Is It the Way She Moves? New Evidence on the Gender Wage Growth Gap in the Early Careers of Men and Women in Italy *

Emilia Del Bono[†] and Daniela Vuri[‡]

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Abstract

This paper explores newly available Italian data derived from a 1:90 sample of social security administrative records (INPS) to investigate gender differences in log wage growth. A significant pay differential between men and women emerges during the first years of labour market experience. These gender differences are highest when workers move across firms and, in particular, for job changes which take place within a very short period of time, involve positive wage growth, and result in the highest salary increases. This gender mobility penalty occurs mainly when workers move to larger firms and this is most likely explained by the fact that women value more than men some of the characteristics of these jobs or employers. Overall our results suggest that job and firm characteristics, rather than differences in worker characteristics or across-the-board discrimination, are the most important determinants of the gender wage growth differential in the Italian labour market.

Keywords: job mobility, gender gap, wage growth, fixed effects panel estimation
JEL classification: J16, J31, C23

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[†]Institute for Social and Economic Research (ISER), University of Essex and IZA, Bonn. E-mail: edelbono@essex.ac.uk

[‡]University of Rome Tor Vergata, CHILD, IZA and CESifo. E-mail: daniela.vuri@uniroma2.it. *Address for correspondence:* Daniela Vuri, Department of Financial Economics and Quantitative Methods, Faculty of Economics, Via Columbia 2, 00133 Roma - Italy. Tel. +39 06 7259 5916, Fax +39 06 2040219

1 Introduction

It has been shown that wage growth in the early years of labour market experience accounts for over two thirds of lifetime wage growth and that over a third of this increase can be attributed to job-to-job wage gains (Topel and Ward, 1992). As far as gender differences are concerned, several studies find that on top of a positive gap between male and female starting wages men gain more than women throughout the initial years of their career (Loprest, 1992; Light and Ureta, 1995). While there seems to be some consensus on the importance of human capital accumulation and family formation in explaining these differences in early career wage growth (Light and Ureta, 1995; Manning and Swaffield, 2005; Napari, 2006), the role of job mobility is less well understood.

Men and women have been found to be different not only in terms of their propensity to change employer (Light and Ureta, 1992), but also in terms of their gains from job mobility (Loprest, 1992). While it is possible that the reasons behind job changes are different according to gender (Sicherman, 1996; Keith and McWilliams, 1997, 1999; Manning, 2003), it is interesting to see that a male-female gap in job-to-job wage gains has been documented even among those continuously employed (Rhum, 1987) or those affected by involuntary separations (Madden, 1987; Crossley *et al.*, 1998).

This paper proposes to investigate the association between job mobility and gender differences in log wage growth by looking at the early career development of a large sample of Italian workers. Our data is derived from the Italian Social Security Administration (INPS) archives to form a 1:90 random sample of private sector employees. Information on these individuals and the firms which employ them is collected every year, so it is possible to derive continuous labour market histories for each worker over the period between 1985 and 1997. The analysis is restricted to workers working full time and who have an almost continuous working experience in order to select a sample of individuals who are relatively homogeneous in terms of labour force attachment and individual preferences.

Although there seems to be very little difference between male and female wages at entry (about 3 per cent), our data shows that this gap widens rapidly over time. By the end of the first ten years of experience real wages are 37.4 per cent higher for men but only 27.6 higher for women. This translates into an average gender wage differential of about 14 per cent, which becomes 18 per cent if we consider only workers with lower education levels. The data also shows a significant relationship between this gender wage differential and job mobility, as we observe that men and women experience similar rates of within firm wage growth but significantly different rates of between firm wage growth.

As suggested by the existing literature, there are many possible explanations for this finding. Observed and unobserved worker characteristics, especially those related to human capital accumulation, may play an important role even in our relatively homogeneous sample of workers, for instance. On the other hand, there might be some form of labour market discrimination which results in higher rates of involuntary separation for women than men or makes it more difficult for women to negotiate a higher salary when moving to a different employer. Finally, it could be that men and women change job for different reasons and therefore assign a different value to certain characteristics of the job or the employer. Our primary interest is to explore these different hypotheses with the data at hand and assess their contribution to the formation of the early career gender mobility gap.

2 The INPS administrative archives

The data used in this paper have been extracted from the Italian Social Security Administration (INPS) archives. These archives cover all private sectors workers that contribute to compulsory social security funds (some 13 million individual records per year). In Italy this dataset is unique in terms of the coverage and the accuracy of the individual labour market histories and the wage information it provides. Its very large sample size and panel structure are attractive features for empirical analysis and have generated a substantial amount of research in the past few years (see for example Favaro and Magrini, 2005; Capellari *et al.*, 2004; Contini and Villosio, 2003; and Borgarello and Devicienti, 2002).

Analyses are generally carried out on a 1:90 random sample of employees. Information on these individuals is collected every year, so it is possible to derive an annual panel of workers and construct their labour market histories for a long period of time. As our focus is on early career wage growth, all individuals analysed in this study must have at least two yearly records. We concentrate our attention on individuals working full time, as they should constitute a more homogeneous group in terms of individual preferences. Our final sample consists of an unbalanced panel of 130,499 person-year observations followed for a maximum period of ten years between 1985 and 1997.[1] Details of the sample selection and of the derivation of the main variables of interest are reported in Appendix 1.

3 Early career mobility and log wage growth: some stylized facts

As mentioned in section 2, our workers are followed for up to 10 years since the beginning of their working career. Therefore, we can observe their entry wage and then analyse how this changes over time. Figure 1 presents log wage profiles disaggregated by sex and level of education at different levels of potential experience.[2] Consistently with the basic prediction of human capital theory, we find concave-shaped profiles for both men and women. Log daily wage rates first increase with experience and then level-off, and this happens slightly earlier for women than for men. The figure also shows the existence of a very small gender wage gap at entry, which increases over time and becomes more evident after the first three years of experience (top-left panel).

We also display the same log wage profiles for low and high education workers separately (respectively top-right panel and bottom-left panel in figure 1). We see that the widening of the gender wage gap observed for the whole sample is mainly due to the behaviour of individuals with low education. Here the difference between the log wage of men and women more than doubles, increasing from 7.5 per cent at the beginning of the career to almost 18 percentage points towards the end of the observation period. By contrast, for those with high education we observe a roughly constant difference in the wage profiles of men and women of about 7 percentage points.

These patterns translate into the log wage growth rates presented in figure 2. Here we notice that wage growth is consistently higher for men than women during the entire working experience. Wages first increase at a rate of about 7 percentage points for the first two years and then start to slow down. There is also substantial heterogeneity in wage growth across education groups; low educated workers exhibit substantially high wage increases earlier in their career and a sharp slowdown later on, while the wage growth profile of highly educated workers appears rather flat.

Figure 3 shows that male workers change firm more frequently than women during their early career. However, this difference is rather small, only about 4 percentage points overall, and much less for more educated workers. This translates into small differences in overall mobility between men and women. Among those who move at least once in the observed period, we calculate that the average man has worked with 1.7 employers while the average woman has changed firm 1.6 times over the period of observation (figure 4). The same results hold for the low and high education groups.

On the other hand, comparing the wage growth of men and women and distinguishing within firm from between firm wage changes we get some striking differences. Table 1 shows that for the sample of all workers the difference in within firm wage growth between men and women is only about 0.4 percentage points. When we look instead at changes between firms we see that men gain about 1.8 percentage points more than women on average. In particular, it looks as if men who move to a different firm gain significantly more than those who stay with the same employer, while women seem to experience the same rate of log wage growth. This is also true for workers with low levels of education, while we observe lower and less significant gender differences for the high education group.

Figure 5 explores the same effects by displaying within firm and between firm gender differences in log wage growth by year of potential experience. The top two graphs show that what found in table 1 holds for all levels of experience. The differences are even more striking if we display within firm and between firm growth rates by level of education (centre and bottom graphs). For low educated workers who stay with the same employer between *t-1* and *t* the gender wage gap is very small, while the between firm male wage growth is clearly much higher than the between firm female wage growth. Looking at highly educated workers we find smaller differences and they tend to appear later on in the workers' experience.

The finding of a significant gender difference in between firm log wage growth is similar to what observed in the U.S. by Loprest (1992) and represents the main focus of our analysis. This gender mobility gap could simply be the result of different individual characteristics, such as general or firm-specific human capital, or it could reflect a significant degree of discrimination in the labour market, whereby women are more subject to involuntary separations or find it systematically more difficult to negotiate their salary when moving to a different employer. As suggested by Crossley *et al.* (1994), this gender penalty could also be the result of differences in the process of search for a new job. These could arise if women are less geographically mobile than men, for example, or if they value more than men certain job and employer characteristics. The next sections address these questions in more detail.

4 The gender gap in log wage growth

We start by considering the difference in log wage growth between men and women after controlling for individual characteristics and the main observed characteristics of the job and the employer. The estimated equation includes current and lagged values of the time-variant regressors as well as time-invariant variables which are thought to affect the rate of growth of wages as well as their levels. In other words, our specification can be expressed as follows:

$$\Delta w_{it} = X_{it}\alpha + X_{it-1}\beta + Z_i\gamma + \delta F_i + \nu_{it}, \tag{1}$$

where Δw_{it} represents the change in log daily wages for individual i between time t and time $t-1$, X_{it} and X_{it-1} represent vectors of observable individual and firm characteristics at time t and $t-1$, respectively, Z_i is a vector of time invariant individual characteristics, F_i is the female dummy, and ν_{it} is an i.i.d. error term. The estimates are shown in table 2. We first present the unadjusted gender log wage growth differential and then control for a set of observable characteristics of the worker and the firm.[3] Each specification is estimated on the whole sample and on the separate groups of workers with low and high education, respectively. This is because we saw from the descriptive analysis that log wage growth rates are very different for these groups and that gender differences are particularly marked among individuals with lower education.[4]

As we can see, the raw gender gap in year-to-year wage growth rates is only about 0.6 per cent for the whole sample, about 0.5 per cent for the sample of low educated workers, and close to zero and not significant for the group of workers with high education (columns 1, 3 and 5 respectively). Contrary to what one would expect, controlling for observed worker and job characteristics increases the differential for the entire sample as well as for the subsamples corresponding to different educational groups (table 2, columns 2, 4 and 6 respectively). This indicates that observed characteristics are such that women should progress even more rapidly than men during the initial years of their career.

Moreover, as we can see from the regression-adjusted estimates, there is a negative relationship between wage growth and potential experience, which reflects what we saw in figure 2. Longer current tenure is instead positively correlated with wage growth, while the higher the tenure in the previous year the lower the growth rate. Looking at current qualification levels, we see that white collar workers enjoy a higher level of wage growth with respect to blue collar workers, while apprentices experience a slower wage growth. This can be explained by the fact that an apprentice's salary is almost entirely fixed for the duration of the apprenticeship period and increases only afterwards, as shown by the positive and significant estimate on the apprenticeship dummy for the initial type of contract.

When considering firm variables, we see a positive effect of age of the firm and firm size on log wage growth. The same relationships are found when looking at the two groups of low and high educated workers. There are a few notable exceptions: a white collar qualification seems to affect wage growth only for high educated workers, starting with an apprenticeship contract benefits mainly the log wage growth rate of high education workers, and starting with a fixed-term contract has a negative effect on the wage growth of the low educated group. Moreover, only working in very large firms seems to matter for highly educated workers, while for low educated workers the relationship between firm size and log wage growth is much stronger.

As we saw in table 1, the gender differential in log wage growth is mainly found in correspondence of a change of employer. Table 3 proposes the same comparisons in a regression framework. We present here the raw and regression-adjusted log wage growth gender differential, distinguishing between periods in which there has been a change of firm by means of a dummy variable and considering its interaction with the female dummy. We estimate the following specification:

$$\Delta w_{it} = X_{it}\alpha + X_{it-1}\beta + Z_i\gamma + \delta F_i + \kappa C_{it} + \eta F_i * C_{it} + \nu_{it}, \tag{2}$$

where C_{it} is a dummy assuming value 1 if the individual has changed employer between $t-1$ and t. The unadjusted differential implies that on top of a gap of about 0.4 percentage points in log wage growth, women cumulate an extra 1.4 percentage points wage loss when moving to another firm. Very similar values for the female penalty associated with a change of employer are seen when looking at different education groups. Controlling for observed characteristics of the worker and the firm does not modify these results.

We further ask whether the same effect can be found when we control for time-invariant unobserved individual characteristics using a fixed-effects estimator. Since some workers move across jobs more than once in their early career, it is possible to identify the gender difference associated with a change of employer by looking at the interaction between the female dummy and the change of firm dummy. In other words, we estimate the following specification:

$$\Delta w_{it} = X_{it}\alpha + X_{it-1}\beta + Z_i\gamma + \delta F_i + \kappa C_{it} + \eta F_i * C_{it} + \mu_i + \epsilon_{it}, \tag{3}$$

where we decompose the error term ν_{it} into an individual specific component μ_i, reflecting individual time invariant differences in preferences and unobservable characteristics, and a component varying with time, ϵ_{it}, which is assumed orthogonal with respect to all the regressors. The coefficient of interest in this case is given by $\widehat{\eta}$, which represents the gender difference due to a change of firm net of any other difference between the wage growth rate of men and women.

As we can see from table 4, the female penalty associated with a change of employer is always negative and significant, whether we control for observable characteristics or not. If anything, the gap becomes even larger (although not significantly so) after taking into account unobserved individual-specific effects. Therefore, although selectivity into job mobility on the basis of individual heterogeneity is certainly present, the direction of the bias would seem to suggest that this type of heterogeneity is not an explanation of the lower log wage growth of women with respect to men.

These estimates of the effect of mobility rely on a comparison between movers and stayers at time t. As a further check, we introduce a second control group given by individuals who are stayers at time t but move to another firm at time $t+1$. As suggested by Mincer (1986), it might be reasonable to assume that the *next period movers* share the same unobservable characteristics of the *current period movers.* This implies that the on-the-job wage growth *next period movers* experience in the current period is a better proxy of the wage gain *current period movers* would have received had they not moved than the *current stayers*' wage growth rate.

The comparison between *current movers* and *future movers* is achieved by estimating the following specification:

$$\Delta w_{it} = X_{it}\alpha + X_{it-1}\beta + Z_i\gamma + \delta F_i + \kappa C_{it} + \eta F_i * C_{it} + \theta * C_{it+1} + \\ + \lambda F_i * C_{it+1} + \mu_i + \epsilon_{it}, \qquad (4)$$

where C_{it+1} represents a dummy with value 1 if the individual has not changed employer between $t-1$ and t but will move to another firm between t and $t+1$. According to this specification, the gain (penalty) associated to a change of firm is given by the difference between $\widehat{\kappa}$ and $\widehat{\theta}$ for men, and an additional term given by the difference between $\widehat{\eta}$ and $\widehat{\lambda}$ for women.

One of the most important findings of table 4 (see columns 5 and 6) is that within the current period the wage change of next period male movers is not significantly different from that of male stayers (coefficient $\widehat{\theta}$), therefore estimates of the mobility gain for men are not very different whether we consider as a comparison current stayers or future movers. This results holds for the entire sample and for the subsamples of low and high educated workers.

The situation is different if we look at women. Here we can see that for the full sample and for the sample of highly educated workers, the wage change of future female movers in the current period is higher than that of the current stayers (coefficient $\widehat{\lambda}$). In other words, if the current wage change of next period movers is a proxy of the wage change current movers would have experienced had they not moved this result suggests that women who move to another firm suffer a penalty even larger than the simple comparison with the group of stayers indicates. Looking at the fixed-effects estimates for the whole sample, for instance, we see that comparing current movers with current stayers would give a gender penalty of about 1.8 per cent (column 4), while using future movers as the control group we would estimate a gender penalty of about 2.8 per cent (column 6). Overall, these section provides strong evidence that even after choosing alternative control groups the gender wage growth gap cannot be explained by the presence of unobserved heterogeneity.

5 Different reasons for changing job

Our first results point out clearly that there is a significant gender gap in between firm wage growth and that this difference is unlikely to be explained by traditional methods which allow to control for observed or unobserved individual heterogeneity. It is therefore important to consider in more detail other explanations and in this section we investigate whether there is any evidence to suggest that men and women move to different jobs for different reasons. It could be argued, for example, that gender discrimination results in higher involuntary separation rates for women than men, so that women may observe lower between firm wage growth rates. On the other hand, it could simply be that while men move to a different firm in search of career advancement, women's mobility might be more closely related to marriage and fertility decisions. In this section we will consider both these hypotheses in turn.

5.1 Voluntary and involuntary firm changes

A possibility we need to consider is whether women are more likely to suffer an involuntary separation than men and therefore experience a larger penalty associated with job mobility. As the INPS archives are not survey-based, we do not have direct information about the reason why a job change occurs, so we cannot directly distinguish between voluntary and involuntary moves. We cannot even identify firm closures or collective dismissals, because we have only a 1:90 sample of the universe of workers covered by the Social Security System, and the risk of misclassifying involuntary and voluntary separations is too high to proceed in this direction.[5]

What we can do, however, is to see whether there are systematic differences in mobility patterns across men and women which could indicate something about the voluntary or involuntary nature of the separation and test whether the gender penalty is sensitive to this distinction. In order to do so we run several checks. First we look at the length of the interruption between job changes. Secondly we analyse the relationship between the mobility gap and tenure in the previous job. Then we distinguish between positive and negative wage changes. Finally we consider the entire distribution of wage changes.

Since we observe the interval of time between the end of a job and the beginning of the next job in another firm, we argue that shorter intervals (less than two months) could result from voluntary moves, while longer gaps (more than two months) could be an indicator that an involuntary separation occurred.[6] The raw data offers no evidence that women are more likely to experience an "involuntary" separation. Looking at the duration of the average job interruption we see that the interval between two jobs is usually longer for men than for women (7 months for men compared to almost 6 for women), and that 39 per cent of men against 43.3 per cent of women move to another firm within 2 months of leaving the previous job. In table 5 we test in a regression framework whether the gender difference in between firm wage growth is sensitive to the length of the interruption. As we can see, there is no evidence that the size of the gender penalty increases with the length of the interval between two jobs. The most significant gender differences are to be found at shorter interval durations, while the gender penalty associated to intervals of more than 2 months is usually not significant, and certainly no larger than the penalty associated with shorter interruptions.

Second, we investigate whether the gender wage growth gap observed after a change of employer is related to the amount of tenure accumulated before the move. If women are more likely to experience an involuntary separation because of discrimination in the labor market the extent of their wage loss after a job change should be positively related to the amount of tenure accumulated in the previous job, as this can be seen as a proxy for firm-specific human capital. Put differently, we should observe higher gender penalties for those who have longer tenure in the previous job. We explore whether this is the case in table 6 by estimating a specification similar to that in equation 2 plus an interaction between the female dummy and the variable representing tenure in the previous job. As we can see, this term is always insignificantly different from zero in all specifications and across all the different subsamples.[7]

As a third test we propose a very crude way of distinguishing between voluntary and involuntary separations, i.e. we distinguish between positive and negative wage changes. This is done in table 7, where we run separate regressions on positive and negative wage changes and consider for each regression the impact of the gender dummy. As we can see, when experiencing negative changes in log wage women lose as much as men and sometimes even less, but when experiencing a wage increase they seem to suffer considerably. Their average wage growth in this case is between 2 and 3.6 percentage points lower than that of men.

Finally, as the distribution of between firm log wage growth is different for men and women (the median wage growth for men is almost 5 per cent while for women it is only 3.5 per cent), another way of performing this test is to investigate whether the gender mobility gap is the same across the entire distribution of log wage changes, or whether it is concentrated in some parts of the distribution. We run quantile regressions of the log of between firm wage growth on a vector of control variables distinguishing the effect of gender at the $25th$, $50th$ and $75th$ percentile of the distribution. The results are very clear-cut. As we can see in table 8, the effect of being female becomes negative and higher in magnitude the higher the between firm wage growth.[8] In other words, it seems that the largest gender penalty is to be found among those who experience significant wage increases.[9]

Overall, these results suggest that the observed gender mobility gap cannot be explained by a higher incidence of involuntary separations among women than men.

5.2 Fertility and marriage

Another likely explanation of a persistent difference in men and women's log wage growth associated with job mobility is that women's mobility might mainly be due to marriage and fertility considerations whereas this is not the case for men. In other words, it could be that women move to a different employer when they get married or have a child because they need to be closer to their partner, or because they are in search of a better work-life balance in terms of reduced hours or more flexible timetable. As long as these types of job moves are less likely to be associated with wage growth than moves due to career considerations we might observe a gender mobility gap.

The INPS archives do not contain information on hours of work, but only on part time and full time status. Since variation in part time hours is relatively high, knowing that an individual worked part time is not enough to take into account differences in hours, so we restricted our sample to individuals who always work full time. By doing so we still cannot completely rule out the possibility that differences in working hours can explain differences in between firm log wage growth, however it is unlikely that variation in working hours among full timers is enough to wash out any observed gender wage growth difference.[10]

Even if we exclude hours of work as an explanation, it is still possible that women who move to a different job for family reasons are prepared to accept a trade-off between their salary and other aspects of the job we cannot control for. So, it would be important to know whether there is any evidence of a correlation between the timing of a job change and the timing of marriage or fertility. Unfortunately, our data does not provide any information on the marital status of individuals or on periods of maternity leave, so we lack any direct evidence in this respect.

We can however indirectly test for the existence of such a correlation by interacting the change of employer dummy with age dummies in order to see whether the largest gender differences associated with mobility across firms occur at a time in which women are more likely to get married or have children.[11] The results of this check are reported in table 9, which shows that a significant gender penalty is only found between 20 and 25 years of age, and that there are small timing differences across groups with different education. In particular, for the low educated sample the most significant effects are found between 20 and 24 years, while for the high educated sample the range is between 23 and 25 years. As we know that age at marriage and childbirth is usually positively correlated with education, there is a suggestion here that the type of job mobility we see in our data might be related to family events.[12]

From our discussion in Appendix 1 we know, however, that the distinction we make between low and high educational levels is subject to a certain degree of inaccuracy, so it is useful to look for further evidence. Official data from the Italian National Institute of Statistics (ISTAT) show that during the '90s the average age of women at marriage was well above 26 years, the average age of women at the birth of the first child was between 27 and 28 years, while the average age at childbearing was even higher (see table A.2). Unfortunately, these statistics are not available by level of education of the mother, or for earlier years, but serve to have an indication of the likely timing of these events.

This evidence suggests that marriage and fertility decisions are unlikely to be a direct explanation of the gender mobility penalty in that this penalty seems to emerge sometime before these events take place. However, we cannot exclude that marriage and fertility considerations influence the process of job search and lead women to choose jobs facilitating the achievement of a work-life balance well in advance of the formation of a family. In this case, the process of search for a new job could be different among men and women, in that the latter could be less geographically mobile, for example, or could value more certain characteristics of the new employer and accept a slightly lower wage in exchange. We return to this point below.

6 Job and firm specific determinants of the gender mobility wage growth gap

So far, we focused on individual-level characteristics controlling for job and firm characteristics using a full set of dummies for occupation, industry, firm size and province at time t and at time t-1 in the wage growth equation. We now turn to analyse more specifically these job and firm characteristics and in order to do so we summarise this information by means of 0/1 dummies indicating whether the worker changed occupation, industry, firm size or province while moving employer.[13]

Table 10 presents a set of regressions which show the effect of these changes. In the first column (Model I) we report the average gender differential in between firm wage growth, controlling only for individual level characteristics, a linear term in the age of the firm and time dummies. This differential is about 1.4 percentage points. In the second column (Model II) we introduce a set of dummies indicating changes of occupation (distinguishing between apprentices, blue collar and white collar workers), industry, firm size (to larger and smaller firms) and province of work between time *t-1* and *t*. As we can see, with the exception of the change of province dummy, all the other dummies are significantly correlated to log wage growth. The overall gender differential decreases, but it remains significant, at least for the full sample.

In the third column (Model III) we introduce interactions between these dummies and the female dummy in order to analyse whether the gender penalty in between firm wage growth rates differs systematically according to a change in job qualification or firm characteristics. An important aspect which emerges from this table is that apprenticeship training is not as rewarding for women as it is for men. This could be due to the fact that the old type of apprenticeship contract (these contracts were modified in 1997 and then later on in 2003) was predominantly used to train workers in manual occupations, and women were less attracted to these types of jobs. Women accepting these contracts might invest less in human capital accumulation during the training period.[14] The other interesting result is that women are observed to gain less than men when moving to larger firms, although this effect is precisely estimated only for the full sample. We also notice that the overall gender wage differential is now less than a quarter of its initial magnitude and totally insignificant, for all levels of education as well as for the entire sample.

As there are several industries, firm size categories and provinces, there are alternative and possibly better ways to take into account the way in which changes in these characteristics of the firm affect log wage growth.[15] Following Loprest (1992) and Winter-Ebmer and Zweimuller (1999), we construct a set of variables which represent the average premium (or penalty) associated with a specific change of industry, province and firm size.[16] These variables are obtained as the difference in the coefficients of a regression in levels of log wages on the usual set of individual variables, plus the full set of occupation, industry, firm size, province and year dummies. The regression in levels is estimated on the whole sample, including periods in which the individual has not changed firm, and does not account for gender differences.[17] It therefore gives us the simple cross sectional coefficients which represent the relationship between average wages and firm or job characteristics.

Using firm size as an example, the OLS estimation of log wages on firm size dummies and all other controls produce the following results:

$$\ln w_{it} = ... + 0.036(size5 - 14)_{it} + 0.089(size15 - 99)_{it} + 0.171(size100+)_{it} + ..., \quad (5)$$

where w_{it} is the gross daily wage rate and firms with less than five employees are the reference category.

We then calculate a new variable representing the premium (or penalty) associated with each possible combination of the coefficients. For example, the average increase in log wages obtained when moving from a firm of size 5-14 to a firm of size 15-99 will be computed as:

$$\Delta \ln w_{i,t|[size(15-99)-size(5-14)]} = 0.089 - 0.036 = 0.053. \quad (6)$$

So, for each change of employer between time *t-1* and t we have a single variable which gives us the premium associated to that specific change of firm characteristics. It is then possible to run a regression of log wage growth onto the usual set of controls and the four variables representing the average premium due to a change of industry, firm size or province so constructed. The coefficient on the variable representing the firm-size premium obtained from the log wage growth regression will tell us, for example, how much of the average premium associated to a change of firm size is to be gained when moving across employers. The interaction between this variable and a gender dummy will reflect whether there are differences between men and women in terms of the firms or jobs they move to or in terms of the premium (or penalty) gained when moving across the same type of firms or jobs.

Table 11 shows the results of applying this procedure to our data. We first present the coefficient for the overall gender wage growth penalty as calculated in the previous table, then consider what happens when adding the industry, firm size and province average premiums.[18] As we can see from the second column, individuals changing industry claim 86 per cent of the OLS estimated industry premium. Similarly, individuals who move to larger firms gain about 51 per cent of the firm size premium implied by the cross-sectional estimates, while those who move to smaller firms see their wage decrease by more than 63 per cent of the estimate predicted by OLS. Individuals changing province experience a wage increase equal to 33 per cent of the cross-sectional province premium, to signify that geographic mobility is an important aspect of between firm log wage growth.

We then consider the interaction between these variables and the female dummy (Model III) and see some very interesting results. First of all, although 13.8 per cent women against 20.8 per cent men change province of work when changing employer, there is no evidence that this translates into a disadvantage for women. Secondly, for the entire sample and the subsamples of workers with low and high education women are always found to gain significantly less than men when moving towards a larger firm. Female workers seem to lose slightly less than men when moving towards a small firm, but this coefficient is never statistically significant. As we can see from the p-value on the differences between these coefficients at the bottom of the table, there is a significant asymmetry between positive and negative changes of firm size for women but not for men. Once again, the "unexplained" sex differential in log wage growth diminishes and becomes completely insignificant once we account for these effects.

In light of this evidence we could argue that larger firms offer jobs with characteristics (more protection, more flexible schedule, more possibilities to change job within the firm, and so on) that women value more than men, so that they are prepared to accept a lower salary in exchange. We propose a test of this hypothesis. If larger firms offer non-monetary job characteristics which are valued by workers *conditional on the current wage* a worker who is employed in a larger firm should be less likely to move to another firm. As we can see from table 12, this is exactly what we find, i.e. we see that there is evidence of a negative relationship between the firm size and probability to change employer in the next period. More to the point, we find that this effect is even stronger for women (Model III), particularly the low educated. This evidence is consistent with the hypothesis that women value certain characteristics of the jobs offered by larger firms more than men and are therefore prepared to accept a lower compensation.

7 Conclusion

This paper presents a study of gender differences in wage growth in the early careers of men and women in Italy. We focus here on wage growth due to job mobility. This is because differences in returns to job mobility are found to be the most important source of the observed differential in log wage growth between men and women during their early career and significantly contribute to the formation of a gender wage gap.

We first show that while men seem to gain when moving to a different employer, this is not the case for women. This difference cannot be attributed to self-selection into mobility. On the contrary, our evidence seems to indicate that observed and unobserved individual heterogeneity exacerbates rather than explain the observed gender mobility penalty.

We then look at whether the difference in between firm log wage growth rate is the result of a different type of job mobility across men and women. We first consider whether there is a higher incidence of involuntary separations among women than men, but we find no evidence to support this hypothesis. In particular, we find that the most significant gender penalty is observed among voluntary moves, defined here as those which occur within a very short period of time, involve positive wage growth and the highest salary increases. We then analyse whether the gap in between firm log wage growth coincides with marriage and fertility decisions. We find that there is not a perfect correspondence between the timing of job changes and fertility or marriage, so that these events are unlikely to be a direct explanation of the gender mobility penalty.

This leads us to speculate that the gender gap in between firm log wage growth might be explained by differences in the process of job search and may reflect different characteristics of the job or the employer. It turns out that unlike other studies (Light and Ureta, 1995; Loprest, 1992) once we control for the specific types of changes into different occupations, industries, firms of various sizes and provinces, we are able to account for the entire gender gap in between firm wage growth. In particular, one of our most important findings is that the gender penalty is higher when workers move towards larger firms and this seems to be explained by the fact that women value more than men certain characteristics of the jobs offered by these employers.

Overall we can say that the existence of a gender wage growth gap in the Italian labour market is explained to a large extent by the characteristics of the job or the employer rather than differences in worker characteristics or across-the-board discrimination. The family formation process may be important, but only insofar as it influences the process of job search and leads women to value more certain non-monetary aspects of the job when moving to a different employer.

Appendix 1 - The selection of the sample and the derivation of the variables of interest

The INPS archives collect data on all employees and employers working in the private sector in Italy and are the first large Italian dataset to provide information on workers' labour market histories and earnings over a long period of time.[19] In order to derive a panel structure, people born on the 10th of March, June, September and December of each year have been selected from these archives to form a 1:90 random sample of employees which is then followed over time.

For each worker in the panel the dataset provides information on gender, date and place of birth, and for each employment spell we know the starting and ending date, the occupation, industry, type of contract (full time or part time), gross earnings, weeks and days of paid work registered during the year. We also have an employer identifier and a set of variables related to the firm, such as the average number of employees employed during the year, geographic location and initial year of activity. Because of its administrative nature, however, the dataset presents some drawbacks. In particular, there is very little demographic information on individual characteristics. For example, information about education or years of schooling is not collected.[20]

In order to overcome this problem, we construct a proxy of the highest completed level of education using the age at which an individual first started to work.[21] We adopt the following procedure. As we do not observe the entire working history of the individuals in our sample, but have information on the employment spells recorded from 1985 onwards, we select our sample by taking all individuals who enter the panel between the age of 15 and 18 in 1985, between the age of 15 and 19 in 1986, between the age of 15 and 20 in 1987, and so on. In this way we are able to track an individual from his or her entry into the labor market because we know that an individual whose first spell in the panel is recorded at age 20 has not been observed in the dataset before 1987 and consider 20 as his or her age of entry in the panel. There is some uncertainty about the previous work experience of those between 15 and 18 years included in 1985, for which we have incomplete information, but we assume that this is not going to affect our results as it concerns only about 3 per cent of our sample.

In order to derive a proxy of educational qualifications, we further specify the age at which the individual first started to work in a non-seasonal job. By seasonal job we intend an employment spell which lasts less than 4 weeks, or a spell which lasts between 4 and 17 weeks and occurs during the period between June and September. In this way we do not consider short spells of employment or spells which are compatible with school as part of the employment history of the worker. We then divide the sample into three groups: (i) individuals who start working (in a non-seasonal job) between the age of 15 and 18, (ii) those who start working between the age of 19 to 25, and (iii) those whose first employment spell in the data is observed between the age of 26 and 29. The same groupings were used by Favaro and Magrini (2005) to define workers with lower secondary, upper secondary and tertiary education level, respectively.

To check whether grouping individuals by their age of entry in the panel is a reasonable approximation of their level of education we use data from the household survey conducted by the Bank of Italy over the period between 1989 and 1998. This dataset provides information on a representative sample of Italian households and collects details of the economic and social status of their components, including the age at which they started working and their educational qualification. Using this data, we calculate that among those entering the labour market between the age of 15 and 18 72.5 per cent had a lower secondary education qualification, about 25 per cent had a high school diploma, while the remaining fraction reported primary or no education. For those entering the labour market between 19 and 25 years the distribution by level of education was as follows: 74 per cent had achieved a high school diploma, 23 per cent had lower secondary education, while the remaining group was equally divided among those who had already completed a degree (1.5 per cent) or had primary or no qualifications (1.5 per cent).[22]

This confirms that age at first job can be considered a good proxy of an individual's level of education. Therefore, in the analysis that follows we will refer to employees entering the panel between 15 and 18 years and to those entering the panel between 19 and 25 years as having *low* and *high* (secondary) education, respectively. Since those who enter the labour market after age 25 are observed for a very short period of time (as they enter the panel quite late by construction) and are very few (less than 3 per cent of the sample), we exclude them from our analysis.

Each record in the original data corresponds to a single employment spell when this begins and ends within the same calendar year, while spells which span more than one year are divided into different yearly records. In order to derive the working histories of individuals and analyse their wages and wage growth over time we reorganise the data into a person-year longitudinal dataset with only one record of employment per year. This implies that if there is more than one employment spell during the year, only the longest spell is included in the data.

We define potential work experience as the total number of years since the first entry in the panel and consider up to a maximum of 10 years. Tenure is calculated as the number of weeks an individual is observed working for the same employer and this is then converted into years. For the purposes of this analysis job mobility is defined in terms of changes of employer. So that when we talk about number of jobs we intend to indicate the number of times a worker has changed employer.[23]

The earning variable used is the real daily (gross) wage.[24] This is obtained by dividing the total amount earned during that year or during that employment spell (if within the year) by the number of days worked over that period, and deflating it by the Consumer Price Index (base year 1995). Finally, we restrict the sample in order to avoid the presence of outliers. In particular, individuals with very high (more than 200 per cent) or very low (less than -200 per cent) wage growth are excluded.

We conduct our analysis on individuals working full time and those who have a period of interruption between two different jobs of no more than 2 years. Only 7 per cent of our sample has a record of part time work (two thirds of them are women), due to the low availability of part time jobs during that period in Italy, while 12 per cent (three quarters of them men) experience a job interruption greater than 24 months. This selection implies that our results cannot be easily generalised, but allows us to focus our analysis on individuals with a very strong attachment to the labour market, both in terms of hours and experience, who should be less heterogeneous in terms of individual preferences.

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Notes

[1]The original file includes the years 1998 and 1999. These years cannot be used in our analysis as information on some firm characteristics is missing for a very large part of the sample in 1998 and for the entire sample in 1999.

[2]For the distinction between low and high education levels see Appendix 1.

[3]Table A.1 displays summary statistics of the main observed characteristics of the individual and the firm at time t. The full set of control variables include: a dummy for female worker, a high education dummy (where applicable), a linear and quadratic term in potential experience, tenure at time t and at time t-*1*, a full set of dummies for occupation at time t and at time t-*1*, a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for firm size at time t and at time t-*1*, a full set of dummies for industry (2 digit) at time t and at time t-*1*, a full set of dummies for province of work at time t and at time t-*1*, and a full set of year dummies.

[4]In the analysis that follows we consider a combined equation for men and women. Although a test of whether two separate equations for men and women differed only by a constant was usually rejected, the analysis conducted on separate equations revealed the same qualitative results. Here we prefer a single equation for ease of exposition as it allows us to highlight more clearly differences across education groups.

[5]Our earlier attempts in this direction were abandoned because of the excessive number of assumption required in identifying firm closures and collective dismissals.

[6]We use a cut-off point of 2 months as there is a very sharp difference in the frequency of moves around this duration; about 26 per cent of job moves take place after an interval of 2 months, while only 6.5 per cent have an interval of 3 months.

[7]Another possibility is that that women accumulate less firm-specific human capital than men, so that an involuntary separation has a smaller effect on female wages after a job change (for a discussion on this point see Madden (1987)). In this case the coefficient on the interaction term should be positive and significant, however.

[8]We test whether the differences of the coefficients over each pair of quantiles are significantly different from zero. All the differences pass the test at 1 per cent significance level except for the difference between the $50th$ and the $75th$ percentile coefficients with controls for low educated workers and between the $25th$ and the $50th$ percentile coefficients with controls for high educated workers.

[9]Fitzenberger and Kunze (2005) perform a similar analysis but they look at the gender gap in wage levels. They find that the gender mobility gap is highest in the lower part of the wage

distribution.

[10]According to data for the Italian Labour Force Survey (RTFL), the average number of weekly hours for men working part time was 29.94 and the standard deviation was 11.26, while the corresponding values for women were 23.25 with a standard deviation of 7.84. Among full time workers, men worked an average of 41.08 hours a week with a standard deviation of 5.09, while women worked on average 40.16 hours a week with a standard deviation of 5.30.

[11]We thank Marco Leonardi for having suggested this test.

[12]We also gained access to another version of the INPS archive, which provides some information on maternity leave by means of a simple dummy variable. According to this version of the data, 8.2 per cent women in the sample had a recorded period of maternity leave over the period between 1985 and 1997, i.e. between 15 and 30 years of age; 10.1 per cent among those who entered the panel between 15 and 18 years, and 6.9 per cent among those who entered the panel between 19 and 25 years. The mean age at the onset of maternity leave was 25.3 for the whole sample, and 24.8 and 25.9 for the subsamples of women with low and high education, respectively. Moreover, since the dataset currently used in the paper does not allow to identify women in maternity leave, we used this alternative dataset to test whether the presence of women in maternity leave in the sample could affect our results. Our estimates did not change significantly when excluding them from the sample. Although it provides additional information with respect to the dataset used in this paper, we decided not to use this version of the INPS dataset since it does not contain information on firm characteristics for the years 1985 and 1986.

[13]In a series of related papers Kunze finds evidence that occupational segregation significantly contributes to the formation of a gender wage gap during the initial stages of a worker's career in Germany (see Kunze, 2003, 2005; and Fitzenberger and Kunze, 2005). We are unable to propose here a more detailed analysis of this hypothesis as our data provides information only on very highly aggregated qualification levels (i.e. apprentices, blue collar, white collar) and the degree of mobility across these categories is very low.

[14]Similarly, Kunze (2005) find that differences in the apprenticeship training occupation explain the main part of the gender wage gap and seem to lead to a permanent wage disadvantage throughout the early career.

[15]Ideally we would like to control for both observable and unobservable firm heterogeneity (Abowd *et al.*, 1999); unfortunately, the INPS archives take as their sampling unit the individual and not the firm, which means that we have too few individual observations at the firm level to estimate a model with both individual and firm fixed-effects.

[16]We continue to take into account occupational changes as 0/1 dummies as the number of

categories is sufficiently small in this case.

[17]In other words, it does not include a gender dummy.

[18]In Models II and III, change of occupation dummies and their interactions with the female dummies are not reported as the results are not significantly different from what shown in table 10.

[19]Two additional Italian microdata sources are: the Bank of Italy Survey (SHIW) and the Labor Force Survey (RTFL). However, even though these datasets are richer than the INPS archives in terms of demographic characteristics of the individuals they have some important drawbacks. In the SHIW too few people are followed over years and therefore the sample size is too small, while in the RTFL workers are followed only for a period of one year and half due to the rotating sampling design and no information on earning is provided.

[20]Also note that the dataset covers only periods in employment and it is therefore impossible to know whether a gap in the records corresponds to a period of unemployment, self-employment or employment in the public sector.

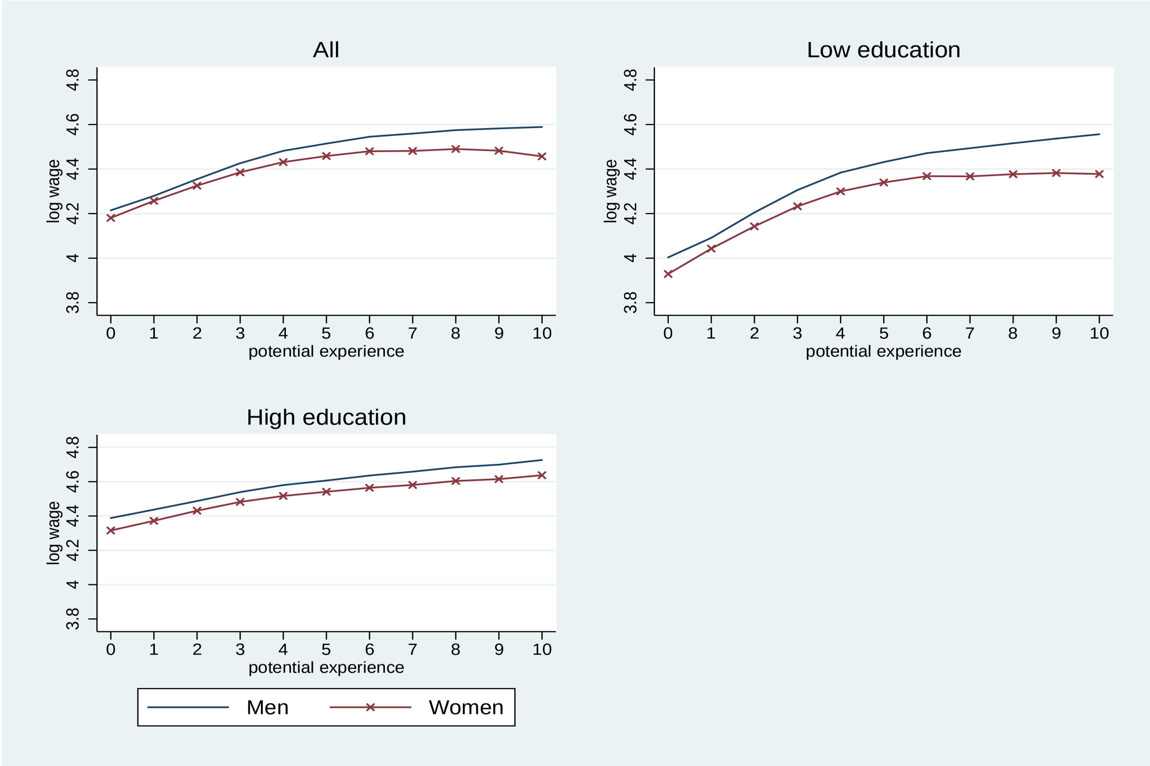
[21]Bonjour and Pacelli (1998) tested on Swiss data the size and the direction of bias when age is used as a proxy for education and experience. They find that using age as a proxy for education leads to a small bias for men and full time working women.

[22]We considered only employees working in the private sector who were born after 1967 in order to replicate the main characteristics of individuals included in our sample.

[23]There is a very limited number of recalls in the data, so that once workers leave an employer do not usually come back.

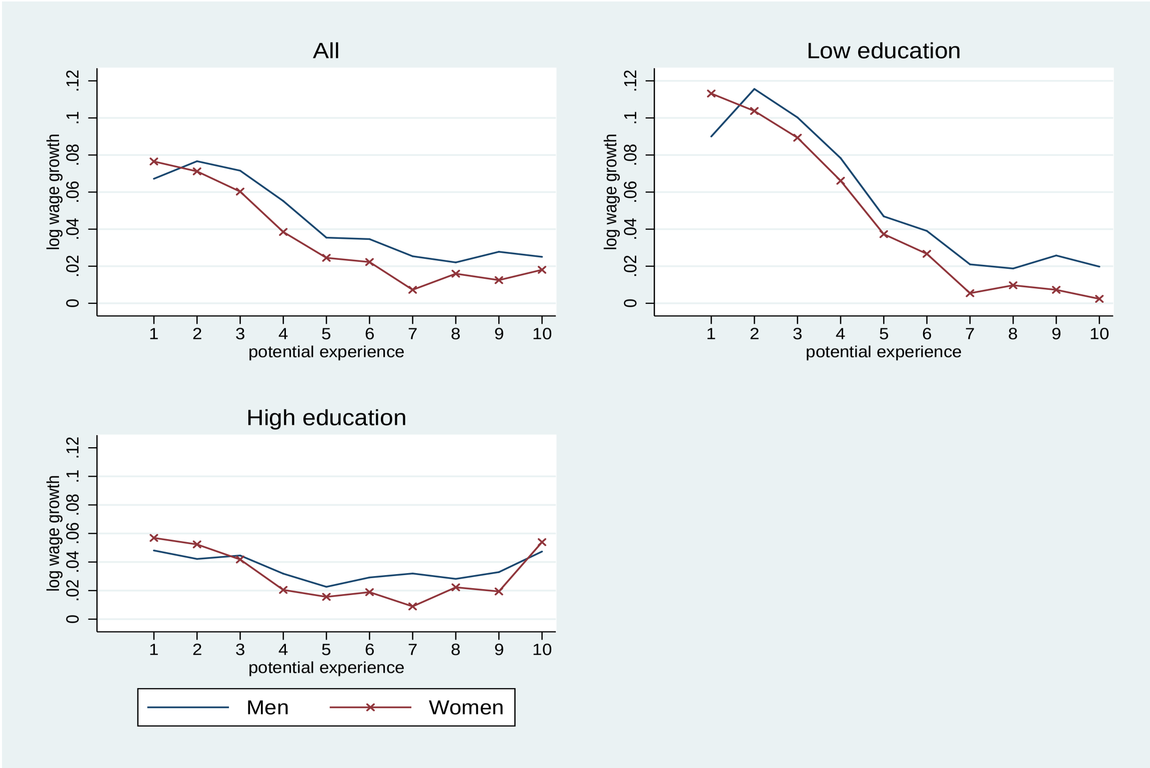
[24]We carried out our analysis also using weekly instead of daily wages. This is because daily wages are potentially more affected by measurement error due to the fact that some employers might declare fewer working days in order to comply with minimum wage requirements. However, using weekly wages did not have a significant impact on our results.

Figure 1: **Log wage by potential experience**



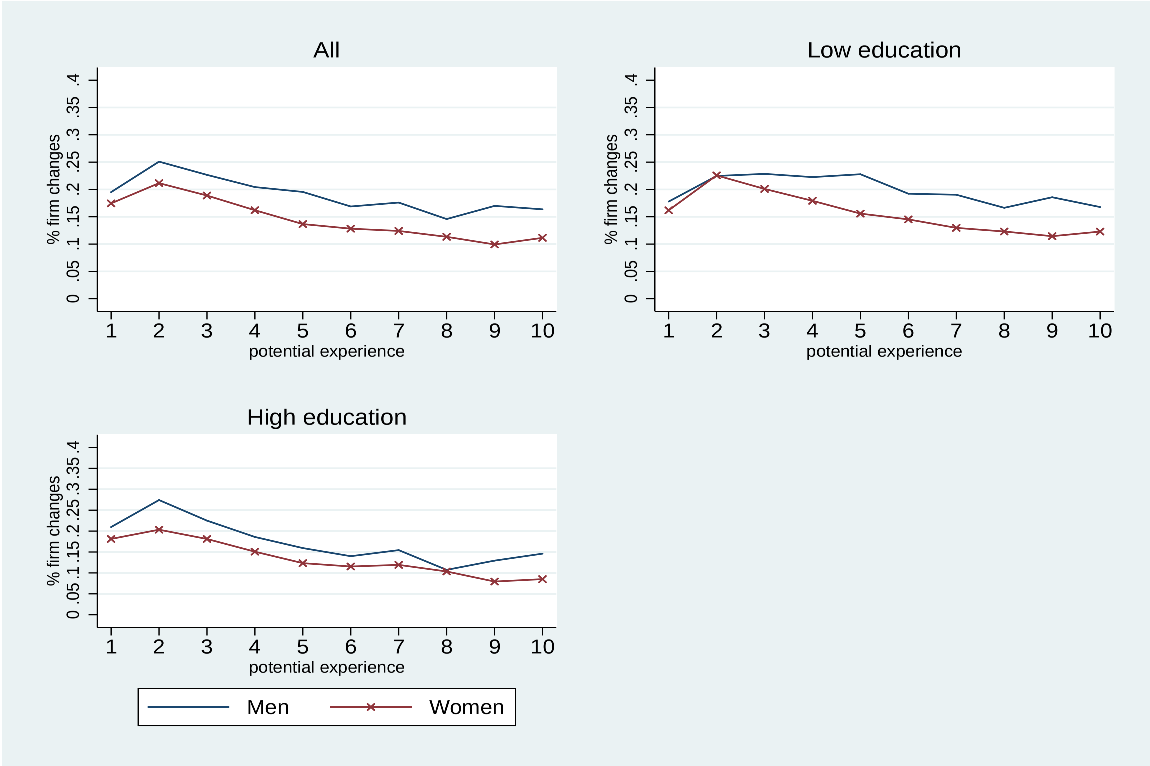
Note: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Plot of average log real daily wages by year of potential experience and sex.

Figure 2: **Log wage growth by potential experience**



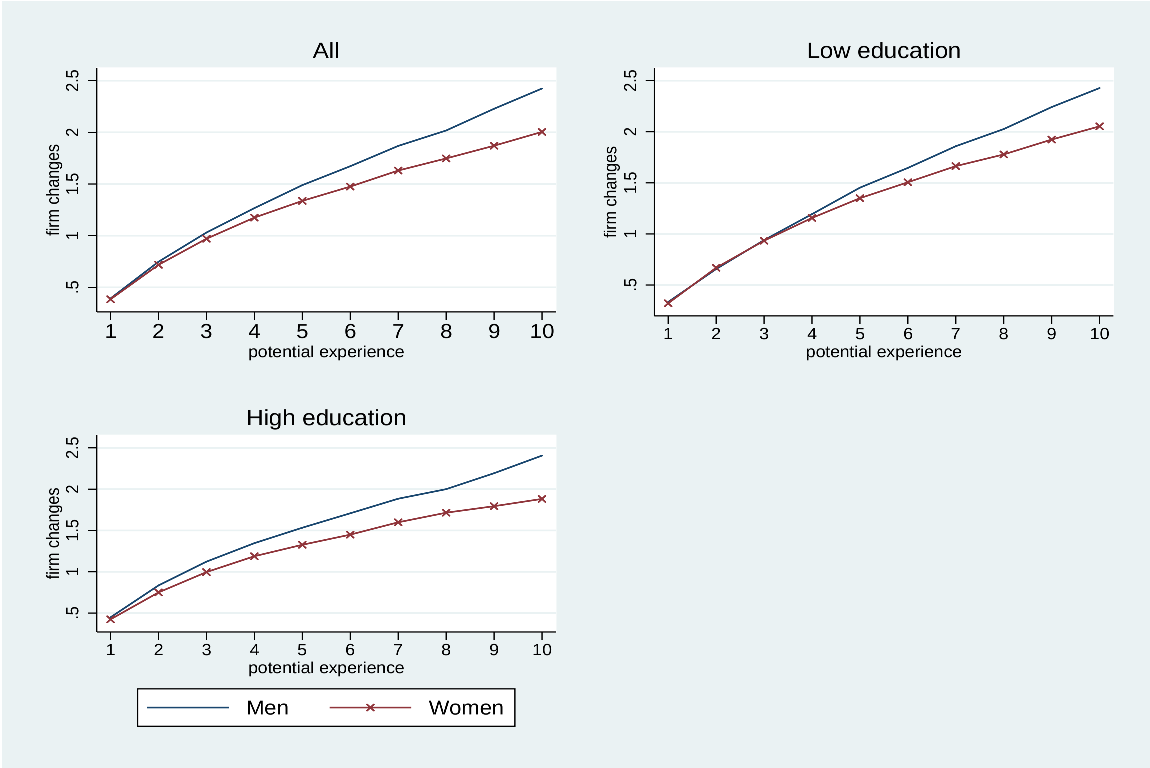
Note: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Plot of average log real daily wage growth by year of potential experience and sex.

Figure 3: **Percentage of firm changes by potential experience**



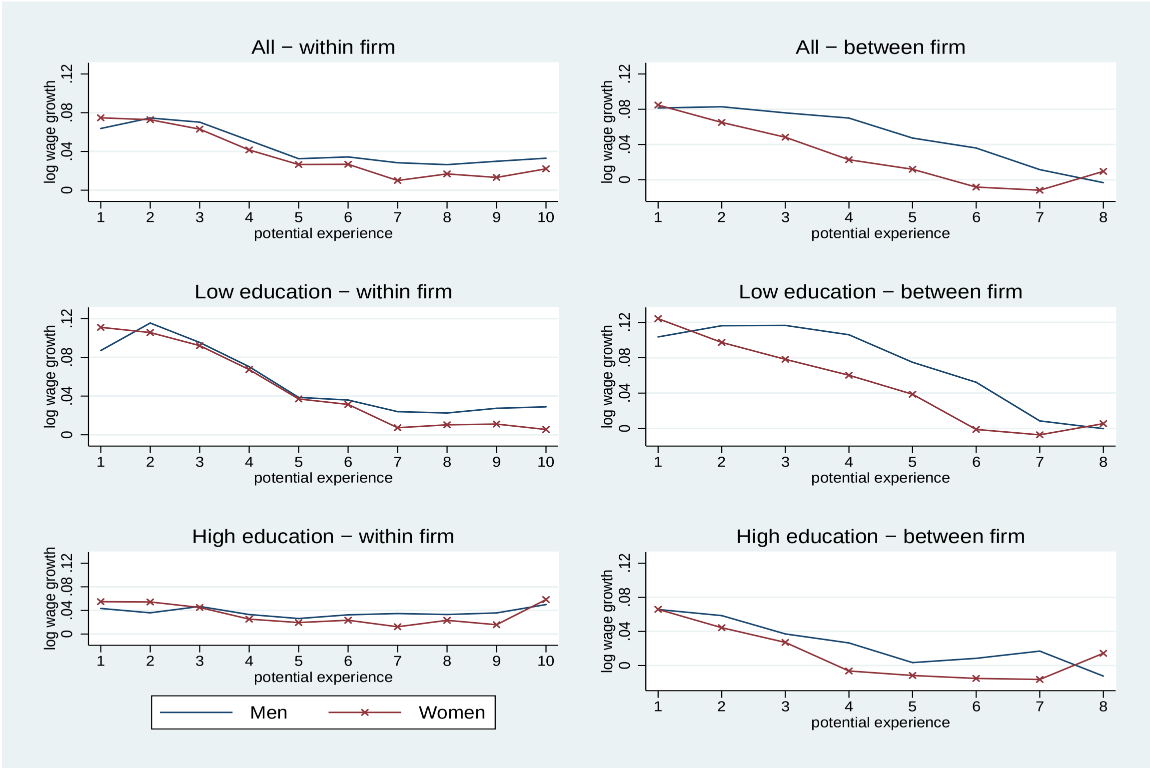
Note: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Percentage of year-to-year firm changes by potential experience and sex.

Figure 4: **Cumulative number of firm changes by potential experience**



Note: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Plot of average cumulative number of firm changes by potential experience and sex. The number of firm changes has been computed only for individuals who changed firm at least once during the period of observation.

Figure 5: **Log wage growth within firm and between firm by potential experience**



Note: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Plot of average log real daily wage growth within firm and between firm by year of potential experience and sex. The maximum number of years of potential experience shown is truncated at 8 because of the very small numbers of individuals who change firm after this period.

Table 1: **Comparison of average log wage growth within firm and between firms by sex and education**

	Men	**Women**	**Difference Men - Women**
Panel A: All			
Within firm (1)	0.0537	0.0501	0.0037**
	(0.0006)	(0.0501)	(0.0010)
Between firms (2)	0.0639	0.0459	0.0179**
	(0.0022)	(0.0033)	(0.0037)
Difference (2)-(1)	0.0101**	-0.0041	
	(0.0024)	(0.0032)	
Observations	78,252	52,247	
Number of individuals	18,019	11,978	
Panel B: Low education			
Within firm (1)	0.0689	0.0666	0.0022
	(0.0008)	(0.0013)	(0.0015)
Between firms (2)	0.0835	0.0668	0.0167**
	(0.0038)	(0.0053)	(0.0056)
Difference (2)-(1)	0.0147**	0.0002	
	(0.0034)	(0.0052)	
Observations	40,260	21,011	
Number of individuals	8,116	4,178	
Panel C: High education			
Within firm (1)	0.0377	0.0390	-0.0013
	(0.0008)	(0.0010)	(0.0012)
Between firms (2)	0.0430	0.0311	0.0119*
	(0.0032)	(0.0037)	(0.0049)
Difference (2)-(1)	0.0052	-0.0079	
	(0.0034)	(0.0039)	
Observations	37,992	31,236	
Number of individuals	9,903	7,800	

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 2: **Log wage growth gender differential**

	All		Low education		High education	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Female	-0.0064**	-0.0109**	-0.0052**	-0.0086**	-0.0011	-0.0125**
	(0.0009)	(0.0010)	(0.0014)	(0.0016)	(0.0012)	(0.0013)
Low education (ref.)		-		-		-
High education		0.0023*				
		(0.0012)				
Potential experience at time t		-0.0092**		-0.0145**		-0.0063**
		(0.0008)		(0.0013)		(0.0012)
Potential experience^2 at time t		0.0074**		0.0116**		0.0048**
		(0.0008)		(0.0012)		(0.0012)
Tenure at time t		0.0093**		0.0118**		0.0072**
		(0.0008)		(0.0011)		(0.0013)
Tenure at time t-1		-0.0109**		-0.0140**		-0.0086**
		(0.0010)		(0.0013)		(0.0015)
Blue collar at time t (ref.)		-		-		-
White collar at time t		0.0421**		0.0168		0.0529**
		(0.0048)		(0.0093)		(0.0056)
Apprenticeship at time t		-0.1572**		-0.1571**		-0.1735**
		(0.0034)		(0.0038)		(0.0084)
Initial contract: permanent (ref.)		-		-		-
Initial contract: apprenticeship		0.0062**		0.0030		0.0056**
		(0.0013)		(0.0020)		(0.0021)
Initial contract: fixed-term		0.0037**		-0.0052*		0.0054**
		(0.0010)		(0.0023)		(0.0012)
Age of the firm at time t		0.0001*		0.0003**		0.0001
		(0.0001)		(0.0001)		(0.0001)
Firm size at time t: 0-4 (ref.)		-		-		-
Firm size at time t: 5-14		0.0102**		0.0169**		0.0006
		(0.0028)		(0.0039)		(0.0040)
Firm size at time t: 15-99		0.0306**		0.0513**		0.0067
		(0.0036)		(0.0051)		(0.0050)
Firm size at time t: 100+		0.0860**		0.1127**		0.0595**
		(0.0050)		(0.0077)		(0.0066)
Observations	130,499	130,499	61,271	61,271	69,228	69,228
Number of individuals	29,997	29,997	12,294	12,294	17,703	17,703

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1. Estimation is by OLS. Where indicated other control variables include: a full set of dummies for occupation at time t-1, a full set of dummies for firm size at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 3: **Log wage growth gender differential within firm and between firms**

	All		**Low education**		**High education**	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Female	-0.0037**	-0.0086**	-0.0022	-0.0058**	0.0013	-0.0106**
	(0.0010)	(0.0010)	(0.0015)	(0.0017)	(0.0012)	(0.0014)
Change of firm at time t	0.0101**	-0.0021	0.0147**	0.0028	0.0053	-0.0084*
	(0.0024)	(0.0026)	(0.0034)	(0.0037)	(0.0034)	(0.0036)
Female*change of firm at time t	-0.0143**	-0.0132**	-0.0145*	-0.0154**	-0.0131*	-0.0125**
	(0.0040)	(0.0036)	(0.0062)	(0.0056)	(0.0052)	(0.0048)
Low education (ref.)		-		-		-
High education		0.0024*				
		(0.0012)				
Potential experience at time t		-0.0088**		-0.0143**		-0.0054**
		(0.0008)		(0.0013)		(0.0012)
Potential experience^2 at time t		0.0071**		0.0115**		0.0039**
		(0.0008)		(0.0012)		(0.0012)
Tenure at time t		0.0074**		0.0111**		0.0034*
		(0.0010)		(0.0014)		(0.0016)
Tenure at time t-1		-0.0092**		-0.0135**		-0.0051**
		(0.0011)		(0.0015)		(0.0017)
Blue collar at time t (ref.)		-		-		-
White collar at time t		0.0425**		0.0172		0.0534**
		(0.0048)		(0.0093)		(0.0056)
Apprenticeship at time t		-0.1576**		-0.1569**		-0.1768**
		(0.0034)		(0.0038)		(0.0084)
Initial contract: permanent (ref.)		-		-		-
Initial contract: apprenticeship		0.0059**		0.0029		0.0051*
		(0.0013)		(0.0020)		(0.0021)
Initial contract: fixed-term		0.0035**		-0.0052*		0.0050**
		(0.0010)		(0.0023)		(0.0012)
Age of the firm at time t		0.0001*		0.0003**		0.0001
		(0.0001)		(0.0001)		(0.0001)
Firm size at time t: 0-4 (ref.)		-		-		-
Firm size at time t: 5-14		0.0103**		0.0170**		0.0007
		(0.0028)		(0.0039)		(0.0040)
Firm size at time t: 15-99		0.0311**		0.0514**		0.0073
		(0.0036)		(0.0051)		(0.0050)
Firm size at time t: 100+		0.0868**		0.1129**		0.0607**
		(0.0050)		(0.0077)		(0.0066)
Observations	130,499	130,499	61,271	61,271	69,228	69,228
Number of individuals	29,997	29,997	12,294	12,294	17,703	17,703

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1. Estimation is by OLS. Where indicated other control variables include: a full set of dummies for occupation at time t-1, a full set of dummies for firm size at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 4: **Log wage growth gender differential and individual fixed-effects**

	OLS No controls	Fixed effects No Controls	OLS With controls	Fixed effects With controls	OLS With controls	Fixed effects With controls
Panel A: All						
Female	-0.0037**		-0.0086**		-0.0098**	
	(0.0010)		(0.0010)		(0.0011)	
Change of firm at time t	0.0101**	0.0157**	-0.0021	-0.0027	-0.0005	0.0014
	(0.0024)	(0.0024)	(0.0026)	(0.0026)	(0.0025)	(0.0028)
Female*change of firm at time t	-0.0143**	-0.0250**	-0.0132**	-0.0181**	-0.0119**	-0.0146**
	(0.0040)	(0.0039)	(0.0036)	(0.0037)	(0.0035)	(0.0039)
Change of firm at time t+1					-0.0041	-0.0023
					(0.0053)	(0.0068)
Female*change of firm at time t+1					0.0123**	0.0130**
					(0.0037)	(0.0046)
*Female*change of firm at time t - female*change of firm at time t+1*					-0.0241**	-0.0276**
					(0.0056)	(0.0049)
Observations	130,499	130,499	130,499	130,499	130,499	130,499
Number of individuals	29,997	29,997	29,997	29,997	29,997	29,997
Panel B: Low education						
Female	-0.0022		-0.0058**		-0.0067**	
	(0.0015)		(0.0017)		(0.0018)	
Change of firm at time t	0.0147**	0.0217**	0.0028	0.0037	0.0051	0.0089*
	(0.0034)	(0.0034)	(0.0037)	(0.0037)	(0.0036)	(0.0040)
Female*change of firm at time t	-0.0145*	-0.0280**	-0.0154**	-0.0205**	-0.0142**	-0.0186**
	(0.0062)	(0.0060)	(0.0056)	(0.0056)	(0.0054)	(0.0060)
Change of firm at time t+1					0.0013	0.0059
					(0.0076)	(0.0096)
Female*change of firm at time t+1					0.0101	0.0079
					(0.0055)	(0.0068)
*Female*change of firm at time t - female*change of firm at time t+1*					-0.0244**	-0.0265**
					(0.0084)	(0.0073)
Observations	61,271	61,271	61,271	61,271	61,271	61,271
Number of individuals	12,294	12,294	12,294	12,294	12,294	12,294
Panel C: High education						
Female	0.0013		-0.0106**		-0.0120**	
	(0.0012)		(0.0014)		(0.0014)	
Change of firm at time t	0.0053	0.0087**	-0.0084*	-0.0103**	-0.0074*	-0.0067
	(0.0034)	(0.0033)	(0.0036)	(0.0036)	(0.0035)	(0.0039)
Female*change of firm at time t	-0.0131*	-0.0203**	-0.0125**	-0.0167**	-0.0109*	-0.0122*
	(0.0052)	(0.0051)	(0.0048)	(0.0049)	(0.0046)	(0.0053)
Change of firm at time t+1					-0.0104	-0.0078
					(0.0076)	(0.0097)
Female*change of firm at time t+1					0.0150**	0.0167**
					(0.0050)	(0.0063)
*Female*change of firm at time t - female*change of firm at time t+1*					-0.0259**	-0.0289**
					(0.0076)	(0.0066)
Observations	69,228	69,228	69,228	69,228	69,228	69,228
Number of individuals	17,703	17,703	17,703	17,703	17,703	17,703

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1. Estimation method shown. Where indicated other control variables include: a quadratic term in potential experience, tenure at time t, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 5: **Log wage growth gender differential by duration of the interruption between job spells**

	All		**Low education**		**High education**	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Female	-0.0037**	-0.0084**	-0.0022	-0.0057**	0.0013	-0.0103**
	(0.0010)	(0.0010)	(0.0015)	(0.0017)	(0.0012)	(0.0014)
Change of firm at time t within 2 months	0.0349**	0.0314**	0.0320**	0.0322**	0.0387**	0.0286**
	(0.0033)	(0.0035)	(0.0048)	(0.0050)	(0.0046)	(0.0048)
Change of firm at time t after 2 months	-0.0060	-0.0199**	0.0039	-0.0122**	-0.0175**	-0.0288**
	(0.0034)	(0.0032)	(0.0047)	(0.0045)	(0.0049)	(0.0047)
Female*change of firm at time t within 2 months	-0.0173**	-0.0161**	-0.0119	-0.0157*	-0.0211**	-0.0170**
	(0.0052)	(0.0047)	(0.0083)	(0.0074)	(0.0067)	(0.0061)
Female*change of firm at time t after 2 months	-0.0148*	-0.0136**	-0.0163	-0.0152	-0.0126	-0.0131
	(0.0058)	(0.0052)	(0.0087)	(0.0078)	(0.0078)	(0.0070)
Observations	130,499	130,499	61,271	61,271	69,228	69,228
Number of individuals	29,997	29,997	12,294	12,294	17,703	17,703

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1. Estimation is by OLS. Where indicated other control variables include: a quadratic term in potential experience, tenure at time t, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 6: **Between firms log wage growth gender differential by tenure in the previous job**

	OLS	Fixed effects	OLS	Fixed effects
	No controls	No controls	With controls	With controls
Panel A: All				
Female	-0.0134**		-0.0106*	
	(0.0042)		(0.0046)	
Tenure at time t-1	-0.0139**	-0.0247**	-0.0091**	-0.0144**
	(0.0020)	(0.0046)	(0.0021)	(0.0044)
Female*tenure at time t-1	-0.0040	0.0019	-0.0002	0.0014
	(0.0030)	(0.0074)	(0.0028)	(0.0066)
Observations	24,598	24,598	24,598	24,598
Number of individuals	14,775	14,775	14,775	14,775
Panel B: Low education				
Female	-0.0093		-0.0040	
	(0.0066)		(0.0074)	
Tenure at time t-1	-0.0149**	-0.0179**	-0.0099**	-0.0155**
	(0.0025)	(0.0063)	(0.0026)	(0.0059)
Female*tenure at time t-1	-0.0078*	-0.0078	-0.0022	0.0012
	(0.0038)	(0.0107)	(0.0036)	(0.0093)
Observations	11,803	11,803	11,803	11,803
Number of individuals	6,533	6,533	6,533	6,533
Panel C: High education				
Female	-0.0101		-0.0145*	
	(0.0055)		(0.0061)	
Tenure at time t-1	-0.0176**	-0.0350**	-0.0097**	-0.0205**
	(0.0034)	(0.0069)	(0.0036)	(0.0071)
Female*tenure at time t-1	0.0026	0.0152	0.0011	0.0045
	(0.0047)	(0.0103)	(0.0046)	(0.0096)
Observations	12,795	12,795	12,795	12,795
Number of individuals	8,242	8,242	8,242	8,242

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1 for periods in which the individual changes firm. Estimation method shown. Where indicated other control variables include: a quadratic term in potential experience, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 7: **Between firms log wage growth gender differential according to negative and positive changes in log wage**

	All		**Low education**		**High education**	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Panel A: Negative change in log wage						
Female	0.0240**	0.0084	0.0164*	0.0121	0.0259**	0.0060
	(0.0045)	(0.0056)	(0.0071)	(0.0094)	(0.0059)	(0.0071)
Observations	10,156	10,156	4,519	4,519	5,637	5,637
Number of individuals	8,171	8,171	3,546	3,546	4,625	4,625
Panel B: Positive change in log wage						
Female	-0.0360**	-0.0216**	-0.0304**	-0.0199**	-0.0339**	-0.0249**
	(0.0042)	(0.0049)	(0.0063)	(0.0075)	(0.0056)	(0.0067)
Observations	14,442	14,442	7,284	7,284	7,158	7,158
Number of individuals	10,761	10,761	5,088	5,088	5,673	5,673

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1 for periods in which the individual changes firm. Estimation is by OLS. Where indicated other control variables include: a quadratic term in potential experience, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 8: **Between firms log wage growth gender differential by quantile**

	All		Low education		High education	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Panel A: 0.25 percentile						
Female	0.0118*	0.0032	0.0081	0.0109	0.0177**	-0.0009
	(0.0041)	(0.0049)	(0.0063)	(0.0088)	(0.0055)	(0.0062)
Panel B: 0.50 percentile						
Female	-0.0143**	-0.0108**	-0.0161**	-0.0115	-0.0074	-0.0081
	(0.0031)	(0.0038)	(0.0049)	(0.0063)	(0.0036)	(0.0048)
Panel C: 0.75 percentile						
Female	-0.0483**	-0.0329**	-0.0495**	-0.0281**	-0.0389**	-0.0325**
	(0.0052)	0.0052	(0.0075)	(0.0077)	(0.0058)	(0.0068)
Observations	24,598	24,598	11,803	11,803	12,795	12,795
Number of individuals	14,775	14,775	6,533	6,533	8,242	8,242

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1 for periods in which the individual changes firm. Estimation is by quantile regression. Where indicated other control variables include: a quadratic term in potential experience, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Standard errors obtained by bootstrap (500 replications) in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 9: **Log wage growth gender differential between firms by age**

	All		Low education		High education	
	No controls	**With controls**	**No controls**	**With controls**	**No controls**	**With controls**
Change of firm at time t*age 16	0.0528	0.0387	0.0528	0.0367	-	-
	(0.0442)	(0.0421)	(0.0442)	(0.0421)		
Change of firm at time t*age 17	0.0026	0.0035	0.0026	0.0059	-	-
	(0.0240)	(0.0220)	(0.0240)	(0.0218)		
Change of firm at time t*age 18	0.0241	-0.0103	-0.0003	-0.0105	-	-
	(0.0205)	(0.0182)	(0.0205)	(0.0181)		
Change of firm at time t*age 19	0.0080	-0.0035	0.00797	-0.0033	-	-
	(0.0174)	(0.0150)	(0.0174)	(0.0150)		
Change of firm at time t*age 20	-0.0521**	-0.0385**	-0.0611**	-0.0448**	-0.0315	-0.0262
	(0.0149)	(0.0126)	(0.0177)	(0.0151)	(0.0294)	(0.0238)
Change of firm at time t*age 21	-0.0313**	-0.0189	-0.0392*	-0.0194	-0.0337	-0.0263
	(0.0118)	(0.0102)	(0.0163)	(0.0143)	(0.0174)	(0.0148)
Change of firm at time t*age 22	-0.0233*	-0.0336**	-0.0486**	-0.0580**	-0.0144	-0.0227
	(0.0107)	(0.0095)	(0.0164)	(0.0145)	(0.0138)	(0.0124)
Change of firm at time t*age 23	-0.0344**	-0.0434**	-0.0359*	-0.0330*	-0.0332*	-0.0428**
	(0.0111)	(0.0101)	(0.0181)	(0.0168)	(0.0137)	(0.0125)
Change of firm at time t*age 24	-0.0101	-0.0205	-0.0488*	-0.0588*	-0.0043	-0.0153
	(0.0120)	(0.0111)	(0.0240)	(0.0230)	(0.0139)	(0.0128)
Change of firm at time t*age 25	-0.0193	-0.0284*	-0.0045	-0.0033	-0.0241	-0.0374**
	(0.0117)	(0.0112)	(0.0218)	(0.0201)	(0.0136)	(0.0130)
Change of firm at time t*age 26	0.0040	-0.0056	-0.0024	-0.0312	-0.0039	-0.0015
	(0.0152)	(0.0143)	(0.0372)	(0.0341)	(0.0168)	(0.0158)
Change of firm at time t*age 27	0.0056	-0.0089	-0.0016	-0.0073	-0.0086	-0.0108
	(0.0170)	(0.0167)	(0.0358)	(0.0399)	(0.0188)	(0.0182)
Change of firm at time t*age 28	-0.0174	-0.0084	0.0020	0.0419	-0.0237	-0.0233
	(0.0236)	(0.0228)	(0.1048)	(0.0960)	(0.0243)	(0.0235)
Change of firm at time t*age 29	-0.0306	-0.0343	-	-	-0.0306	-0.0390
	(0.0330)	(0.0335)			(0.0330)	(0.0328)
Change of firm at time t*age 30	-0.0081	-0.0403	-	-	-0.0081	-0.0412
	(0.0385)	(0.0374)			(0.0385)	(0.0377)
Observations	130,499	130,499	61,271	61,271	69,228	69,228
Number of individuals	29,997	29,997	12,294	12,294	17,703	17,703

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1. Estimation is by OLS. The reported coefficient represent the difference between male and female wage growth associated with a change of firm by age. The specification includes: female dummy, change of firm dummy and its interaction with a full set of age dummies, interactions between female dummy, the change of firm dummy and the full set of age dummies, a quadratic term in potential experience, tenure at time t, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t and at time t-1, a full set of dummies for firm size at time t and at time t-1, a full set of dummies for industry (2 digit) at time t and at time t-1, a full set of dummies for province at time t and at time t-1, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 10: **Between firms log wage growth by change of qualification, industry, firm size and geography**

	All			Low education			High education		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Female	-0.0141**	-0.0091**	0.0035	-0.0184**	-0.0095	0.0045	-0.0104*	-0.0092	0.0007
	(0.0036)	(0.0035)	(0.0061)	(0.0055)	(0.0052)	(0.0096)	(0.0047)	(0.0047)	(0.0079)
Blue collar to white collar		0.0481**	0.0459**		0.0198	0.0046		0.0571**	0.0562**
		(0.0094)	(0.0117)		(0.0206)	(0.0293)		(0.0106)	(0.0129)
Blue collar to apprentice		-0.3284**	-0.3509**		-0.3159**	-0.3387**		-0.4086**	-0.4293**
		(0.0153)	(0.0188)		(0.0172)	(0.0212)		(0.0330)	(0.0398)
White collar to blue collar		-0.0952**	-0.0983**		-0.0847**	-0.0712*		-0.0962**	-0.1047**
		(0.0123)	(0.0162)		(0.0275)	(0.0324)		(0.0138)	(0.0188)
White collar to apprentice		-0.2590**	-0.3059**		-0.2541**	-0.3650**		-0.2700**	-0.2466*
		(0.0552)	(0.0672)		(0.0836)	(0.0856)		(0.0516)	(0.1008)
Apprentice to blue collar		0.2630**	0.2708**		0.2584**	0.2652**		0.2837**	0.3001**
		(0.0073)	(0.0085)		(0.0082)	(0.0096)		(0.0162)	(0.0188)
Apprentice to white collar		0.2904**	0.3558**		0.2766**	0.3670**		0.3162**	0.3550**
		(0.0170)	(0.0315)		(0.0245)	(0.0469)		(0.0237)	(0.0422)
Change of industry		-0.0098**	-0.0093*		-0.0157**	-0.0144*		-0.0019	-0.0020
		(0.0037)	(0.0046)		(0.0054)	(0.0063)		(0.0050)	(0.0066)
Change to larger firm		0.0297**	0.0371**		0.0438**	0.0508**		0.0163*	0.0221*
		(0.0047)	(0.0059)		(0.0067)	(0.0081)		(0.0066)	(0.0087)
Change to smaller firm		-0.0440**	-0.0403**		-0.0403**	-0.0387**		-0.0470**	-0.0425**
		(0.0050)	(0.0062)		(0.0074)	(0.0088)		(0.0067)	(0.0087)
Change of province		-0.0050	-0.0048		-0.0062	-0.0087		-0.0038	-0.0016
		(0.0049)	(0.0059)		(0.0079)	(0.0092)		(0.0062)	(0.0077)
Female*blue collar to white collar			0.0061			0.0370			0.0029
			(0.0195)			(0.0401)			(0.0224)
Female*blue collar to apprentice			0.0608			-0.0647			0.0568
			(0.0311)			(0.0348)			(0.0695)
Female*white collar to blue collar			0.0077			-0.0344			0.0208
			(0.0247)			(0.0576)			(0.0276)
Female*white collar to apprentice			0.0619			0.1435			-0.0375
			(0.0982)			(0.1361)			(0.1164)
Female*apprentice to blue collar			-0.0302*			-0.0268			-0.0510
			(0.0145)			(0.0172)			(0.0292)
Female*apprentice to white collar			-0.0980**			-0.1315*			-0.0603
			(0.0368)			(0.0545)			(0.0489)
Female*change of industry			-0.0011			-0.0050			0.0014
			(0.0076)			(0.0117)			(0.0101)
Female*change to larger firm			-0.0212*			-0.0225			-0.0154
			(0.0094)			(0.0139)			(0.0128)
Female*change to smaller firm			-0.0089			-0.0029			-0.0110
			(0.0103)			(0.0160)			(0.0136)
Female*change of province			-0.0008			0.0130			-0.0072
			(0.0103)			(0.0177)			(0.0128)
Observations	24,598	24,598	24,598	11,803	11,803	11,803	12,795	12,795	12,795
Number of individuals	14,775	14,775	14,775	6,533	6,533	6,533	8,242	8,242	8,242

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1 for periods in which the individual changes firm. Estimation is by OLS. Other control variables include: a quadratic term in potential experience, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, and a full set of year dummies. Huber-White heteroskedasticity robust standard errors adjusted in order to take into account the presence of multiple observations for each individual shown in parentheses. Symbols: ** significant at 1%; * significant at 5%.

Table 11: **Between firms log wage growth according to change of qualification, industry, size of the firm and geography average premium**

	All			**Low education**			**High education**		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Female	-0.0141**	-0.0110**	0.0041	-0.0184**	-0.0100	0.0088	-0.0104*	-0.0118**	-0.0019
	(0.0036)	(0.0035)	(0.0046)	(0.0055)	(0.0053)	(0.0079)	(0.0047)	(0.0044)	(0.0058)
Change of industry		0.8572**	0.8787**		0.8578**	0.8523**		0.8594**	0.8921**
		(0.0248)	(0.0329)		(0.0375)	(0.0463)		(0.0345)	(0.0443)
Change to larger firm [1]		0.5131**	0.6450**		0.7253**	0.8523**		0.3749**	0.4721**
		(0.0436)	(0.0543)		(0.0655)	(0.0463)		(0.0644)	(0.0706)
Change to smaller firm [2]		0.6307**	0.6215**		0.7621**	0.7146**		0.5647**	0.5745**
		(0.0561)	(0.0686)		(0.0801)	(0.099)		(0.0747)	(0.0984)
Change of province		0.3333*	0.2921		0.2914	0.2855		0.5585**	0.5824**
		(0.1200)	(0.1398)		(0.2021)	(0.2141)		(0.1685)	(0.1914)
Female*change of industry			-0.0475			0.0378			-0.0830
			(0.0550)			(0.0820)			(0.0725)
Female*change to larger firm [3]			-0.4083**			-0.4794**			-0.2551*
			(0.0850)			(0.1230)			(0.1084)
Female*change to smaller firm [4]			0.0152			0.1383			-0.0260
			(0.1195)			(0.2041)			(0.1445)
Female*change of province			0.1576			0.0255			-0.1581
			(0.3204)			(0.4674)			(0.3597)
P-value [1]=[2]		[0.13]	[0.80]		[0.076]	[0.34]		[0.06]	[0.43]
P-value [3]=[4]			[0.01]			[0.02]			[0.26]
Observations	24,598	24,598	24,598	11,803	11,803	11,803	12,795	12,795	12,795
Number of observations	14,775	14,775	14,775	6,533	6,533	6,533	8,242	8,242	8,242

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is the difference in log real daily wages between year t and year t-1 for periods in which the individual changes firm. Estimation is by OLS. Other control variables include: a quadratic term in potential experience, tenure at time t-1, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, and a full set of year dummies. Standard errors obtained by bootstrap (100 replications) in order to take into account the presence of generated regressors. Symbols: ** significant at 1%; * significant at 5%.

Table 12: **Propensity to change firm in the next period by firm size**

	All			**Low education**			**High education**		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Female	-0.031**	-0.0302**	-0.0222**	-0.0330**	-0.0319**	-0.0077	-0.0316**	-0.0306**	-0.0367**
	(0.028)	(0.0028)	(0.0050)	(0.0045)	(0.0045)	(0.0073)	(0.0036)	(0.0036)	(0.0071)
Log wage at time t		0.0202**	0.0198**		0.0277**	0.0205**		0.0144*	0.0144*
		(0.0051)	(0.0051)		(0.0075)	(0.0075)		(0.0071)	(0.0071)
Firm size at time t: 0-4 (ref.)	-	-	-	-	-	-	-	-	-
Firm size at time t: 5-14	-0.0025	-0.0033	-0.0027	-0.0057	-0.0066	-0.0013	0.0004	-0.0000	-0.0051
	(0.0031)	(0.0031)	(0.0038)	(0.0042)	(0.0043)	(0.0051)	(0.0005)	(0.0046)	(0.0056)
Firm size at time t: 15-99	-0.0228**	-0.0246**	-0.0191**	-0.0318**	-0.0342**	-0.0213**	-0.0138**	-0.0147**	-0.0173**
	(0.0032)	(0.0032)	(0.0062)	(0.0046)	(0.0047)	(0.0057)	(0.0045)	(0.0046)	(0.0058)
Firm size at time t: 100+	-0.0525**	-0.0555**	-0.0500**	-0.0740**	-0.3163**	-0.0589**	-0.0407**	-0.0428**	-0.0453**
	(0.0038)	(0.0038)	(0.0046)	(0.0058)	(0.0058)	(0.0071)	(0.0051)	(0.0052)	(0.0063)
Female*firm size at time t: 0-4 (ref.)			-			-			-
Female*firm size at time t: 5-14			-0.0019			-0.0198*			0.0119
			(0.0062)			(0.0084)			(0.0094)
Female*firm size at time t: 15-99			-0.0148*			-0.0402**			0.0061
			(0.0062)			(0.0084)			(0.0090)
Female*firm size at time t: 100+			-0.0588**			-0.0587**			0.0060
			(0.0071)			(0.0118)			(0.0094)
Observations	130,499	130,499	130,499	61,271	61,271	61,271	69,208	69,208	69,208

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997. Dependent variable is a 0/1 dummy for whether the worker changes firm in the next period. The numbers shown represent marginal effects from a probit model. Other control variables include: a quadratic term in potential experience, tenure at time t, a high education dummy (where applicable), a full set of dummies for the type of initial contract, a linear term in the age of the firm, a full set of dummies for occupation at time t, a full set of dummies for industry (2 digit) at time t, a full set of dummies for province at time t, and a full set of year dummies. Standard errors obtained by bootstrap (100 replications) in order to take into account the presence of generated regressors. Symbols: ** significant at 1%; * significant at 5%.

Table A.1: Main descriptive statistics for full sample and different education groups

	All		**Low education**		**High education**	
Variable	Mean	s.d.	Mean	s.d.	Mean	s.d.
Log daily wage growth	0.05	0.22	0.07	0.22	0.04	0.20
Female	0.60	0.49	0.66	0.47	0.55	0.50
Change of firm	0.15	0.36	0.16	0.37	0.15	0.35
Potential experience	3.01	2.61	3.36	2.79	2.71	2.41
Tenure	1.10	1.67	1.15	1.71	1.05	1.64
Occupation:						
Blue collar	0.50	0.50	0.50	0.50	0.50	0.50
White collar	0.27	0.44	0.06	0.24	0.44	0.50
Apprenticeship	0.23	0.42	0.43	0.50	0.06	0.24
Initial contract:						
Permanent	0.3	0.47	0.1	0.33	0.5	0.50
Fixed term	0.4	0.50	0.8	0.40	0.1	0.34
Apprenticeship	0.2	0.41	0.1	0.28	0.3	0.47
Age of the firm	12.0	9.32	2.9	8.08	13.0	10.14
Firm size:						
0-4	0.26	0.44	0.31	0.46	0.21	0.40
5-14	0.26	0.44	0.31	0.46	0.21	0.41
15-99	0.28	0.45	0.28	0.45	0.28	0.45
100+	0.20	0.40	0.10	0.30	0.30	0.46
Number of observation	130,499		61,271		69,228	

Notes: Sample of individuals from the INPS administrative records for the period between 1985 and 1997.

Table A.2: Marriage and fertility statistics

	Mean age at marriage	Mean age at first child	Mean age at childbearing
1980	n.a.	25.1	27.5
1990	n.a.	26.9	28.9
1991	n.a.	27.1	29.1
1992	n.a.	27.4	29.3
1993	n.a.	27.5	29.4
1994	26.5	27.7	29.6
1995	26.9	28.1	29.8
1996	27.1	28.2	29.9
1997	27.4	28.4	30.1
1998	27.6	n.a.	n.a.

Notes: Mean age at marriage, at the birth of the first child, and at childbearing in Italy. Source: ISTAT.
Symbols: n.a. indicates that data are not available.