and by 4.5% for white collars, on the other hand, returns to tenure are 0.6% per year for the less skilled individuals and about 1% for more skilled white collars. Squared terms have the expected sign, showing concave wage-skill profiles.

[19]This is not a very surprising result, as including sector tenure both groups increase their wages by about 2.5% per year from staying in the same sector. I further discuss the role of sector tenure in the next subsection.

Table 5: Experience and Tenure, Blue Collars

	OLS	IV	IV FE	IV GLS	Hausman Taylor
	1	2	3	4	5
experience	0.0054	0.1131	0.1325	0.0973	0.0300
	(0.0014)	(0.0058)	(0.0203)	(0.0028)	(0.0008)
experience^2	0.0007	-0.0062	-0.0068	-0.0063	-0.0014
	(0.0001)	(0.0005)	(0.0005)	(0.0002)	(0.0000)
firm tenure	-0.0054	0.0032	-0.0169	-0.0031	-0.0005
	(0.0012)	(0.0014)	(0.0046)	(0.0011)	(0.0008)
firm tenure^2	0.0007	-0.0000	0.0015	0.0006	0.0004
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0000)
overid p value		0.293	0.427	0.097	
observations	214472	214472	208754	214472	214472
R^2	0.17	0.10	0.07	0.13	

Note: Robust standard errors are in parentheses. Sector tenure exogenous.

to tenure are negative for both groups.[20] This result is partly confirmed by random effects estimates in column 4 that indicates no returns to firm tenure but again substantial returns to experience for both groups (about 10%). Finally, in the last column, I eventually report results for a standard Hausman and Taylor (1981) estimator in which all endogenous variables (experience, tenure and sector tenure) are instrumented with deviations from their own mean and some correlation between endogenous regressors and the individual random effect is allowed.[21] Results somewhat confirm previous findings with positive returns to experience and no returns to firm tenure.

These estimates clearly indicate returns to experience are a fundamental source of wage growth for young men in Italy, while firm tenure appears to have small or nil effect on the capacity of increasing their earnings possibilities. In particular, tenure effects are of no importance when using panel data methods, while are of some relevance when using IV. Higher IV estimates when compared to OLS indicate that selection effects induced by search and matching considerations are negative, better workers do not tend to stay longer employed and they have lower labour market experience. Theoretically, the increase in returns to tenure when correcting for selection is a

[20] In this case, it is not possible to separately identify the effects of tenure and experience as they increase by the same amount for workers that don't change job. The coefficient for experience is identified for those that change the job.

[21] In this case I don't use information on age and displacement as in previous cases. Hence, comparison must be careful.

Table 6: Experience and Tenure, White Collars

	OLS	IV	IV FE	IV GLS	Hausman Taylor
	1	2	3	4	5
experience	0.0306	0.1312	0.0712	0.1041	0.0667
	(0.0029)	(0.0099)	(0.0266)	(0.0045)	(0.0017)
experience^2	-0.0005	-0.0065	-0.0030	-0.0045	-0.0024
	(0.0002)	(0.0009)	(0.0005)	(0.0004)	(0.0001)
firm tenure	-0.0012	0.0146	-0.0022	-0.0005	-0.0018
	(0.0026)	(0.0032)	(0.0046)	(0.0020)	(0.0015)
firm tenure^2	-0.0001	-0.0014	-0.0002	-0.0003	-0.0000
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
overid p value		0.243	0.493	0.105	
observations	57093	57093	54625	57093	57093
R^2	0.33	0.28	0.32	0.28	

Note: Robust standard errors are in parentheses. Sector tenure exogenous.

prediction of a matching model, where workers with a high individual effects in returns to tenure have strong incentives to move and match with a better firm. But this is not probably the whole story. In fact, the selection effect can be also explained by strong union presence in the labour market. As Williams (2009) and Zangelidis (2008) discuss for the UK, wage policies in strongly unionised labour markets (as Italy), oriented towards strong wage compression, can neutralize endogenous and selection effects, so that individuals with lower ability accumulate more tenure and experience.[22]

On the other hand, it is possible to interpret this result as an upward bias in IV estimates instead of a downward bias in OLS. Essentially instruments have different effects on different individuals. If there is heterogeneity both in the returns to experience and in preferences for work, IV returns are representative only for a subsample of the population. If the subsample is not randomly selected, the difference between OLS estimates and IV estimates could be only a difference between average returns in the entire population and average returns for that particular group. This is most likely if the instruments are likely not to randomly select the latter group, because they are more effective on individuals with certain characteristics.[23]

[22] See Boeri et al. (2001) for evidence on the importance of unions in Italy and comparison with other countries.

[23] I further discuss the relevance of instruments and overidentification tests in the next subsections.

Table 7: Experience, Tenure and Sector Tenure, Blue Collars

	OLS	IV	IV FE	IV GLS	Hausman Taylor
	1	2	3	4	5
experience	0.0054	0.1024	0.1634	0.1017	0.0300
	(0.0010)	(0.0059)	(0.0235)	(0.0032)	(0.0008)
experience^2	0.0007	-0.0063	-0.0088	-0.0066	-0.0014
	(0.0000)	(0.0005)	(0.0009)	(0.0002)	(0.0000)
firm tenure	-0.0054	-0.0068	-0.0064	0.0001	-0.0003
	(0.0009)	(0.0015)	(0.0031)	(0.0013)	(0.0008)
firm tenure^2	0.0007	0.0003	0.0003	0.0003	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
sector tenure	0.0265	-0.0401	-0.0609	-0.0436	0.0111
	(0.0011)	(0.0051)	(0.0077)	(0.0040)	(0.0010)
sector tenure^2	-0.0019	0.0038	0.0055	0.0040	-0.0008
	(0.0001)	(0.0004)	(0.0006)	(0.0002)	(0.0001)
overid p value		0.088	0.423	0.064	
observations	214472	214472	208754	214472	214472
R^2	0.17	0.12	0.05	0.13	

Note: Robust standard errors are in parentheses.

3.3 Further Issues: Sector Tenure

In Tables 7 and 8, I report estimates of the same equations by treating sector tenure as an endogenous variable. As long as there is correlation between sector tenure and sector-specific effects in the error term, previous estimates would neglect an important aspect of the story, hence this new approach should help to better analyse the relation between wage growth and skill accumulation. As Parent (2000) suggested, deviations from the individual sector mean tenure serve this purpose (as for firm tenure). Previous instruments are as in the preceding section.

Including sector tenure as a further endogenous variable, it is immediately clear that results for tenure and experience don't change a lot. For both blue and white collars, IV estimates in column 2 indicate high returns to experience (10%) and in this case no returns to tenure, while returns to sector tenure become negative and statistically significant when controlling for selection and endogeneity. Panel data estimators do not show particular differences with respect to those in Tables 5 and 6.

Although coefficients' estimates do not differ a lot when including sector tenure, standard overidentification tests for instrumental variables show

Table 8: Experience, Tenure and Sector Tenure. White Collars

	OLS	IV	IV FE	IV GLS	Hausman Taylor
	1	2	3	4	5
experience	0.0306	0.1097	0.0870	0.1046	0.0665
	(0.0021)	(0.0098)	(0.0251)	(0.0048)	(0.0017)
experience^2	-0.0005	-0.0054	-0.0037	-0.0048	-0.0024
	(0.0001)	(0.0009)	(0.0008)	(0.0004)	(0.0001)
firm tenure	-0.0012	-0.0012	0.0014	-0.0000	-0.0020
	(0.0019)	(0.0027)	(0.0033)	(0.0021)	(0.0015)
firm tenure^2	-0.0001	-0.0003	-0.0005	-0.0004	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
sector tenure	0.0284	-0.0264	-0.0187	-0.0252	0.0124
	(0.0024)	(0.0084)	(0.0079)	(0.0048)	(0.0020)
sector tenure^2	-0.0013	0.0024	0.0014	0.0021	-0.0010
	(0.0002)	(0.0007)	(0.0007)	(0.0004)	(0.0001)
overid p value		0.056	0.475	0.092	
observations	57093	57093	54625	57093	57093
R^2	0.33	0.30	0.32	0.28	

Note: Robust standard errors are in parentheses.

important differences. In what follows, I further discuss these issues and compare my findings to those in the literature.

3.4 Discussion

In this section, I discuss in more detail results obtained in previous sections. Firstly, I investigate the robustness of my results through a series of tests to account for the relevance of instruments and identification of the model.[24] Secondly, I compare my results to those obtained by Cingano (2003) for two provinces in Italy and by Dustmann and Pereira (2008) for the UK and Germany respectively. The different institutional settings of these two countries in wage determination allow me to draw some conclusions regarding the relevance of my results in comparison with the literature.

The relevance of instruments is considered through an F test on the overall significance of excluded instruments in the first stage regressions, separately on the sample of blue and white collars. Both test always return a value bigger than 10, hence, excluded instruments are relevant for the estimation

[24] The complete battery of results is available upon request.

of returns to experience and tenure. The quality of instruments and the validation of their use is performed by checking their orthogonality with the error term. The latter condition is verified with standard overidentifying restriction tests on excluded instruments. I reported all of them in separate row in Tables from 5 to 8. When treating sector tenure as exogenous, p values of the Sargan statistic indicate that for both groups I cannot reject the null that the instruments are uncorrelated with the error term, indicating excluded instruments are safely excluded from the wage equation. Things change when sector tenure is treated as endogenous; in this case p values are much lower indicating the instruments can have some correlation with the error term, at least some of them, invalidating the overall procedure. However, the p value of Durbin-Wu-Hausman tests strongly rejects the null of exogeneity of experience, tenure and sector tenure, indicating OLS methods are inappropriate and IV methods must be used.

Finally, as far as identification is concerned, all models satisfy both the order and rank condition. The former requires the number of instruments to be higher than the number of endogenous variables, and in this case is easily satisfied as there are more excluded instruments and endogenous variables; the second requires that the rank of the matrix of the coefficients on the instruments has maximum value as many as the reduced forms. I test the null hypotheses of rank 3 and 5 respectively and obtain that the p-value for this test is zero for both skilled and unskilled workers, decisively rejecting the null.

Results obtained in this paper indicate there are substantial returns to experience and small or insignificant returns to tenure. When considering panel estimates, the same results is found with blue collars having flatter wage growth profiles for each year of experience, I also find negative returns to sector tenure. These findings are substantially in line with those found in similar studies. For example, Cingano (2003) provides estimates of returns to tenure and experience for two provinces in the North of Italy, including district tenure as third source of wage growth. Comparability is not very simple as there is a lot of heterogeneity across different regional contexts; however, his estimates indicate a return on year of experience of 12% and barely significant returns to firm tenure. He doesn't find any evidence of returns to district tenure (actually they are negative). Interestingly, this study also finds that higher experience is associated with lower unobserved productivity in the job, and the OLS bias is negative.

When comparing the Italian labour market with other European countries, the direction of the bias persists. A common finding in Dustmann and Pereira (2008) for both Germany and the UK is that after controlling for endogeneity and selection, returns to firm tenure drop to zero; this is true for both unskilled and medium skilled workers. On the other hand, returns to experience are higher in Britain than in Germany (about 8% for unskilled and 9% for medium skilled against 9% and 3% for German workers respectively).

4 Concluding Remarks

In this paper, I provide different estimates for the average returns to experience and firm-specific tenure for a sample of young Italian male workers in the private sector. Using different empirical strategies, the relative contribution of general and specific skills to overall wage growth is analysed and theoretical considerations are discussed to explain the patterns found in the data.

To overcome standard selection and endogeneity problems that arise when past workers' behaviour influences the wage outcome, I estimate wage equations using instrumental variables techniques on cross section and panel data; in particular, the estimation method excludes age and deviations of tenure from its mean over the duration of a job as instruments for experience and tenure. I also consider a dummy of displacement as further excluded instrument: as long as this is exogenous and correlated with mobility, displaced workers can be considered as a random sample of the population.

Econometric estimates of returns to experience and tenure indicate both white and blue collars enjoy substantial returns to general labour market experience (about 9% per year with IV estimates); however, both groups have very small or insignificant returns to firm tenure. Different panel data estimators substantially confirm these results.

Reported estimates indicate the individual and job match components are important in shaping the wage profile of young workers, and OLS estimates of returns to experience are downward bias. There is some evidence of less productive individuals staying longer in the market and accumulating more experience; on the other hand, the increase in returns to tenure when correcting for selection is a consistent with a matching model in which workers have interest to move and find a good match. Still, heterogeneity in the returns to experience and in preferences for work can also generate an upward bias in IV returns when these estimates are representative only for a subsample of the population. In general, the evidence indicates returns to general skills in the labour market are more important than firm specific skills for wage growth of young Italian workers. At least for this group, increasing participation is of fundamental importance for better career prospects.

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