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Education, Educational Mismatch and Wage Inequality: Evidence for Spain

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RESUMO/ABSTRACT

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Keywords: Returns to education, educational mismatch, quantile regression.

JEL-Codes: C29, D31, I21

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Education, Educational Mismatch, and Wage Inequality: Evidence for Spain

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Abstract

In this paper we explore the connection between education and wage inequality in Spain for the period 1994-2001. Drawing on quantile regression, we describe the conditional wage distribution of different populations groups. We find that higher education is associated with higher wage dispersion. According to this, the educational expansion that took place in Spain over the last years contributed to raise wage inequality through the within- dimension. A contribution of the paper is that we explicitly take into account the fact that workers who are and workers who are not in jobs commensurate with their qualifications have a different distribution of earnings. We differentiate between three different types of educational mismatch: 'over-qualification', 'incorrect qualification', and 'strong mismatch'. We find that while over-qualification and incorrect qualification are not associated with lower wages, strong mismatch carries a pay penalty that ranges from 13% to 27%. Thus, by driving a wedge between matched and mismatched workers, the incidence of strong mismatch contributes to enlarge wage differences within education groups. We find that over the recent years, the proportion of strongly mismatched workers rose markedly in Spain, contributing towards further within-groups dispersion.

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0. Introduction

Conventional wisdom asserts that policies aimed to increase average schooling levels are expected to reduce earnings inequality by increasing the proportion of high-wage workers. A more balanced distribution of education, it is argued, will result in a more balanced distribution of earnings. Even though such policies may reduce *average* differences between otherwise differently educated individuals, their final impact on overall inequality is not clear cut. Recent empirical research by Martins and Pereira (2004) has shown that in most countries wage dispersion is higher among more educated individuals. A similar result is reported by Buchinsky (1994) for the US, Gosling *et al.* (2000) for the UK, and Hartog *et al.* (2001) for Portugal. This evidence warns that an educational expansion may raise overall wage inequality by enlarging wage differences *within* similarly educated individuals.

In this paper we use recent Spanish data to shed further light on the relation between education and wages. The analysis of this relation, which has a long tradition among labour economists, has been conventionally in terms of averages, i.e., assuming that to each level of education corresponds an average wage. This approach, however, has limitations, as individuals with the same qualification may earn a different return from their educational investment. By focussing on averages, researchers ignore the amount of wage inequality that arises from differences within groups. The perspective used in this paper is that education, rather than assuring a certain amount of earnings, gives access to a distribution of earnings. We characterize that distribution by using Ordinary Least Squares (OLS) and Quantile Regression (QR) methods.

Estimation by OLS assumes that the marginal impact of education on wages is constant over the wage distribution. In this case, the effect of having one additional level of education can be represented by a shift (to the right) of the conditional wage distribution. Quantile returns, in turn, measure the wage effects of education at different points of the distribution, thus describing changes not only in the location but also in the shape of the distribution. By combining OLS with quantile regression, we can assess the impact of education on wage inequality between and within groups: while OLS returns measure the average differential between education groups, differences in quantile returns represent the wage differential between individuals that are in the same group but located at different quantiles.

Our approach is similar to Buchinsky (1994) and Martins and Pereira (2004). Rather than providing explanations, we concentrate on characterizing the conditional wage distribution of different population groups. A contribution of the paper is that we explicitly control for the fact that given a level of education, workers who are and workers who are not in jobs commensurate with their qualifications have a different distribution of earnings. This perspective is based on the fact that educational mismatched workers earn substantially lower returns from education relative to their matched peers (Hartog, 2000, Sloane, 2002). The information contained in our dataset provides us with three alternative definitions of educational mismatch, which we call 'over-qualification', 'incorrect qualification', and 'strong mismatch'. We contribute to the over-education literature by estimating the average impact of the different types of educational mismatch on wages as well as the impact at different points of the wage distribution. This approach allows us to describe conditional wage dispersion within education groups for matched and mismatched workers separately.

Besides, we analyze changes in the returns to education for the period 1994-2001. In recent years, average schooling levels increased dramatically in Spain. Alongside this process, a large proportion of high-educated workers entered jobs that required less schooling than they had obtained. As these workers are typically penalised in terms of wages, it is intriguing to speculate that a rise in the proportion of mismatched workers resulted into higher wage dispersion within the high-educated.

Our main findings can be summarized as follows. First, returns to tertiary education are not constant over the conditional wage distribution. Workers at high-pay jobs earn substantially higher returns from a university degree than workers at low-pay jobs. This is interpreted as a positive impact of higher education on wage dispersion. Second, the wage effects of educational mismatches depend largely on the nature of the mismatch. Specifically, while ‘over-qualification’ and ‘incorrect qualification’ are not associated with a significant pay penalty, ‘strong mismatch’ depresses wages by between 13% and 27%. Third, by driving a wedge between matched and mismatched workers, the incidence of strong mismatch contributes towards wage dispersion within education groups. Still, the incidence of strong mismatch is not responsible for the high wage dispersion found in the tertiary group. Fourth, returns to education decreased from 1994 to 2001, resulting into lower inequality between education groups. Changes in inequality within groups were, in general, small. However, changes in the composition of the workforce contributed towards within-groups dispersion. This was due to a rising proportion of university graduates as well as to a rising proportion of strongly mismatched workers in the Spanish labour market.

The rest of the paper is organized as follows. Section 1 briefly presents the dataset, variables, and estimating sample used in the paper. Section 2 motivates the analysis by reporting some facts on wage inequality in Spain. Section 3 presents the quantile regression model. Section 4 explores the relation between education and wage inequality using cross-sectional data for the year 2001. Section 5 documents changes in the conditional wage structure that have taken place over the last years. The role that education and educational mismatches have had in shaping the wage distribution is discussed. Section 6 presents the concluding remarks. The paper includes an Appendix describing the data source and variables used in the analysis. It also includes a set of additional tables.

1. Data and Variables

We use the Spanish waves (1994-2001) of the European Community Household Panel (ECHP, henceforth). This survey contains personal and labour market characteristics, including monthly wage, education level, hours worked, tenure, experience, sector, firm size, marital status and immigrant condition. Individuals are asked to report the maximum level of education that they have completed according to three categories: less than upper secondary, upper secondary and tertiary education.

We focus on wage earners in the private sector, aged between 18 and 60, who work normally between 15 and 80 hours a week, and are not employed in the agricultural sector. Thus, self-employed individuals, as well as those whose main activity status is paid apprenticeship, training, and unpaid family worker have been excluded from the sample.

Table 1 contains a set of descriptive statistics. Relative to men, women work less hours, earn lower wages, are more educated, have less experience and tenure, and are more prone to work in the service sector.

---------- Insert Table 1 about here -------

2. Some facts on wage inequality

During the second half of the eighties and the first half of the nineties wage inequality increased in Spain. This phenomenon was partially accounted for by the evolution of wage differentials across education groups (Barceinas *et al.,* 2000, Cantó *et al.*, 2000).

Using more recent data, we find that from 1994 to 2001 wage inequality tended to decrease. Changes were small, though. As the first columns of Table 2 show, the Gini index, the ratio between wages at the 1st and the 5th deciles, and the ratio between wages at the 1st and the 9th deciles fell, respectively, from .31, 1.91, and 4.46 to .30, 1.90, and 4.08. Differentiating between education groups, we find that wage inequality decreased within workers with upper secondary education or less and increased within workers with tertiary education. At the end of the period, wage inequality is highest among the high-educated.

---------- Insert Table 2 about here -------

In computations not reported here, we found that inequality between education groups tended to decrease over the period considered. In 2001 tertiary and secondary educated workers earned, respectively, 47.0% and 13.2% more than workers in the lowest education category. In 1994, these differentials were 72.4% and 26.5%, respectively.

Overall, the slight decrease in overall wage inequality can be attributed to decreases in within-groups inequality and, more primarily, between-groups inequality. This evidence is taken from raw statistics, which do not control for the groups' characteristics. In what follows, we investigate what is the role of education and educational mismatches in generating wage inequality.

3. The model

The quantile regression model can be written as

$$ln\, w_i = X_i \beta_\theta + e_{\theta i} \qquad \text{with } Quant_\theta(ln\ w_i | X_i) \ = \ X_i \beta_\theta \tag{1}$$

where X_i is the vector of exogenous variables and β_θ is the vector of parameters. $Quant_\theta(ln\ w_i|\ X_i)$ denotes the θth conditional quantile of $ln\ w$ given X. The θth regression quantile, $0<\theta<1$, is defined as a solution to the problem

$$\underset{\beta \in R^k}{Min} \left\{ \sum_{i:ln\ w_i \geq x_i \beta_\theta} \theta \left| ln\ w_i - X_i \beta_\theta \right| + \sum_{i:ln\ w_i < x_i \beta_\theta} (1-\theta) \left| ln\ w_i - X_i \beta_\theta \right| \right\} \tag{2}$$

which, after defining the check function $\rho_\theta(z)=\theta z$ if $z \geq 0$ or $\rho_\theta(z)=(\theta-1)z$ if $z < 0$, can be written as

$$\underset{\beta \in R^k}{Min} \left\{ \sum_i \rho_\theta (ln\ w_i - X_i \beta_\theta\ ) \right\} \tag{3}$$

This problem is solved using linear programming methods. Standard errors for the vector of coefficients are obtainable by using the bootstrap method described in Buchinsky (1998).

Our wage equation is

$$ln\, w_i = \alpha_\theta + \delta_{\theta 1} X_i + \beta_{\theta 1} uppersec_i + \beta_{\theta 2} tertiary_i + e_{\theta i} \tag{4}$$

where $ln\ w_i$ is the logarithm of the gross hourly wage and X_i is a vector of explanatory variables, including experience (and squared), tenure, marital status, immigrant condition, sector (industry or service), and firm size[2]. The construction of these variables is described in Appendix A. The dummies *uppersec* and *tertiary* are activated only when the individual's maximum level of education is, respectively, upper secondary or tertiary education. Thus, *less than upper secondary* is the excluded education category. The choice of dummies rather than years of schooling is motivated by two reasons. First, the use of education groups highlights the non-linearities of the response of wage levels and wage dispersion to additional education. Second, we believe that the labour market reward to formal qualifications is better captured by levels rather than by years of schooling.

4. Empirical results

In this section we calculate OLS returns and conditional returns to education at five representative quantiles: .10, .25, .50, .75, and .90. This is done separately for men and women. To simplify the analysis, we do not control for female self-selection into the labour market[3]. The results correspond to the 2001 wave of the ECHP.

In Table 3 we report the coefficients on education. The full sets of estimates are reported in Tables 1B and 2B in the Additional Tables section. As expected, more educated individuals earn significantly higher wages. The OLS returns to a tertiary and upper secondary level are, respectively, 38.8% and 14.7% for men and 43.0% and 17.4% for women.

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[2] We do not include controls for occupation. As the acquisition of education allows individuals to access certain occupations that are better rewarded, we prefer to interpret these wage gains as a return to education rather than a return to occupation.

[3] This is also the perspective used in Gardeazabal and Ugidos (2004), who use quantile regression and Spanish data to analyze the gender wage gap over the wage distribution. In a similar work, De la Rica, Dolado and Llorens (2005) control for female selectivity and find, using the ECHP, that the inverse of the Mill's ratio is not significant in the wage equation. Overall, the impact of the correction for sample selection on the return to schooling is found to be minor in most Spanish studies. Thus, for example, Barceinas *et al.* (2000) find that controlling for selectivity reduces the return to an additional year of schooling from 8.3% to 7.4%.

---------- Insert Table 3 about here -------

However, returns to education are not constant over the wage distribution. The average return to tertiary education for men masks a return of 29.6% in the lowest quantile and 53.0% in the top quantile. To facilitate the analysis, in Figures 1 and 2 we plot the quantile-return profiles. For men and women, the coefficient of tertiary education is clearly increasing as we move towards higher quantiles, meaning that workers at high-pay jobs earn substantially higher returns from university education than workers at low-pay jobs. This finding implies that if we give tertiary education to workers that are apparently equal but located at different quantiles, then their wages will become more dispersed. Thus, by raising the weight of the high-spread group, an educational expansion towards tertiary education may increase overall wage inequality. In contrast, the coefficient of secondary education exhibits low dispersion across quantiles. An educational expansion towards secondary education is expected, therefore, to have a more limited impact on within-groups dispersion[4].

---------- Insert Figures 1 and 2 about here -------

Our results are in range with the evidence reported in Martins and Pereira (2004) for other European countries: returns to education tend to be increasing when moving up along the wage distribution. In a related work, Budría and Pereira (2005) use recent data from nine European countries and find that, among men, the differential between the return to tertiary education at the .90 and at the .10 quantiles ranges from 61 percentage points (pp) in France to 2 pp in Greece, at an average of 26 pp. Similarly, the differential between the return to upper secondary education at the top and at the lowest quantiles ranges from 18 pp in Portugal to -3 pp in Greece, at an average of 9 pp. In

[4] These predictions are based on a partial equilibrium analysis, i.e., assuming that the wage structure within education groups remains unaltered after the educational expansion. We are aware that changes in the educational distribution as well as in the types of qualifications within education levels may have an effect on the wage structure. Still, the available evidence indicates that these composition effects are unlikely to result into lower wage dispersion among the high educated. As we show in Section 5, for all the years covered in this paper and despite changes in the educational structure, tertiary educated workers exhibit larger wage dispersion than less educated workers. Similarly, the international evidence reported in Martins and Pereira (2004) and Budría and Pereira (2005) shows that, across countries and consistently over time, conditional wage dispersion is highest among the high-educated.

Spain these differentials are, respectively, 23 pp and 6 pp, indicating that conditional wage dispersion within education groups is somewhat below the European average in Spain.

4.1. Educational mismatches

In this section, we differentiate between matched and mismatched workers, depending on whether or not they are in jobs commensurate with their qualifications. There are several approaches to measure the degree of mismatch, each of one having its own limitations[5]. Following most other authors, we use the worker's self-assessment regarding the match between the worker's skills and the firm's job requirements. In particular, we use two questions included in the ECHP,

- *Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?*
- *Have you had formal training or education that has given you skills needed for your present type of work?*

The previous questions provide us with different types of educational mismatch (Alba-Ramírez and Blázquez, 2002). Specifically, we can differentiate between:

i) 'over-qualified' workers: those who answer 'yes' to both the above questions.
ii) 'incorrectly qualified' workers: those who answer 'no' to both the above questions.
iii) those workers that answer 'yes' to the first question and 'no' to the second question, that is, those who have excess education and, at the same time, did not acquire necessary skills. We will denote them by 'strongly mismatched'.

As an illustration of the different types of mismatch, consider a psychologist employed:

[5] These approaches are basically three: job analysis, the statistical approach, and the worker's self-assessment. For a description of these methods, see Hartog (2000) and Sloane (2002).

i) as a car seller. In this situation, he may feel that his university degree allows him to do a more demanding job, even though it helps him to perform his current job. Thus, he would be considered an 'over-qualified' worker.
ii) as an accounting controller. In this case, he may feel that his formal education does not allow him to perform a more demanding job nor has provided him with the skills needed to perform his current job. Thus, he would be labelled as 'incorrectly qualified'.
iii) as a gardener. In this case, the individual presumably will report that his university degree allows him to do a more demanding job, yet it has not provided him with the skills needed to be a gardener. Thus, he will be considered as 'strongly mismatched'.

Our first definition, 'over-qualification', is typically labelled in the literature as 'over-education'. Most papers on the field are based on this single definition to explore the wage effects of 'over-education'. However, as is clear from the previous examples, 'over-educated' workers may differ depending on whether or not they are also 'incorrectly qualified'. Those who are 'over-qualified' and, additionally, 'incorrectly qualified' (i.e., 'strongly mismatched') can be hardly labelled as 'over-educated', as their formal education did not provide them with the skills needed at their jobs[6]. By exploiting three different categories of mismatch, we explicitly take into account these differences.

In Table 4 we report the incidence of educational mismatches. Overall, 36.7%, 19.2% and 24.1% of the sample workers are, respectively, over-qualified, incorrectly qualified, and strongly mismatched[7]. Relative to men, women are more prone to be over-qualified and less prone to be incorrectly qualified. Yet, the proportion of strongly mismatched workers is similar among men and women.

---------- Insert Table 4 about here -------

[6] We thank an anonymous referee for this remark.
[7] According to these figures, the extent of educational mismatch in the Spanish labour market is somewhat high by international standards. See Groot and Van den Brink (2000) for an international comparison on this subject.

To explore the effects of educational mismatch on wages, we extend our wage equation to differentiate between matched and mismatched workers. A common practice is to introduce a dummy variable that captures the effect of mismatch (Verdugo and Verdugo, 1989, Dolton and Vignoles, 2000, Chevalier, 2003). However, as this effect may differ across education levels, we prefer to use the following specification

$$ln\, w_i = \alpha_\theta + \delta_{\theta 1} X_i + \beta_{\theta 1} uppersec_i + \beta_{\theta 2} tertiary_i + \beta_{\theta 3} misuppersec_i + \beta_{\theta 4} mistertiary_i + e_{\theta i} \qquad (5)$$

where *uppersec* and *tertiary* are activated if the worker is matched and has, respectively, upper secondary or tertiary education, and *misuppersec* and *mistertiary* are activated if the worker is mismatched and has upper secondary or tertiary education[8]. This equation is then estimated using, alternatively, our three definitions of mismatch[9].

4.2. OLS results

In Table 5 we report the pay penalty of educational mismatch, as measured by the differential in the return to education earned by matched and mismatched workers. We find that over-qualification is associated with a negative penalty or, to put it different, with higher wages, while incorrect qualification seems to depress wages. However, none of these effects turns out to be significant. Interestingly, we find that while over-qualification and incorrect qualification, taken separately, do not carry a significant pay penalty, when combined they exert a large negative impact on wages. This impact is 17.6% for men and 26.7% for women in the tertiary level, and 14.1% for men and 12.7% for women in the upper secondary level.

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[8] An alternative specification is the ORU model, in which years of schooling are decomposed into required, surplus and deficit years of schooling in relation to those necessary to do the job. Relative to our specification, the ORU model has one advantage: it controls for the amount of mismatch. However, it presents two shortcomings. First, it assumes that the impact of mismatch on wages is constant across education levels. Second, and more important, in the quantile regression framework the ORU model would assume that the marginal impact of education (and mismatch) on within-groups dispersion is the same for all education levels. Clearly this is not the case, since, as we show, tertiary education has a much larger impact on within-groups dispersion than secondary and primary education.

[9] Ideally, we would like to estimate a single equation with separate effects for each type of mismatch. However, the small number of observations within some specific groups precludes us from conducting such analysis.

---------- Insert Table 5 about here -------

Three main conclusions can be inferred from these results. First, educational mismatched workers cannot be considered to be homogeneous. Specifically, over-qualified workers earn less only if their formal education has not provided them with the skills needed to perform their current job. Otherwise, over-qualification itself does not appear to depress wages. In line with Chevalier (2003), our results warn that using a single measure of educational mismatch (typically, 'over-qualification') may be too restrictive, as it may pool together workers that differ in the nature of their match (i.e., workers who are and workers who are not incorrectly qualified)[10].

Second, conventional estimates of the returns to education ignore the type of educational match attained by individuals and, thus, disregard the amount of variation within education groups that arises from the incidence of mismatch. We find that, by driving a wedge between matched and mismatched workers, strong mismatch contributes to enlarge wage differences within education groups.

Third, our estimates reject a pure human capital model. According to human capital theory, mismatched workers will earn the same return from education as matched workers, insofar as wages are solely determined by the educational level of the individuals. Yet, we find that strongly mismatched workers earn substantially lower returns than their matched counterparts. This result lends support to an assignment theory functioning of the labour market (Sattinger, 1993): wages are determined by human capital variables as well as by job characteristics, including the type of educational match. Previous work by Hartog and Oosterbeek (1988), Groot (1996),

[10] Most studies find that over-qualified workers earn less than workers who have the same education but hold jobs for which they are adequately educated (Alba-Ramírez, 1993, Battu *et al.,* 1999, Sloane *et al.,* 1999, Dolton and Vignoles, 2000, Dolton and Silles, 2001). In most cases, the estimated differential ranges from about 10 to 20 percentage points. These estimates, however, are typically based on a definition of over-qualification that includes workers who are incorrectly qualified as well as workers who are not. Our results are more in line with Chevalier (2003), who, differentiating between 'apparently' and 'genuinely' over-qualified workers, finds a pay penalty that ranges from 5% for the 'apparently' over-qualified up to 29% for the 'genuinely' over-qualified.

Battu *et al.* (1999), and Dolton and Vignoles (2000), among others, lend further support to this view.

4.3. Quantile regression results

Next, we turn to the quantile estimates. For the sake of brevity, we will concentrate solely on the wage effects of strong mismatch, as the other types of mismatch do not appear to exert a significant impact on wages[11]. Sometimes we will abuse the language somewhat, and will talk about 'mismatch' when we really mean 'strong mismatch'.

In Table 6 we report the quantile returns to education, together with the average returns, for matched and strongly mismatched workers. The estimates are plotted in Figures 3 and 4. We find that the return differential between matched and mismatched workers is not constant over the wage distribution. For men in the tertiary group, this differential is much lower at the top quantile than at the other quantiles, while the opposite holds for men in the secondary group. For women, the estimated pay penalty fluctuates across quantiles without a clear tendency.

---------- Insert Table 6 about here -------

---------- Insert Figures 3 and 4 about here ------

However, the most prominent result has to due with the positive association between tertiary education and wage dispersion. We find that, regardless of the educational match, tertiary educated workers exhibit more dispersion than less educated workers. Thus, for example, mismatched men with higher education earn on average 4.6% and 18.7% more, respectively, than adequately-educated men with a secondary level and mismatched men with a secondary level. However, these differentials are -.2% and 13.1% in the bottom quantile and as high as 22.9% and 48.9% in the top quantile. This pattern, which also holds for women, suggests that an educational expansion from

[11] We also examined the wage effects of over-qualification and incorrect qualification at different points of the wage distribution, and found that in most cases the estimated effects failed to be significant at the relevant quantiles. The results are available from the authors upon request.

secondary to tertiary education is expected, regardless of the educational match attained by university students, to increase overall within-groups dispersion.

4.4 Are educational mismatches responsible for the positive association between higher education and within-groups wage dispersion?

Machin (1996), Green *et al.* (1999), Fersterer and Winter-Ebmer (2003) and Martins and Pereira (2004), among others, have suggested that educational mismatches may account for the positive association between higher education and within-groups dispersion found in the data. A situation where a proportion of high-educated individuals take jobs with low skill requirement and low pay would be consistent with having increasing returns to higher education over the wage distribution. This hypothesis, however, has not been empirically tested to date.

The results reported in Table 6 can be used to test this hypothesis. If wage dispersion among the high-educated is due to the incidence of mismatch, then we should observe low dispersion among the group of matched workers. We find, however, that returns among matched workers also exhibit a substantial amount of variation. For instance, the return to a tertiary level earned by the adequately-educated is clearly increasing over the wage distribution, going from 32.9% to 52.2% among men and from 48.2% to 58.8% among women. Therefore, arguably, the positive association between tertiary education and within-groups earnings dispersion hinges, at least in Spain, on factors other than educational mismatches[12].

5. Changes over time

In the following, we use the 1994-2001 waves of the ECHP to examine the recent

[12] Notwithstanding this, educational mismatches contribute to enlarge wage differences among university graduates. Using equation (4), the .90-.10 differential for the tertiary group was found to be 23.4 pp for men and 19.3 pp for women. With equation (5), instead, this differential falls to 19.3 pp for adequately-educated men and 10.6 pp for adequately-educated women. It seems, therefore, that in a world without educational mismatches the relation between higher education and wage dispersion would be somewhat less acute, though still existent.

evolution of the returns to education in Spain. Specifically, we concentrate on changes in inequality between groups, within groups, and between matched and mismatched workers.

In Figures 5-16 we show the average estimates as well as the estimates at four selected quantiles: .10, .25, .75, and .90. Each line can be interpreted as the centre of a symmetric confidence interval whose evolution can be used to describe changes in the conditional wage distribution of the different groups (Buchinsky, 1994). When conducting such analysis, we must keep in mind that, even though the ECHP is designed to be representative of the total population, we can not avoid that part of the year-to-year fluctuations are due to sampling variation. To get a clearer view, we report two-year rolling averages rather than yearly estimates[13]. The analysis must be qualified further because of differences in the sizes of the different population groups. The number of female workers and mismatched workers is lower than the number of male workers and matched workers. Consequently, year-to-year fluctuations in the returns to education are greater and have larger standard errors for the former than for the later groups.

In Figures 5-8 we do not differentiate between matched and mismatched workers. The general trend is one of decreasing returns to education. However, changes in the returns are not uniform across quantiles or across different education levels. The downward trend is more noticeable at the higher quantiles and for tertiary educated workers. All in all, these results point to an overall decrease in inequality between groups and, to a lesser extent, inequality within groups during the sample period.

To get a more detailed view, in Figures 9-12 we focus on matched workers. Among men with tertiary education changes in within-groups dispersion were small. Still, the decreasing differential between the .75 and the lower quantiles points to a period of compression in the first two thirds of the wage distribution. Among women, an increase in wage dispersion during the first half of the sample period is followed by a mild decrease during the second half of the period. As for secondary educated workers, the

[13] The estimates for each year are available from the authors upon request.

results for men suggest that, within this group, wage inequality tended to decrease. The pattern for women is less clear cut, as a period of relatively high dispersion is followed by a year, 2001, of low dispersion.

In Figures 13-16 we show the results for strongly mismatched workers. Even though year-to-year variations are typically larger at the extreme quantiles than at the intermediate quantiles (Buchinsky, 1994), variations in the .10 quantile for this group are exceedingly large due to sampling variation and the smaller size of workers in this group. Thus, the estimates at the .10 quantile should be interpreted cautiously.

Among the tertiary educated, men show decreasing inequality from 1994 to 1998 and rising inequality from 1998 onwards. Overall, wage dispersion seems to be large at the bottom tail of the distribution in 1994 and at the top tail in 2001. Among women, differences across quantiles tend to be higher in the extreme years than in the intermediate years. The pattern of change for secondary educated workers is somewhat erratic, with no clear ordering across quantiles. If any, wage dispersion among men seems to be higher at the end of the period than in previous years.

Finally, we analyze changes in the return differential between matched and mismatched workers. As Figures 17 and 18 show, from 1994 to 2001 the pay penalty of mismatch tended to decrease, from about 25% to 15%. An exception is the group of men with secondary education, for which the effects of mismatch became more acute over the sample period. To complement the analysis, in Table 3B we have tested the significance of the pay penalty of mismatch for all the surveyed years. The test is performed for the OLS estimates as well as for the estimates at different quantiles. A glance to the p-values reveals that, in most cases, differences between matched and mismatched workers are statistically significant.

5.1 How should we understand the evidence?

From the previous analysis, we can draw important conclusions regarding the role that education and, particularly, tertiary education has had in shaping wage inequality in recent years. A remarkable feature of the data is that, consistently overt time, tertiary educated workers exhibit larger wage dispersion than less educated workers. This regularity points to a positive and stable relation between higher education and within-groups wage dispersion. Similarly, mismatched workers earn consistently less than their matched peers, contributing towards wage dispersion within education groups.

With this evidence at hand, we can draw the following two conclusions. First, the educational expansion that took place in Spain over the last years contributed to increase overall within-groups dispersion. The educational update resulted into a larger proportion of university graduates and, thus, into an enlargement of the high-spread group[14]. This process, moreover, was accompanied by a rising proportion of workers entering jobs for which they were mismatched. The data reveals that from 1994 to 2001, the proportion of strongly mismatched workers increased from 14.8% up to 24.1%[15]. Given that these workers are penalized in terms of wages, this process resulted into further wage dispersion within education groups.

The second conclusion is that changes in the structure of pay contributed to reduce wage inequality. This was primarily driven by a decrease in the returns to education, which resulted into smaller differences between groups. As an additional effect, the wage differential between matched and mismatched workers tended to decrease, contributing towards lower wage dispersion within groups.

In Section 2 we showed that in Spain over the last years, changes in (unconditional) overall wage inequality were small. As far as education is concerned, the evidence

[14] This process was intense during the nineties. Among the 25-64 age group, the proportion of individuals with less than upper secondary education fell from 78% in 1991 to 58% in 2001, while the proportion of individuals with completed tertiary education rose from 10% in 1991 to 24% in 2001 (OECD, 2004).

[15] Differentiating between types of mismatch, we find that while the proportion of over-qualified workers increased only by 1.3 pp, the proportion of incorrectly qualified and strongly mismatched workers increased by more than 7 and 9 pp, respectively. These results seem to suggest that if educational mismatches are a real economic problem, then policy makers should be concerned with the rising fraction of workers (over-qualified or not) entering jobs for which they lack necessary skills.

reported here suggests that this apparent stability was the result of multiple and sometimes opposing effects.

6. Conclusions

In this paper we attempted to shed further light on the impact that education has on wage levels and wage dispersion. Our findings were several. First, returns to tertiary education are highly increasing as we move towards higher quantiles of the conditional wage distribution. This implies that, conditional on observable characteristics, tertiary educated workers show larger wage dispersion than workers with less education. This pattern is stable over time and suggests that the educational expansion that took place in Spain over the last years contributed towards overall wage inequality through the within- dimension.

Second, we analyzed the wage effects of different types of educational mismatch. We found that 'over-qualification' and 'incorrect qualification' are not associated with lower wages. As opposite, 'strong mismatch' carries a pay penalty that ranges from 12.7% to 26.7%. From a theoretical perspective, this evidence is at odds with the pure human capital interpretation of the labour market that wages are solely determined by the educational level of the individual. According to human capital theory, mismatched workers will earn the same return from education as matched workers. Our results, that show important differences between matched and mismatched workers, seem to fit better in an assignment theory functioning of the labour market: wages are determined by human capital variables as well as by job characteristics, including the type of educational match.

Third, by driving a wedge between matched and mismatched workers, the incidence of strong mismatch has a positive impact on wage inequality within education groups. This impact, moreover, differs across education groups and across quantiles of the conditional earnings distribution.

Fourth, we tested whether educational mismatches are responsible for the positive association between higher education and within-groups dispersion found in the data. As conditional wage dispersion was found to be also large among matched workers, we concluded that educational mismatches are not a satisfactory explanation. Arguably, there are a number of other potential causes. Higher dispersion in skill and ability requirements among individuals with higher education, and differences in the types and qualities of qualifications awarded by universities could account for some of the observed variation. A complementary view is that higher education does not function as a screening device and, consequently, the group of university graduates is rather heterogeneous in terms of ability. If ability interacts with schooling, then returns to education must be higher among workers at high-pay jobs, i.e., with more ability. The acquisition of new data containing detailed information on the type of qualifications, ability scores, school quality, and occupational categories may help to test these hypotheses.

Fifth, we analyzed changes in the returns to education from 1994 to 2001. We found that changes in the structure of pay contributed to reduce wage inequality. This was basically driven by decreasing returns to education. This finding contrasts sharply with the rising returns to education reported in Barceinas *et al.* (2000) and Cantó *et al.* (2000) for the eighties and early nineties. In a recent book, Asplund and Barth (2005) document that despite large increases in average schooling levels, returns to education in European countries have remained at high levels over the last years. As a candidate explanation, they suggest that skill-biased technological change has fostered the demand for skilled labour, contributing to maintain education premia at high levels. According to his view, over the last years in Spain the demand of skilled labour has grown at a lower rate than the supply, resulting into a decline in the market price of education.

In turn, changes in the educational composition of the workforce contributed towards wage inequality. The rising proportion of university graduates in Spain resulted into an expansion of the high-spread group and, at the same time, into a larger proportion of mismatched workers. These changes contributed towards overall within-groups dispersion.

A clear implication of our analysis regards the demand for education. The return to a university degree shows variation, ranging from about 30% at the lowest quantile to 55% at the upper quantile of the earnings distribution. To the extent that prospective students are not aware of the characteristics which will place them at some point of the wage distribution, the returns to their educational investment are largely unpredictable. This uncertainty is reinforced by the fact that they may end up in jobs that are not commensurate with their qualifications and, thus, earn substantially lower wages. It seems, therefore, that from an individual perspective investing in education is subject to a substantial amount of wage risk.

It may be criticised that educational mismatches are a temporary phenomenon and, as such, they do not embody a real economic problem. Thus, for example, the ‘stepping stone’ hypothesis suggested by Sicherman (1991) suggests that high-educated individuals may take up mismatched work to acquire other forms of human capital, such as training, and move into matched work as their work experience increase. Similarly, employers may compensate with excess education other forms of human capital. However, analyzing the Spanish case, Alba-Ramírez (1993) founds that training is not treated by employers as a substitute for formal education. Furthermore, there is consisting evidence that for some workers mismatch is a long-run phenomenon[16].

Finally, there is evidence that in Europe the incidence of mismatch has increased over time (Hartog, 2000). Unfortunately, existing knowledge on the connection between mismatch and wage inequality is still too limited. Our analysis for Spain can be easily extended to other European countries that integrate the ECHP. The data harmonization provided by this dataset would allow for a straight comparison between different countries. To our eyes, assessing the impact that the mismatch phenomenon is having in the European wage structure is a compelling task for future research.

[16] Thus, for example, Sloane *et al.* (1999) and Dolton and Vignoles (2000) show for the UK that a substantial fraction of workers remain in jobs for which they are over-qualified during long periods.

Appendix A. Description of data source and estimating samples

The European Community Household Panel (ECHP) is a yearly survey that is carried out in the European Union. The Spanish waves of the ECHP are available from 1994 to 2001. The sample, which is designed to be representative of the Spanish population, has a size of about 5,000 households and 14,000 individuals, who are interviewed over time. Individuals are asked to report personal and family characteristics, including marital and educational status, as well as gross monthly wages and worked hours. We have dropped workers with a monthly wage rate that is less than 10% or over 10 times the average wage. This correction for outliers affects only 1.9% of the total sample. The variables used in the analysis are the following:

Gross hourly wage. Defined as monthly gross salary in the main job divided by four times the weekly hours worked in the main job.

Level of education. Individuals are asked to report the maximum level of completed schooling, according to three categories: less than upper secondary, upper secondary, and tertiary education. These education categories are constructed following the ISCED-97 classification.

Experience. Defined as age minus age of first job.

Tenure. Defined as the difference between the year of the survey and the year of the start of the current job. We have constructed three categories: from 1 to 4 years, from 5 to 14 years, and 15 years or more.

Married. It is a dummy that takes the value 1 if the individual is married, zero otherwise.

Immigrant. It is a dummy activated if the individual was born in a foreign country.

Industry. It is a dummy that takes the value 1 if the individual works in the industry sector, zero if he works in the service sector. The agricultural sector, which accounted for 6% of the working population in 2001, was dropped on the account of the particularities of this sector.

Firm size. Individuals are asked to report the number of employees that actually work in their firm. We have constructed four categories, from 1 to 19 employees, from 20 to 99 employees, from 100 to 499 employees, and 500 employees or more.

References

Alba-Ramírez, A. (1993), Mismatch in the Spanish Labour Market. Overeducation?, *Journal of Human Resources* 28, 259–278.

Alba-Ramírez, A. and M. Blázquez (2002), Types of Job Match, *Overeducation, and Labour Mobility in Spain*, in Büchel, F., A. de Grip and A. Meitens (eds), Overeducation in Europe: Current Issues in Theory and Policy. Edward Elgar Publishing, Cheltenham, UK.

Asplund, R. and E. Barth (2005), *Education and Wage Inequality in Europe: A Literature Review.* The Research Institute of the Finnish Economy, Helsinki 2005.

Barceinas, F., J. Oliver, J.L. Raymond and J.L. Roig (2000), *Private rates of return to human capital in Spain: new evidence.* Fundación de las cajas de ahorro confederadas para la investigación económica y social, Working Paper 162/2000.

Battu H., C. Belfield and P. Sloane (1999), "Mismatch among graduates: a cohort view", *Education Economics*, 7, 21-38.

Buchinsky, M. (1994), Changes in the US Wage Structure 1963-1987: Application of Quantile Regression, *Econometrica* 62, 405-458.

Buchinsky, M. (1998), Recent advances in quantile regression models: a practical guideline for empirical research, *Journal of Human Resources* 33, 88-126.

Budría, S. and P. Pereira (2005), *Educational Qualifications and Wage Inequality: Evidence for Europe*, IZA Discussion Paper 1763.

Cantó, O., A.R. Cardoso, C. Farinha, M. Izquierdo and J.F. Jimeno (2000*), Integration and Inequality: Lesson from the Accessions of Portugal and Spain to the EU.* FEDEA Working Paper 2000-10.

Chevalier, A. (2003), Measuring mismatch, *Economica* 70, 509-531.

De la Rica, S., J.J. Dolado and V. Llorens (2005), *Ceiling and Floors: Gender Wage Gaps by Education in Spain*, IZA Discussion Paper 1483.

Dolton, P. and A. Vignoles (2000), The incidence and effects of mismatch in the UK graduate labour market, *Economics of Education Review* 19, 179-98

Dolton, P. and M. Silles (2001), *Mismatch in the Graduate Labour Market: Some Evidence from Alumni Data.* Centre for the Economics of Education, Discussion Paper Series, 9.

Fersterer, J. and R. Winter-Ebmer (2003), Are Austrian Returns to Education Falling Over Time?, *Labour Economics* 10(1), 73-89.

Gardeazábal, J. and A. Ugidos (2004), Measuring the gender gap at different quantiles of the wage distribution, *Journal of Population Economics* 44, 224–236.

Gosling, A., S. Machin and C. Meghir (2000), The changing distribution of Male Wages in the UK, *Review of Economic Studies* 67, 635-666.

Green, F., S. McIntosh and A. Vignoles (1999), *Overeducation' and Skills – Clarifying the Concepts*, Centre for Economic Performance, London School of Economics, 1-54.

Groot, W. (1996), The incidence of, and returns to overeducation in the UK, *Applied Economics* 28, 1345-1350.

Groot, W. and H. Van den Brink (2000), Overeducation in the Labor Market: A Meta-Analysis, *Economics of Education Review* 19, 149-158.

Hartog, J. (2000), Mismatch and earnings: where are we, where should we go, *Economics of Education Review* 19, 131-147.

Hartog, J. and Oosterbeek, H. (1988), Education, allocation and earnings in the Netherlands: overschooling?, *Economics of Education Review* 7, 185-194

Hartog, J., P. Pereira and J.A. Vieira (2001), Changing Returns to Education in Portugal during the 1980s and Early 1990s: OLS and Quantile Regression Estimators, *Applied Economics* 33, 1021-1037.

Machin, S. (1996), Wage Inequality in the UK, *Oxford Review of Economic Policy*, 12(1), 47-64.

Martins, P. and P. Pereira (2004), Does Education Reduce Wage Inequality? Quantile Regressions Evidence from Fifteen European Countries, *Labour Economics*, 11(3), 355-371.

OECD (2004), *Education at a Glance*. Paris.

Sattinger, M. (1993), Assignment models of the distribution of earnings, *Journal of Economic Literature* 31, 831-880.

Sicherman, N. (1991), Mismatch in the Labor Market, *Journal of Labor Economics* 9(2), 101-122.

Sloane, P. J. (2002), Much Ado About Nothing? What does the Mismatch Literature really Tell Us? Keynote Address, International Conference on Mismatch in Europe: What Do We Know? 22-23 November, Berlin.

Sloane, P.J., H. Battu and P.T Seaman (1999), Mismatch, Undereducation and the British Labour Force, *Applied Economics* 31(11), 1437–1453.

Verdugo, R. and N.T. Verdugo (1989), The impact of surplus schooling on earnings: Some additional findings, *Journal of Human Resources* 24, 629-695.

Tables

Table 1. Descriptive statistics (2001)

	Men		Women	
	Mean	St. dev	Mean	St. dev
No. of observations	1,749		937	
Age	37.00	10.54	34.13	9.58
Married	0.64	0.48	0.50	0.50
Immigrant	0.01	0.78	0.02	0.70
Weekly hours	43.32	7.27	38.70	6.19
Ln (monthly wage)	14.48	11.63	14.07	11.16
Ln (hourly wage)	6.78	8.26	6.51	7.95
Experience	19.14	12.25	14.07	10.91
Education				
Tertiary	25.27		37.25	
Secondary	22.18		26.25	
Primary	52.54		36.50	
Tenure				
0-4 years	56.83		64.57	
5-14 years	21.78		22.84	
≥ 15 years	9.26		5.12	
Sector				
Industry	56.95		25.72	
Services	43.05		74.28	
Firm size				
1-19 employees	46.77		53.26	
20-99 employees	29.90		25.29	
100-499 employees	14.87		14.73	
≥ 500 employees	8.46		6.72	

Table 2. The evolution of inequality by education groups (1994-2001)

	Total Sample			Tertiary			Upper Secondary			Less than upper secondary		
	Gini	**W1/W5**	**W1/W9**	Gini	W1/W5	W1/W9	Gini	W1/W5	W1/W9	Gini	W1/W5	W1/W9
2001	**0.30**	**1.90**	**4.08**	0.30	1.80	4.21	0.29	1.80	4.07	0.24	1.58	3.23
1994	**0.31**	**1.91**	**4.46**	0.28	1.78	3.56	0.29	1.86	4.14	0.26	1.64	3.93

Table 3. Conditional returns to education (2001)

MEN	**OLS**	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
TERTIARY	**0.388***** (0.030)	0.296*** (0.069)	0.307*** (0.035)	0.336*** (0.034)	0.464*** (0.038)	0.530*** (0.042)
UPPER SECONDARY	**0.147***** (0.028)	0.105*** (0.057)	0.093*** (0.038)	0.152*** (0.028)	0.182*** (0.032)	0.162*** (0.041)
WOMEN	**OLS**	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
TERTIARY	**0.430***** (0.043)	0.375*** (0.112)	0.430*** (0.064)	0.414*** (0.052)	0.479*** (0.045)	0.568*** (0.060)
UPPER SECONDARY	**0.174***** (0.041)	0.239*** (0.106)	0.172*** (0.058)	0.154*** (0.046)	0.150*** (0.044)	0.198*** (0.061)

Note: i) * signals significant at the 10% level, ** signals significant at the 5% level, and *** signals significant at the 1% level; ii) standard errors in parenthesis; iii) OLS estimation is heteroskedastic-robust; iv) quantile standard errors are obtained using 500 replications. The reference individual is a worker with less than upper secondary education, less than 5 years of tenure, single, not immigrant, working in the service sector in a firm with less than 20 employees.

Table 4. Proportion of mismatched workers (2001)

	Over-qualified	Incorrectly qualified	Strongly mismatched
MEN	34.6	22.1	24.7
WOMEN	40.1	14.1	23.0
TOTAL SAMPLE	36.7	19.2	24.1

Table 5: Average pay penalty of educational mismatch (2001)

	Tertiary		Upper Secondary	
	Men	Women	Men	Women
OVER-QUALIFICATION	-0.04	-6.0	-1.5	-5.5
INCORRECT QUALIFICATION	8.3	9.3	3.3	13.7
STRONG MISMATCH	17.6***	26.7***	14.1***	12.7*

Note: i) * signals significant at the 10% level, and *** signals significant at the 1% level.

Table 6. Conditional returns to education – Matched and strongly mismatched workers (2001)

MEN	**OLS**	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
TERTIARY MATCHED	**0.415***	0.329***	0.335***	0.378***	0.495***	0.522***
	(0.031)	(0.075)	(0.037)	(0.039)	(0.040)	(0.045)
TERTIARY STRONGLY MISMATCHED	**0.239***	0.185	0.184**	0.222***	0.242***	0.480***
	(0.071)	(0.161)	(0.082)	(0.056)	(0.085)	(0.140)
UPPER SECONDARY MATCHED	**0.193***	0.187***	0.121***	0.173***	0.204***	0.251***
	(0.032)	(0.062)	(0.038)	(0.032)	(0.041)	(0.063)
UPPER SECONDARY STRONGLY MISMATCHED	**0.052**	0.054	-0.049	0.077	0.067**	-0.009
	(0.040)	(0.071)	(0.068)	(0.060)	(0.035)	(0.057)

WOMEN	**OLS**	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
TERTIARY MATCHED	**0.472***	0.482***	0.470***	0.449***	0.541***	0.588***
	(0.045)	(0.115)	(0.060)	(0.057)	(0.050)	(0.060)
TERTIARY STRONGLY MISMATCHED	**0.205**	0.281**	0.070	0.218**	0.252***	0.245***
	(0.081)	(0.170)	(0.168)	(0.086)	(0.090)	(0.123)
UPPER SECONDARY MATCHED	**0.210***	0.303***	0.229***	0.162***	0.167***	0.233***
	(0.043)	(0.108)	(0.057)	(0.044)	(0.055)	(0.076)
UPPER SECONDARY STRONGLY MISMATCHED	**0.083**	0.204	0.021	0.025	0.114**	0.052
	(0.069)	(0.182)	(0.108)	(0.093)	(0.056)	(0.098)

Note: i) * signals significant at the 10% level, ** signals significant at the 5% level, and *** signals significant at the 1% level; ii) standard errors in parenthesis; iii) OLS estimation is heteroskedastic-robust; iv) quantile standard errors are obtained using 500 replications. The reference individual is a worker with less than upper secondary education, less than 5 years of tenure, single, not immigrant, working in the service sector in a firm with less than 20 employees.

Figures

Figure 1 – Conditional returns to education – Men (2001)

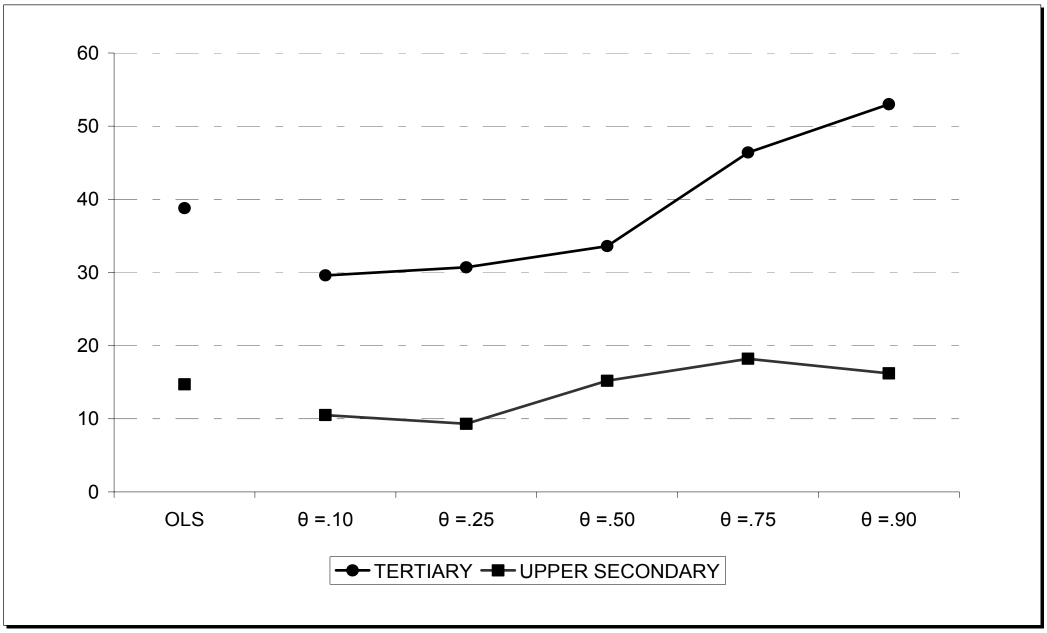


Figure 2 – Conditional returns to education – Women (2001)

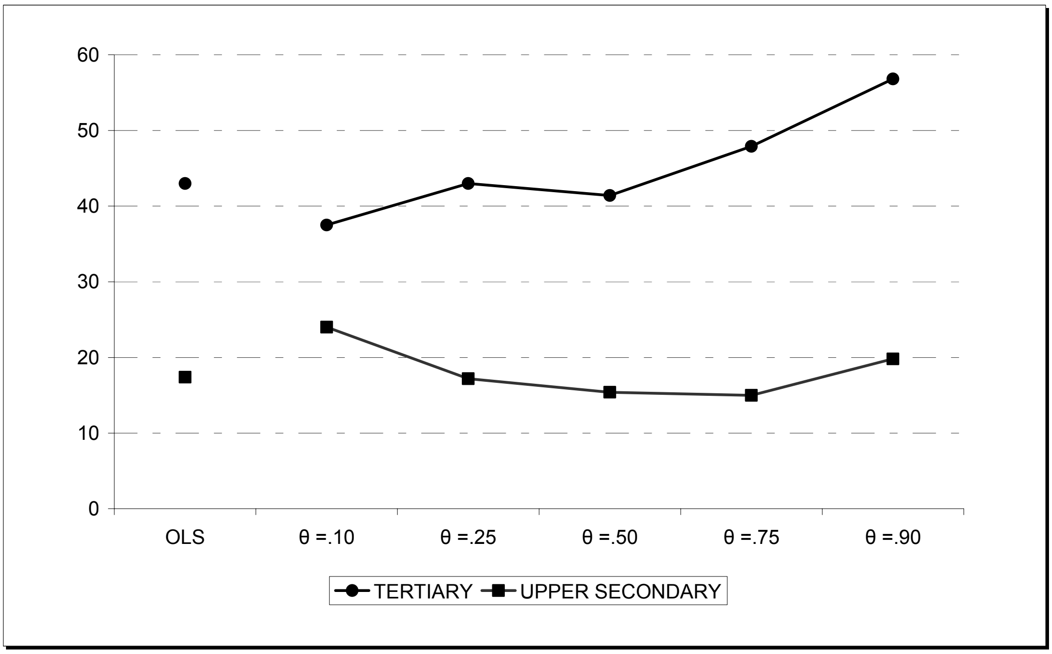


Figure 3 – Conditional returns to education – Matched and strongly mismatched men (2001)

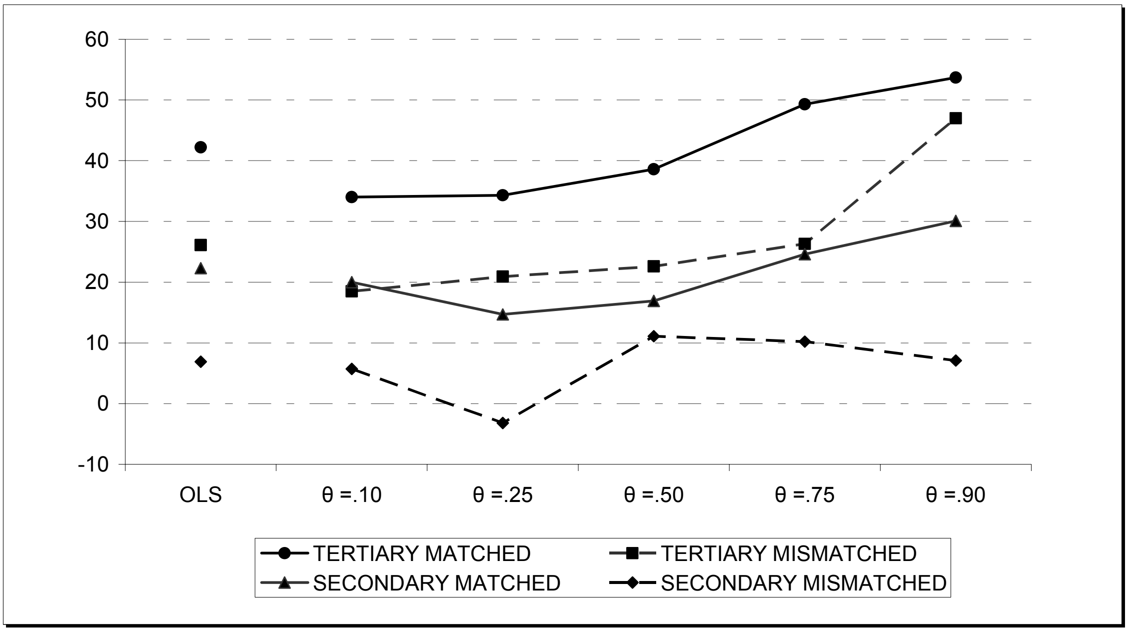
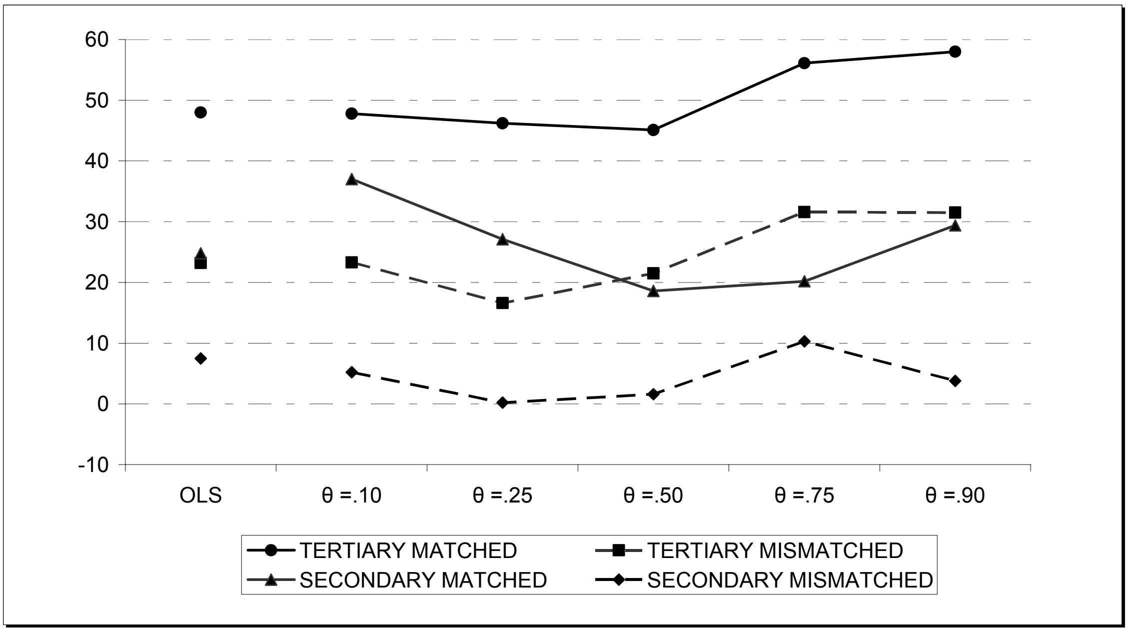
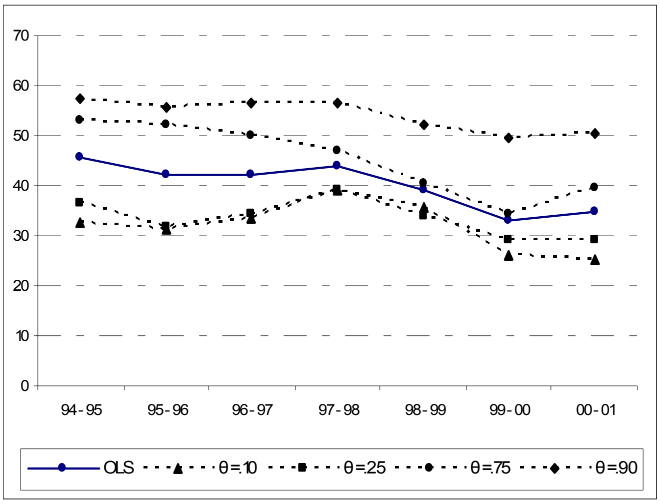


Figure 4 – Conditional returns to education – Matched and strongly mismatched women (2001)

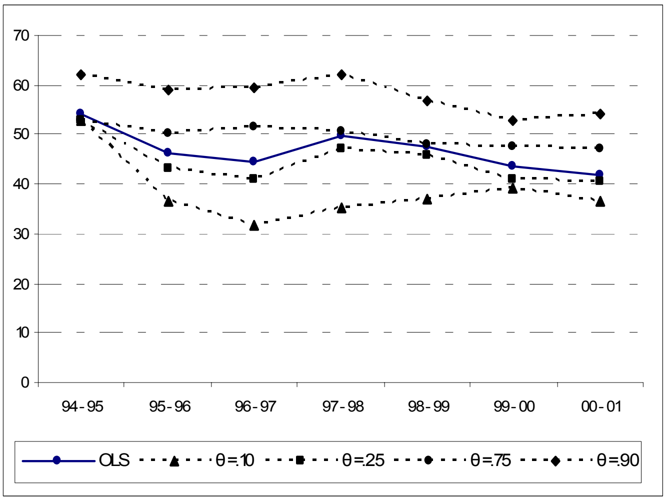


Figures 5-8. Evolution of the returns to education (1994-2001)

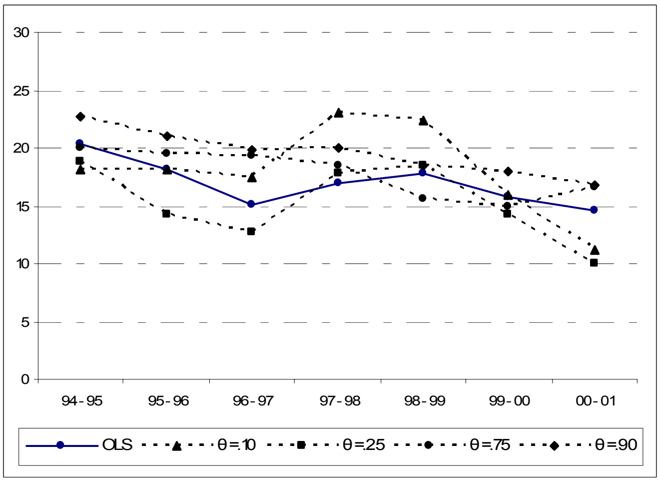
Men Tertiary



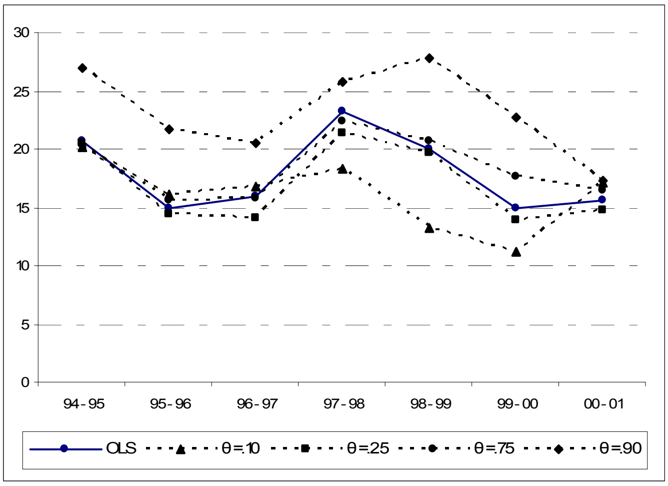
Women Tertiary



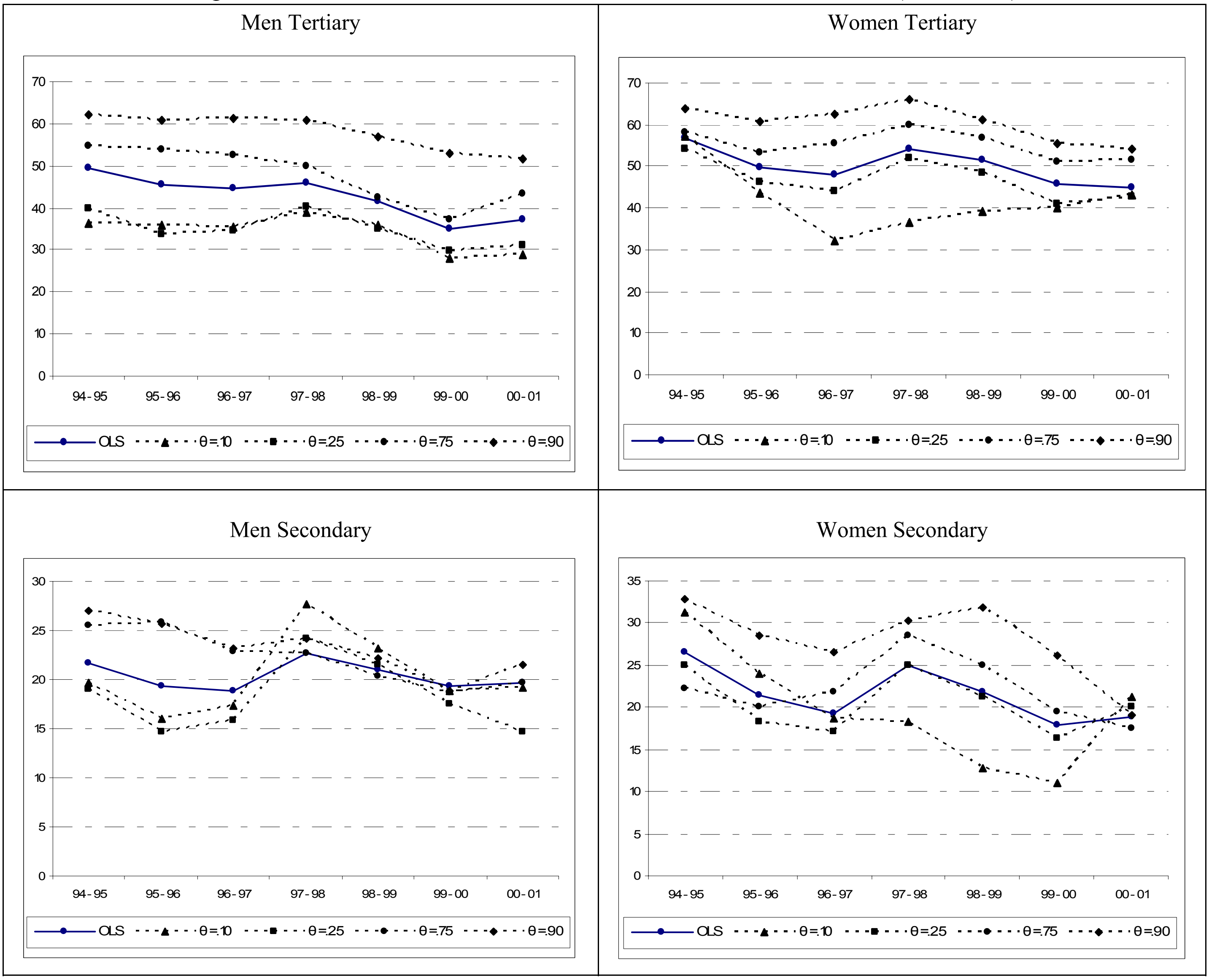
Men Secondary



Women Secondary



Figures 9-12. Evolution of the returns to education – Matched workers (1994-2001)



Figures 13-16. Evolution of the returns to education – Strongly mismatched workers (1994-2001)

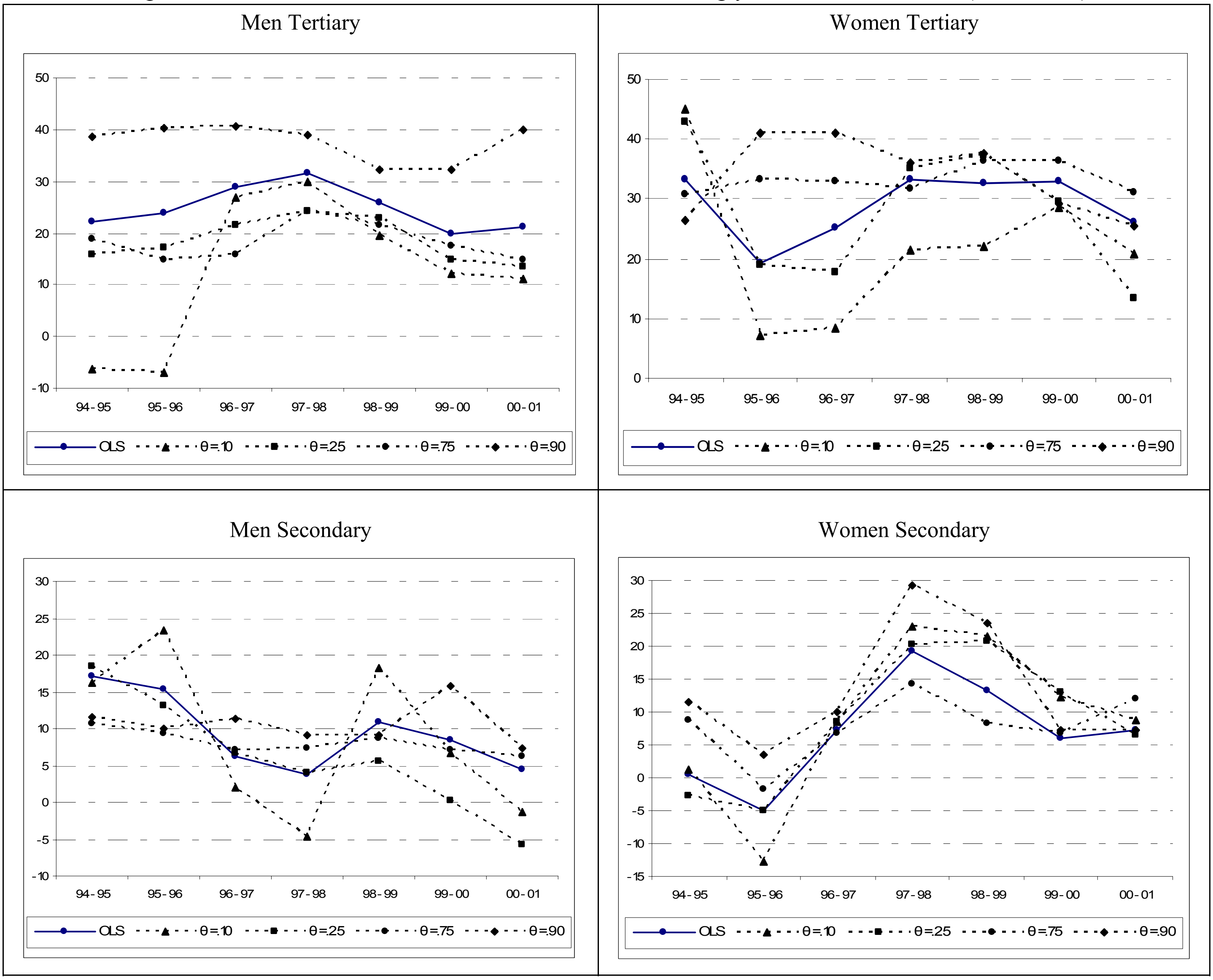


Figure 17. Evolution of the average pay penalty of strong mismatch – Men (1994-2001)

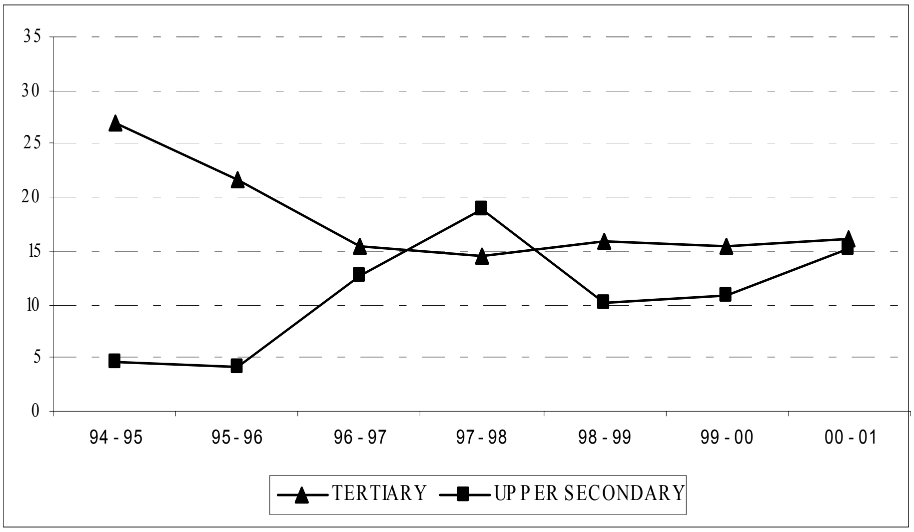
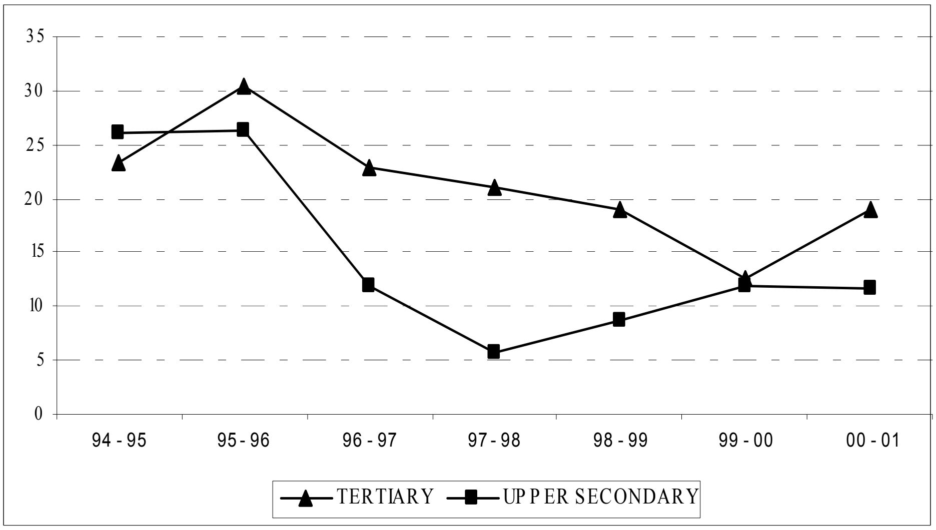


Figure 18. Evolution of the average pay penalty of strong mismatch – Women (1994-2001)



Additional Tables

Table 1B. OLS and Quantile Regression (2001) – Dependent variable: Ln. Gross hourly wage

	Men					
	OLS	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
Tertiary	0.388*** (0.030)	0.296*** (0.069)	0.307*** (0.035)	0.336*** (0.034)	0.464*** (0.038)	0.530*** (0.042)
Upper Secondary	0.147*** (0.028)	0.105*** (0.057)	0.093*** (0.038)	0.152*** (0.028)	0.182*** (0.032)	0.162*** (0.041)
Experience*100	0.038*** (0.004)	0.048*** (0.008)	0.032*** (0.006)	0.026*** (0.004)	0.029*** (0.004)	0.033*** (0.005)
$(\text{Experience*100})^2$	-0.010*** (0.002)	-0.008*** (0.002)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Tenure: 5-14 years	0.100*** (0.023)	0.220*** (0.051)	0.088*** (0.031)	0.062*** (0.026)	0.043* (0.026)	-0.006*** (0.047)
Tenure: ≥ 15 years	0.189*** (0.037)	0.306*** (0.058)	0.131*** (0.036)	0.150*** (0.033)	0.122** (0.068)	0.279 (0.071)
Married	0.089*** (0.027)	0.170*** (0.064)	0.087*** (0.035)	0.055** (0.029)	0.055** (0.029)	0.069* (0.035)
Immigrant	0.021 (0.110)	-0.155 (0.200)	0.012 (0.201)	0.066 (0.092)	-0.060 (0.147)	0.179 (0.241)
Industry	0.001 (0.023)	0.128** (0.051)	0.079*** (0.029)	0.040 (0.026)	-0.060*** (0.027)	-0.124*** (0.031)
Firm size: 20-99 employees	0.094*** (0.025)	0.061 (0.055)	0.087*** (0.032)	0.098*** (0.024)	0.108*** (0.030)	0.076*** (0.031)
Firm size: 100-499 employees	0.221*** (0.033)	0.175** (0.086)	0.217*** (0.043)	0.256*** (0.033)	0.242*** (0.038)	0.268*** (0.050)
Firm size: ≥ 500 employees	0.309*** (0.041)	0.328*** (0.069)	0.278*** (0.048)	0.320*** (0.043)	0.330*** (0.053)	0.209*** (0.067)
Constant	6.032*** (0.041)	5.279*** (0.081)	5.881*** (0.064)	6.181*** (0.040)	6.426*** (0.039)	6.661*** (0.043)

Note: i) * signals significant at the 10% level, ** signals significant at the 5% level, and *** signals significant at the 1% level; ii) standard errors in parenthesis; iii) OLS estimation is heteroskedastic-robust; iv) quantile standard errors are obtained using 500 replications. The reference individual is a worker with less than upper secondary education, less than 5 years of tenure, single, not immigrant, working in the service sector in a firm with less than 20 employees.

Table 2B. OLS and Quantile Regression (2001) – Dependent variable: Ln. Gross hourly wage

	Women					
	OLS	θ =.10	θ =.25	θ =.50	θ =.75	θ =.90
Tertiary	0.430***	0.375***	0.430***	0.414***	0.479***	0.568***
	(0.043)	(0.112)	(0.064)	(0.052)	(0.045)	(0.060)
Upper Secondary	0.174***	0.239***	0.172***	0.154***	0.150***	0.198***
	(0.041)	(0.106)	(0.058)	(0.046)	(0.044)	(0.061)
Experience*100	0.045***	0.060***	0.052***	0.040***	0.034***	0.039***
	(0.006)	(0.011)	(0.008)	(0.008)	(0.006)	(0.008)
$(\text{Experience*100})^2$	-0.008***	-0.011***	-0.010***	-0.007***	-0.006***	-0.007***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure: 5-14 years	0.252***	0.469***	0.293***	0.216***	0.127***	0.072
	(0.035)	(0.085)	(0.047)	(0.045)	(0.040)	(0.058)
Tenure: ≥ 15 years	0.326***	0.335***	0.246***	0.292***	0.318***	0.164
	(0.072)	(0.133)	(0.085)	(0.141v	(0.086)	(0.144)
Married	0.023	0.138*	0.061	-0.020	-0.013	0.006
	(0.035)	(0.081)	(0.047)	(0.045)	(0.033)	(0.049)
Immigrant	-0.188*	-0.425***	-0.108	-0.195	-0.266	-0.011
	(0.127)	(0.231)	(0.212)	(0.156)	(0.189)	(0.205)
Industry	0.009	0.112	0.064	0.022	-0.049	-0.082
	(0.037)	(0.105)	(0.056)	(0.043)	(0.042)	(0.056)
Firm size: 20-99 employees	0.131***	0.125*	0.148***	0.117***	0.128***	0.058
	(0.041)	(0.082)	(0.052)	(0.047)	(0.048)	(0.060)
Firm size: 100-499 employees	0.207***	0.101	0.225***	0.217***	0.205***	0.155**
	(0.052)	(0.111)	(0.075)	(0.064)	(0.052)	(0.078)
Firm size: ≥ 500 employees	0.268***	0.320***	0.296***	0.277***	0.271***	0.212***
	(0.063)	(0.125)	(0.073)	(0.083)	(0.075)	(0.082)
Constant	5.767***	4.877***	5.420***	5.898***	6.228***	6.446***
	(0.056)	(0.123)	(0.109)	(0.071)	(0.054)	(0.059)

Note: i) * signals significant at the 10% level, ** signals significant at the 5% level, and *** signals significant at the 1% level; ii) standard errors in parenthesis; iii) OLS estimation is heteroskedastic-robust; iv) quantile standard errors are obtained using 500 replications. The reference individual is a worker with less than upper secondary education, less than 5 years of tenure, single, not immigrant, working in the service sector in a firm with less than 20 employees.

Table 3B: P-values of testing equality of coefficients

MEN TERTIARY – matched = strongly mismatched								
	1994	1995	1996	1997	1998	1999	2000	2001
OLS	0.10	0.01	0.01	0.02	0.01	0.01	0.04	0.02
θ=.10	0.13	0.09	0.54	0.38	0.04	0.38	0.27	0.59
θ=.25	0.09	0.17	0.13	0.28	0.03	0.07	0.02	0.07
θ=.75	0.00	0.17	0.00	0.00	0.09	0.11	0.06	0.00
θ=.90	0.00	0.04	0.02	0.13	0.02	0.00	0.13	0.06
MEN SECONDARY – matched = strongly mismatched								
	1994	1995	1996	1997	1998	1999	2000	2001
OLS	0.05	0.09	0.39	0.00	0.00	0.10	0.00	0.01
θ=.10	0.65	0.62	0.24	0.02	0.10	0.98	0.05	0.10
θ=.25	0.37	0.45	0.47	0.02	0.02	0.24	0.00	0.03
θ=.75	0.11	0.05	0.01	0.10	0.00	0.06	0.06	0.01
θ=.90	0.17	0.28	0.04	0.28	0.00	0.13	0.78	0.01
WOMEN TERTIARY – matched = strongly mismatched								
	1994	1995	1996	1997	1998	1999	2000	2001
OLS	0.11	0.01	0.02	0.00	0.00	0.02	0.12	0.00
θ=.10	0.84	0.52	0.04	0.81	0.03	0.39	0.23	0.34
θ=.25	0.75	0.19	0.07	0.06	0.01	0.69	0.82	0.02
θ=.75	0.00	0.01	0.33	0.00	0.01	0.00	0.04	0.00
θ=.90	0.00	0.13	0.63	0.00	0.01	0.00	0.16	0.03
WOMEN SECONDARY – matched = strongly mismatched								
	1994	1995	1996	1997	1998	1999	2000	2001
OLS	0.11	0.00	0.01	0.08	0.36	0.04	0.11	0.08
θ=.10	0.63	0.02	0.03	0.69	0.77	0.90	0.44	0.63
θ=.25	0.25	0.00	0.06	0.55	0.81	0.95	0.17	0.06
θ=.75	0.92	0.00	0.02	0.00	0.14	0.00	0.64	0.43
θ=.90	0.50	0.01	0.27	0.12	0.79	0.00	0.35	0.13

Note: i) p-value < 0.10: significantly different at the 10% level; p-value < 0.05: significantly different at the 5% level; p-value < 0.01: significantly different at the 1% level.