Profitable Career Paths: Accumulated Skills in Work, Their Degree of Transferability and Wage Premia

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1. Introduction

This paper is an examination on the degree of transferability of skills individuals acquire in work and their wage premia. Several studies have explored the role that employer-tenure plays in an individual's earnings profile (e.g. Abraham and Farber 1987; Altonji and Shakotko 1987), under the assumption that a worker's total working experience can be divided into two main parts: employer-specific and general labour market skills. In this paper I challenge this assumption and explore whether the typical worker's human capital stock should be further decomposed. Particularly, I examine the existence of industry and occupation-specific skills.

Studies on displaced workers have revealed that industry may be an important dimension across which skills are transferable. Although most displaced workers suffer wage losses, workers who switch industries following displacement usually suffer greater losses than observationally similar workers who find jobs in their pre-displacement industry (Podgursky and Swaim 1987; Addison and Portugal 1989 a, b; Kletzer 1991; Ong and Mar 1992; Carrington 1993; Ong and Lawrence 1993; Neal 1995). If the accumulated skills in work are mainly industry-specific rather than firm-specific, then it is expected that employer-tenure will have only a modest effect on wages. Furthermore, the observed wage losses of the displaced workers will be more severe for those who find employment in another industry, since they will forego their previously accumulated industry-specific skills. According to Neal, "*the difference between switchers and stayers is that switchers forfeit compensation for their industry-specific skills*". The author acknowledges the fact that a portion of industry-specific compensation reflects labour market rents. Nevertheless, there are still important wage profile differences between stayers and switchers due to the fact that

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the latter forfeit, in the post-displacement job, compensation for their already obtained industry-specific skills. Furthermore, the author argues that, after all, firm-specific factors may contribute little to the observed slope of the wage tenure profile.

Parent in a recent study (2000), based on a standard wage equation model, establishes that the returns to seniority are very small or they do not exist at all. From the author's point of view, what is important for the wage profile in terms of human capital is industry specificity rather than employer specificity. According to his findings, it appears that past studies have overlooked an important factor in analysing the effect of tenure on wages. Industry-specific skills are found to play a far more significant role in the wage growth process than employer-specificity.

The question addressed here is whether the accumulated in work human capital should be further decomposed, apart from the employer-specific and the general labour market components. A possible candidate, as already outlined above, is the industry-specific skills. A worker through the years may acquire some skills that are appreciated and rewarded not solely by the current employer, but by other employers as well in the same industry. If that proves to be true, then that implies that industry-specificity does exist and furthermore it has a significant role in the wage determination process. In this framework, an individual working in the manufacturing sector, for example, should obtained some skills that will be equally appreciated by other employers in that industry. Therefore, it is expected that her experience in the manufacturing industry should have a positive effect on her wages in any future employment in the same industry. On the other hand, if she moves to another industry, then she should forfeit these industry-specific human capital wage premia.

One may argue though that it is occupational experience that matters instead of industry experience. Let's consider again the example of the worker that is employed in the manufacturing sector, as a secretary. In the case of industry-specificity of human capital, these accumulated skills, specific to the manufacturing industry, should not have any effect on her wages if she switches industries, for instance if she is employed in the banking sector, as a secretary again. However, one might wonder what sort of skills a secretary could obtain in the manufacturing industry, that are specific to this particular industry. Probably, it would be more reasonable to assume that it is occupational-specificity of human capital that should be examined. A secretary would most likely acquire skills that are specific to her current occupation, therefore transferable among different employers and industries, as long as she is working as a secretary. In the case, an individual changes occupations, then it should be expected that she would forfeit these wage premia associated to her expertise in her previous occupation.

Individuals are not equally well equipped to enter each occupation, and they self-select on the basis of their comparative advantage for the occupation. The occupational choice process can be described as a utility maximisation problem. If we assume that occupational choice determines, on average, subsequent earnings growth, then each individual acts as far-sighted optimiser. This economic agent early in her adult life chooses her career path[2], in other words, chooses the occupation which best achieves her lifetime objectives that are represented both by her lifetime income stream and tastes for specific occupations. The parameters that determine the self-selection of workers into occupations can be distinguished into two main groups. On the one hand, there are the personal taste and motivation, allied to family background, of the individual. In general, socio-economic variables play an important role in the occupational choice (Robertson and Symons, 1990), since, in a way, they form the future expectations of the individual and her taste and preferences towards life-style, priorities and quality in life. One the other hand, ability and the attributes of the individual are important determinants of the choice of occupation. Each worker is endowed with a level of ability for each sector, so they will sort themselves into occupations according to their comparative advantage (Roy, 1951). Since individuals aim to maximise their utility, they tend to choose occupations that cater their personal strengths. A worker consists of a bundle of characteristics that are embodied within the person and sold on the market as a package deal. The way these characteristics are utilised and valued will differ across occupations, because technology varies across occupations. It is technology therefore that determines the weights that are placed on various personal characteristics and consequently different technologies might require the use of different characteristics or at least emphasise them differently. Thus each individual, knowing her ability, forms an estimate of her expected earnings in each occupation and, taking into account her particular taste for each occupation, chooses the one which offers the greatest utility.

The first paper, to the authors knowledge, that directly examines the significance of occupational investment, as part of the post-school human capital, in the wage determination is a study by Shaw (1984). Shaw in her paper argues that occupational investment, which is the accumulation of skills an individual acquires to perform work within a particular occupation, is a strong determinant of earnings and far superior to general labour market experience. Total occupational investment in a particular occupation is calculated as the weighted sum of the individual's accumulated quantities of occupation-specific investment, based on the hypotheses that some portion of the occupational skills are transferable across the various occupations and that occupations are characterised by different degrees of general investment. According to the author, although total labour market experience and occupational investment are both proxies of the individual's stock of general human capital, the latter is a far better measure. The reason is that occupational investment can be considered as a heterogeneous measure of general labour market skills. Therefore, the introduction of occupational investment, which replaces the homogeneous measure of years of experience in the labour market (total labour market experience), reduces the otherwise unobservable heterogeity in individual's general post-school investment. The main empirical framework of this study is based on a standard Mincer wage equation model, where the author introduces occupational investment at the place of total labour market experience. The findings from these wage equations strongly suggest that occupational investment has a very important contribution on individual's earnings profiles, "empirically dominating the standard experience variable as a proxy for the stock of general human capital investment embodied in the individual" (Shaw, 1984).

In the analysis that follows, I examine whether there exists industry-specific or occupation-specific human capital, or both, and their contribution to the wage determination process. In section 2, I explain the methodology employed for the purpose of the analysis, followed by a description of the data set used here. The main

[2] Despite the fact that there is both upward and downward movement, the position of individuals in the

findings are summarised in section 4, with a discussion on their implications with respect to the evolution of an individual's earnings profile. The estimates on the wage equation models suggest the existence of occupational specific skills and the significance of individuals' expertise in their wages determination process. The evidence on the industry-specific human capital, on the other hand, is not so strong. Nevertheless, despite the uncertainty concerning the industry experience, even in the case where industry specificity matters, the estimated effect does not appear to be of great magnitude. In section 5 a more detailed examination is pursued. Here the author explores whether these derived effects are uniform across the various occupations or industry sectors or not. Indeed, the findings suggest that there is heterogeneity in the returns to industry and occupational experience, suggesting that the previous estimates in section 4 are driven by particular occupational and industry choices. Finally, in section 6 we conclude our discussion highlighting the major findings and implications of this study.

2. Methodology

The framework adopted here, similar to the one Parent (2000) employs in his study, is based on a standard wage equation model. My working assumption is that employer-tenure, total industry and occupational experience are competing effects in the wage determination process. Initially, consider the following wage equation model

$$\ln w_{ijt} = \alpha + \beta_1 T_{ijt} + \beta_2 Exp_{it} + \beta_n X'_{ijt} + \varepsilon_{ijt} \tag{1}$$

for the individual i, with the j employer, the period t, where T_{ijt} represents the employer tenure, Exp_{it} is the total labour market experience and X_{ijt} is a $1 \times n$ control vector that does not include industry or occupational experience. If industry experience plays a significant role in the wage setting, then I would expect that the inclusion of this variable in the control vector, alongside employer tenure, would decrease the magnitude of tenure effect on wages. The reason is that the returns to tenure are most likely overestimated when industry experience is not controlled for in

occupational hierarchy is highly stable over time (Nickell, 1982).

a wage equation model. A portion of this estimated tenure effect should be attributed to the industry-specific skills that an individual has obtained in work rather than to those skills that are only appreciated by the current employer. In like manner, if it is occupational experience that matters, then its inclusion in the covariates should have a similar negative impact on the magnitude of the estimated returns to employer-specific skills.

The main framework of my analysis has already been outlined in the paragraph above. In order to address the issue of industry-specific and occupational-specific human capital, I investigate whether employer tenure effect decreases when they are alternatively controlled for in the estimated model. Initially I estimate a wage equation model without including a variable for either industry experience or occupational experience. The wage equation model is then re-estimated including alternatively industry and occupational experience and both. Any observed significant decrease in the magnitude of tenure effect in these models may provide us with the insight on how total working experience should be decomposed and have important implications on the evolution of life cycle earnings and on job mobility issues.

Consider now a wage equation model

$$\ln w_{ijkht} = \alpha + \beta_1 T_{ijt} + \beta_2 Exp_{it} + \beta_3 Ind_{ikt} + \beta_4 Occ_{iht} + \beta_n X'_{ijkht} + \varepsilon_{ijkht} \qquad (2)$$

where w_{ijkht} represents the hourly wage of individual i, with the j employer, having the h occupation in the k industry, the t period, and industry experience Ind_{ikt} and occupational experience Occ_{iht} are included in the regressors alongside employer tenure T_{ijt} and total labour market experience Exp_{it}. One issue of concern related to the estimation process is the fact that the obtained coefficients of interest (β_1, β_2, β_3 and β_4), based on OLS, are likely to be biased due to potential correlation between these variables and unobserved individual and job/sector match effects. In particular, the error term ε_{ijkt} can be decomposed into five components,

$$\varepsilon_{ijkht} = \alpha_i + \vartheta_{ij} + \gamma_{ik} + \omega_{ih} + \eta_{ijkht} \qquad (3)$$

where unobserved heterogeneity is analysed into an individual effect (α_i), a job-match effect (θ_{ij}) ,an industry-match effect (γ_{ik}) and an occupation-match effect (ω_{ih}). The individual effect (α_i) represents the individual's unobserved ability, while the job-match effect (θ_{ij}) captures the quality of the employment relationship stemming from search activity. The inclusion of industry experience variable in the wage equation adds an extra source of unobserved heterogeneity. That is the unobserved industry-match effect (γ_{ik}), that represents the unobserved quality of the match between the individual and the industry where she works in (Parent, 2000). Furthermore the self-selection of workers into occupations means that there is an additional source of endogeneity bias driven by unobserved quality match between the individual and her current occupation. Therefore, in total there are four sources of potential endogeneity bias in the wage equation model, given by equation (2). Individuals with high unobserved ability (high αs) most likely experience lengthy and less interrupted employment spells, while better matches, choices of job and industry (high θs and γs) are more likely to occur to individuals with more experience, as the result of human capital and lengthy search. In addition, individuals with high unobserved ability are likely to choose well paid and prestigious occupations (high ωs).

The analysis is carried out based on OLS, generalised least squares (GLS) and within-group fixed-effects (FE) estimators. For the panel estimators, two alternative identification units are considered in the estimation process. Apart from the standard route of using the individual as the identification unit, I explore the potentials of regarding an individual working with a particular employer as a unit. In this framework, when a respondent in my sample is observed working for different employers, she is treated as a different individual. The idea behind this is that potential endogeneity bias in employer tenure estimates, driven by unobserved job-match effects, may be more effectively controlled when we reckon, in the estimation process, that the employer-employee match has some "unique features".

The use of FE estimator gives rise to a problem concerning the estimation of the returns to general labour market skills. In our analysis, we use the potential labour market experience (*PotExp*) of an individual as a proxy of her accumulated general labour market human capital. *PotExp* is defined as the difference between current age and the age the individual fist left full-time education, therefore we expect that it will increase by one year from wave to wave for all respondents irrespectively to their true employment status. However, in the estimated earnings models we include, alongside the other regressors (and *PotExp*), a time trend variable that increases by one unit each wave, in order to capture potential unobserved time effects. The inclusion of both the linear term of *PotExp* and of the time trend in the wage equation model makes their identification impossible when the FE estimator is employed, since they both increase by one (unit) each wave[3]. As a remedy to this identification problem, we estimate the wage equation, based on FE, but we exclude the linear term of *PotExp* and consider only its quadratic term. The estimate, in this case, of the time trend represents the joint effect of the linear term of PotExp and of time trend peculiarities. Obviously, the downside of this solution is that we cannot distinguish these two effects, therefore we cannot precisely derive an estimate on the contribution of general labour market skills in the wage determination process. Hence, in the findings that we present in the following sections, when FE estimators are employed, the estimated returns to *PotExp* are not calculated due to this identification problem.

3. Data Description

The sample used for my empirical analysis is drawn from the first eight waves of BHPS data set. The individuals included in this sample are those, male and female, who are observed in at least two waves (unbalanced panel sample), are between 18 and 60 and are full-time employed, where full-time employment status is defined as at least 30 hours of work normally per week. Respondents with missing information on their employment spells are excluded from the sample. In addition, the sample is restricted to those individuals that information on employer-tenure, industry and occupational experience is available. Some summary statistics of the sample are provided in the table below.

[3] The deviation from their mean $\left(x_{it} - \overline{x}_i\right)$ in each wave is exactly the same for both of them, making the identification of these two effects impossible.

Table 1

Sample Characteristics (BHPS): Waves 1-8

	Male		Female	
No. of Individuals	985		734	
No. of Observations	5027		3587	
No. of Employer Changes	1155		850	
No. of Industry Changes (1-digit)	1347		909	
No. of Industry Changes (2-digit)	1584		1068	
No. of Occupational Changes (1-digit)	1502		1005	
No. of Occupational Changes (2-digit)	1770		1256	
No. of Industry Changes (1-digit) per ind.†	2.24		2.19	
No. of Industry Changes (2-digit) per ind.†	2.41		2.31	
No. of Occupational Changes (1-digit) per ind.†	2.27		2.24	
No. of Occupational Changes (2-digit) per ind.†	2.86		2.55	
	%		%	
Individuals who Changed Industry (1-digit)	29.6		20.0	
Individuals who Changed Industry (2-digit)	43.0		34.6	
Individuals who Changed Occupation (1-digit)	41.2		29.7	
Individuals who Changed Occupation (2-digit)	50.3		45.8	
	Mean	(S.D.)	Mean	(S.D)
Employer Tenure	7.64	(6.53)	6.40	(5.09)
Industry Experience (1-digit)	13.26	(9.83)	11.96	(8.26)
Industry Experience (2-digit)	10.66	(9.33)	9.40	(7.70)
Occupational Experience (1-digit)	11.37	(9.78)	11.21	(8.70)
Occupational Experience (2-digit)	8.95	(9.09)	8.38	(7.86)
Potential Labour Market Experience	22.45	(10.43)	21.76	(10.81)
Actual Labour Market Experience (full-time)	21.83	(10.39)	14.98	(7.95)

†: Computed only for those individuals who changed industry/occupation at least once.

Our panel sample consists of 985 male and 734 female workers that give a total of 5027 and 3587 observations, respectively. Male respondents appear to spend on average seven years and a half with a particular employer, while their female peers report staying one year less on average. Furthermore, male employees overall accumulate more industry experience than female workers do, however both of them report on average similar years of occupational experience. These observed patterns in the accumulation rate of various kind of working experiences between male and female employees should probably be attributed though to the fact that female individuals tend to take more time off the labour market than their male colleagues do. As we can see from the table, although potential labour market experience is at similar levels for both of them, actual labour market experience based on true employment spells suggests that it is the male respondents that have the longest job-market history.

In addition, despite what industry and occupational experience imply, male workers change occupations and industry sectors where employed slightly more frequently than female employees. One thing that may raise some concern is that both male and female respondents sometime report that they are changing industry or occupation, while they remain with the same employer. From the table above we can see that the number of industry and occupation changes exceeds the total number of employer changes, the sample was employed by. Whether these reported movements are true mobility patterns or just misclassification errors is an issue of concern. However the answer is not an obvious one.

For the purpose of the analysis the construction of two new variables, the industry and the occupational experience, is required[4]. The former refers to the years an individual has been working in a particular industry and can be thought as a proxy of the industry-specific human capital accumulated in work. Similarly, the latter, measures the years a worker has spent in a certain occupation, which corresponds to the individual's occupation-specific skills acquired over these years. The variables are constructed, alternatively, both on the 1-digit and 2-digit level of industry and occupation classification and only employment spells where the respondent reported working for an employer (not self-employed), either part-time or full time, are taken into consideration.

Before moving on to the description of the way industry and occupational experience are constructed, a distinction has to be made between two alternative ways of measuring them. They can be measured based on either continuous spells, or non-continuous spells. In the first case, industry experience, for example, is measured by the consecutive years an individual has been working in the same industry. While, in the case of non-continuous spells, industry experience is measured by the years a worker has been in the same industry in total, not necessarily consecutive. In order to make this distinction clear, consider the case of a worker who has spent a few years with an employer and then has been employed in a different job in an industry, different than the previous one, that she has been working sometime in the past. Now, if we measure industry experience based on the continuous spells then when the

[4] For the construction of employer-tenure variable, Zangelidis (2002).

worker changes jobs, her industry experience should reset to zero. However, when we measure it based on non-continuous spells, the industry experience should not reset to zero but to the number of years she has spent in that industry in the past. The difference between these two ways of measuring industry experience can be thought of as reflecting different rates of depreciation of the industry-specific human capital. If one thinks that industry-specific skills depreciate rapidly, then it might be better to use continuous spells. However, another point that we should mention is that the industry experience variable based on non-continuous spells most likely does not eliminate much of the variance in employer tenure that is important in the identification of the tenure effect. Since I do not have any information on the rate at which industry-specific human capital depreciates, I am in favour of the latter method for their desirable feature in the estimation process of tenure effect. A similar argument can be raised for occupational experience, therefore all the estimates presented below are based on spells of industry and occupational experience that do not have to be necessarily continuous. Moving now with the description of the method followed for the construction of the two variables of interest, it should be mentioned that both industry and occupational experience are constructed with exactly the same. Thus in what follows, I focus my attention to the steps followed in order to construct the industry experience[5]. One should be able to calculate the occupational experience as well by simply repeating this process.

The starting point on the construction of the industry experience is the Wave C, where retrospective information on respondents' employment history is collected, covering the period from the time individuals first left full-time education since the 1st September 1990, where the collection of data in the main panel began. First, I restrict my attention to those who reported being either part-time or full-time employees, excluding the self-employed respondents. Then, I calculate the duration of their past employment spells and collect the related information on industry. Finally, I add up the spells by industry for each respondent separately, in order to construct the industry experience. The industry experience variable constructed up to this point refers to employment spells of the respondents' labour market history, where the last reported employment spell began before the 1st September 1990 and may have terminated

[5] A more detail description that will enable the reader to reproduce the construction of these variables is

either before or after the date of Wave A interview. In the next step, I use this variable as the basis for the construction of industry experience in Wave A, at the time of the interview. For that purpose I use two records from Wave A, one that refers to the employment status of the individuals for the period between the 1st September 1990 and the date of Wave A interview and the main record that contains information on the respondent and her current employment status. There are three possible cases that I encounter here, concerning the already calculated industry experience. First, it may be the case that the most recent employment spell, used in the first step, terminated before or at the date of Wave A interview and there was no other employment spell. Then industry experience in Wave A coincides with the one already estimated. Alternatively, this last employment spell may have indeed terminated before the date of interview but there were more recent employment spells reported in Wave A job history record. In that case, these employment spells should be included in the industry experience. Finally, the date the most recent employment spell ended may be after the date of interview. If this is the case, then the above calculated industry experience variable includes a period of time after the Wave A interview that should be subtracted. The construction of the Wave A industry experience is completed here. The calculation of industry experience for the following waves is based on this one. The methodology employed for the construction of the industry experience for the remaining waves is the same for all of them. Therefore, I briefly discuss how to proceed on Wave B and exactly similar should be the analysis for the rest of the waves (C-H). The two records used here are the Wave B job history record and the main record. Similar to the analysis above, there are three alternative cases. Individuals over the period between the Wave A and B interviews may have changed jobs or employment status. Then we need to calculate any additional employment spells from the date of Wave A interview and onward, group them according to the industry sector and add them to the Wave A industry experience. On the other hand, respondents may have retain their employment status from Wave A, i.e. either stay employed in the same job or unemployed. In the former case, the industry experience in Wave B equals the one in Wave A plus the period between the two consecutive interviews, while in the latter case, industry experience is exactly the same as in the

provided in the Appendix.

previous wave. The construction of industry experience for the remained waves is exactly the same as the one described above.

Occupational experience is constructed in equivalent way to industry experience. The spells are identified in a similar pattern and the only difference is that instead of using information on the industry individuals are working in, here I use the occupation of the individual reported in each employment spell, in order to estimate the period of time spent in each occupation.

4. Empirical Analysis

The aim of my analysis is to examine whether part of the estimated employer-tenure effect on wages should actually be attributed to industry-specific or occupational-specific human capital or both. In order to explore that I estimate a wage equation model where initial only employer-tenure, alongside potential total labour market experience and other regressors, is included. This wage equation model is re-estimated, this time with the inclusion of industry experience or/and occupational experience. The attention is focused on the estimated coefficients of the variables of interest. Any significant change in the estimated effects across these models, could be quite informative on how transferable are skills acquired in work and on their wage premia.

The estimates are based on a standard Mincer (1974) wage equation model, where the dependent variable is the log of hourly wage rate. The control vector on the right-hand side of the equation includes a quadratic in potential labour market experience, a cubic in employer-tenure, industry and occupational experience and controls for the characteristics of the individual and of the workplace where employed[6]. The analysis is carried out separately for male and female employees and the findings are summarised in **Tables 2** and **3** below. In each table, the estimated effect of ten years of employer-tenure (*T10*), industry experience (*Ind10*), occupational experience (*Occ10*) and total labour market experience (*PotExp10*) are presented, a fairly standard way in the literature to present the estimates. The first column in each table refers to the wage equation model where employer-tenure and total labour market experience are included (from the four candidate variables/proxies of the labour market skills). In the second and fourth column 1-digit industry and occupational experience are included, respectively and in the third and fifth at a 2-digit level. Finally, the last two columns show estimates when both industry and occupational experience, alongside employer-tenure and total labour market experience, are considered.

Starting the analysis with the sample of male-employees, OLS estimates are summarised in the first part of **Table 2**. As we can see from the first column, the returns to ten years of employer-tenure, when industry and occupational experience are not controlled for, are around 8.5%. General labour market skills in this case are estimated to have a contribution of 24.4%. When industry experience is included in the wage equation (second column), the tenure effect is slightly reduced while industry-specific skills appear to explain only a small part of the variation in wages (3.5% ten-year effect). The impact is stronger when 2-digit level industry experience is used; tenure effect is further reduced while industry-experience has a 5% effect. The inclusion of occupational experience in the regressors restricts the contribution of employer-tenure around 6%. Conversely, occupation-specific human capital appears to matter more in the wage determination process, with the effect varying between 8 and 10% depending the level of occupational classification. The picture remains the same in the last two columns, where both industry and occupational experience are included in the covariates. Occupation-specific skills have a similar effect on wages, while employer tenure appears to contribute even less than before. Interestingly enough, industry experience does not seem to have a significant role anymore. The fact that the effect of industry-experience is increased, while in the case of occupation is reduced, when 2-digit level of classification is used can probably be explained by the different rates of industry and occupational mobility in the male sample. As we can see from **Table 1**, male workers tend to change more frequently occupations than industries[7]. Finally, the returns to total labour market experience are slightly reduced when either industry or occupational experience or both are included in the estimated

[6] The Appendix gives a list of the regressors included in the wage equation model.
[7] Whether this observed difference in the patterns of mobility is actually true or not, is unknown to the author.

model, nevertheless the ten-year effect in all cases is around 20%. The first impression we get from these estimates is that occupation-specific human capital may have a significant contribution on an individual's earnings profile. On the contrary, the evidence is not so supportive to industry experience.

One should acknowledge that the estimates based on OLS may suffer from potential endogeneity bias, driven by unobserved individual characteristics and job and/or sector match effects. Therefore, the wage equation model is re-estimated using panel estimators[8] and the findings are summarised in the remained of the table. The picture remains fairly similar to the one discussed above, however there are some slight differences depending on the choice of estimator. The addition of industry experience in the regressors vector has an effect similar to the one suggested by OLS (columns 2 and 3). Although employer-tenure effect reduces it still remains larger than the industry experience effect, with the only exception the case where FE estimators are employed and the identification unit is an individual working for a particular employer. Furthermore, the contribution of industry-specific human capital increases in magnitude when a more detailed industry classification is used. Moving in the next two columns, we see that, in general, when panel estimators are employed the impact of occupational experience on wages is reduced, especially in the case of fixed-effects. Although the picture is not completely uniform, on average we can say that the effect of occupational experience appears to be more significant than, or in the worst case equal to, the effect of tenure. As before, the use of 2-digit classification in occupation reduces its estimated magnitude. Finally, when both industry and occupational experience are included, we observe no significant difference between OLS and GLS in the "ranking" of the contribution of the human capital variables, although their size is altered to some extent. The only case where employer-tenure effect is more significant, in terms of magnitude, compared with occupational experience is when FE estimator is employed and the identification unit is the individual. Regarding the returns to potential labour market experience, the estimates in **Table 2** seem to be problematic when FE estimators are used. Considering that both potential labour market experience and the time trend included in the wage

[8] Parent (2000) argues that residuals are likely to be serially correlated due to the presence of a fixed individual effect, driven by the fact that individuals are observed over a number of years. The author

equation model increase by one unit (one year) from wave to wave, the identification of the linear term of potential experience and of the time trend is not feasible, when FE estimators are employed. Therefore, we exclude the linear term of potential experience from the estimated model and the obtained coefficient of the time trend now reflects their joint effect. Consequently, we do not report the ten-year effect of labour market experience, as we do with the other estimators (OLS and GLS), since we cannot distinguish these two effects. Overall, the analysis presented above clearly suggests that occupation-specific human capital is wrongly overlooked in the literature so far. The estimated tenure-effect should probably be attributed to those skills that are specific to the worker's current occupation rather than to his employer.

The evidence on industry specificity, although not so clear, is generally not very supportive to its existence. Even if industry-specific accumulated skills do exist, it is occupational experience and expertise that dominates the wage determination process.

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for that reason employed feasible GLS, allowing for AR(1). However the findings appear to be quite similar to those based on GLS. Therefore estimates are not presented in the paper.

Table 2

Estimates on male employees

			1-digit	2-digit	1-digit	2-digit	1-digit	2-digit
OLS	**T10**	.085 (.031)*	.075 (.031)	.066 (.031)	.062 (.031)	.059 (.032)	.055 (.031)	.046 (.032)
	PotExp10	.244 (.031)	.232 (.033)	.233 (.032)	.212 (.033)	.222 (.033)	.204 (.033)	.218 (.033)
	Ind10		.035 (.029)	.050 (.025)			.016 (.029)	.033 (.025)
	Occ10				.097 (.026)	.078 (.024)	.099 (.026)	.077 (.024)
GLS	**T10**	.083 (.017)	.075 (.017)	.067 (.017)	.065 (.017)	.064 (.017)	.059 (.017)	.052 (.017)
(I)†	**PotExp10**	.276 (.024)	.271 (.025)	.268 (.024)	.248 (.025)	.261 (.024)	.246 (.025)	.256 (.024)
	Ind10		.034 (.016)	.051 (.013)			.025 (.016)	.043 (.014)
	Occ10				.077 (.014)	.060 (.013)	.073 (.015)	.053 (.014)
GLS	**T10**	.065 (.020)	.057 (.021)	.050 (.021)	.050 (.021)	.051 (.021)	.044 (.021)	.040 (.021)
(II)‡	**PotExp10**	.249 (.024)	.244 (.025)	.243 (.024)	.227 (.025)	.236 (.024)	.224 (.025)	.232 (.025)
	Ind10		.033 (.016)	.045 (.014)			.024 (.016)	.038 (.014)
	Occ10				.067 (.015)	.053 (.017)	.064 (.015)	.047 (.014)
FE	**T10**	.081 (.018)	.074 (.018)	.068 (.018)	.067 (.018)	.066 (.018)	.062 (.019)	.057 (.019)
(I)†	**PotExp10**							
	Ind10		.034 (.017)	.049 (.014)			.027 (.017)	.043 (.014)
	Occ10				.061 (.015)	.046 (.013)	.057 (.015)	.038 (.014)
FE	**T10**	.033 (.032)	.025 (.032)	.023 (.032)	.022 (.032)	.025 (.032)	.017 (.032)	.018 (.032)
(II)‡	**PotExp10**							
	Ind10		.022 (.017)	.035 (.014)			.017 (.018)	.032 (.014)
	Occ10				.041 (.015)	.030 (.014)	.038 (.017)	.024 (.014)
Sample	5027							

*****: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.

Table 3

Estimates on female employees

			1-digit	2-digit	1-digit	2-digit	1-digit	2-digit
OLS	**T10**	.091 (.037)*	.050 (.037)	.046 (.036)	.039 (.036)	.053 (.037)	.017 (.037)	.025 (.037)
	PotExp10	.154 (.037)	.113 (.038)	.120 (.036)	.098 (.039)	.132 (.038)	.082 (.040)	.116 (.036)
	Ind10		.082 (.037)	.078 (.030)			.057 (.036)	.050 (.030)
	Occ10				.158 (.034)	.091 (.029)	.150 (.033)	.100 (.027)
GLS	**T10**	.045 (.020)	.033 (.020)	.024 (.020)	.030 (.020)	.028 (.020)	.022 (.020)	.012 (.021)
(I)†	**PotExp10**	.135 (.024)	.121 (.025)	.121 (.024)	.107 (.025)	.117 (.024)	.098 (.025)	.109 (.024)
	Ind10		.033 (.020)	.054 (.016)			.024 (.020)	.044 (.017)
	Occ10				.075 (.017)	.064 (.015)	.073 (.017)	.062 (.015)
GLS	**T10**	.081 (.025)	.065 (.025)	.056 (.025)	.062 (.025)	.062 (.025)	.050 (.025)	.043 (.025)
(II)‡	**PotExp10**	.123 (.024)	.106 (.025)	.109 (.024)	.098 (.025)	.109 (.024)	.085 (.025)	.100 (.024)
	Ind10		.043 (.020)	.052 (.017)			.036 (.020)	.044 (.017)
	Occ10				.074 (.017)	.051 (.015)	.071 (.018)	.049 (.015)
FE	**T10**	.015 (.022)	.011 (.023)	-.000 (.023)	.008 (.022)	.005 (.022)	.005 (.023)	-.006 (.023)
(I)†	**PotExp10**							
	Ind10		.023 (.021)	.044 (.017)			.016 (.021)	.037 (.017)
	Occ10				.048 (.018)	.048 (.015)	.045 (.018)	.043 (.015)
FE	**T10**	.137 (.042)	.130 (.042)	.124 (.042)	.128 (.042)	.127 (.042)	.123 (.042)	.118 (.042)
(II)‡	**PotExp10**							
	Ind10		.029 (.022)	.034 (.017)			.023 (.022)	.029 (.018)
	Occ10				.036 (.018)	.031 (.015)	.033 (.019)	.027 (.015)
Sample	3587							

*****: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.

Turning now our attention to the female sample of employees, **Table 3** presents the estimated effects of accumulated skills in work. Based on the OLS estimator, employer tenure appears to have an effect of 9% (ten-year effect), that is reduced when either industry or occupational experience is included and becomes insignificant when both are considered in the estimated model. On the other hand, industry experience appears to have an 8% effect that reduces with the inclusion of occupational experience. The latter is estimated to have an effect of around 15% (1-digit level) and 10% (2-digit level) irrespective to whether industry experience is included or not in the wage equation model. Total labour market experience appears to have an effect of 15% that falls notably when either industry or occupational experience or both are included in the wage equation. When the GLS estimator is employed, with the individual used as an identification unit, we observed that, first of all, the magnitude of estimated effects is reduced in all cases. Furthermore, at the 1-digit level, industry experience and employer-tenure appear to have a similar modest contribution on earnings. However, at the more detail level of classification, the former has an effect of around 5% (ten-year effect) while the latter becomes insignificant. Occupational experience throughout the estimates, although reduced, seems to play a far more important role than the previous two with an effect of 6-7%. When the individual-employer is used as an identification unit, the estimates slightly change. Employer-tenure effect is noticeably increased and now it exceeds the industry-experience effect at the 1-digit level, and is similar to it at the 2-digit level. The picture does not change a lot for occupational experience, which still appears to have a significant role in the wage determination process. Finally, the estimates based on the FE estimator appear to alter only when the identification unit considered is the individual in a particular employer. In this case, employer-tenure effect increases significantly[9] (above 10% the returns to ten-year of tenure) and is estimated to have a more important role on wages, compared to industry and occupational experience.

[9] One thing that probably worthies mention here is that there is a considerable difference between male and female workers in what happens in the returns to tenure when the identification unit in the panel estimators changes. If the individual working for a particular employer is defined as a unit in the panel estimators, then we observed a reduction in the estimated employer-tenure effect in the case of male employees and an increase in the case of female workers. The fact that these two effects go to opposite direction probably suggests that there may be some sort of positive selection of male workers in high paid jobs and a negative one for the female workers. To put that in a more formal way, endogeneity bias in the returns to tenure driven by unobserved job-match effects appears to overestimate the effect of tenure for the male sample and underestimate it for the female employees.

Overall, the estimates in **Table 3** strongly suggest the existence of occupational-specific human capital and its significance in the wage determination process. On the other hand, the evidence on industry-experience is not conclusive, although there are some indications that it may have a modest effect on an individual's earnings. A final comment concerning the returns to total labour market experience. The estimated effect appears throughout the estimates to be rather limited, however that is something that probably we should expect since the variable used is the potential labour market experience. As we can see in **Table 1**, there is an enormous difference between potential and actual labour market experience. The former is 7 years lengthier than the latter, which is something quite common in the female population in general, because female workers take more time out of the labour market, mainly due to family reasons. The author replicated the analysis this time using actual (full-time) labour market experience[10] (not included in the paper) and found that the estimated returns to total labour market experience seem to be more "realistic" than before. The effect appears to be below 20% based on OLS estimators, around 20% when GLS is employed. The inclusion of actual instead of potential labour market experience does not have a dramatic impact on the magnitude of the other human capital variables of concern, despite the slight variation in the estimates. In the case of FE estimator, there is an identification issue related to actual labour market experience. Since both employer-tenure and actual labour market experience increase by the same amount between waves, the estimation process based on FE makes the distinction of the effect of the linear terms of these two variables impossible. Therefore, one of these terms is dropped out of the estimated wage equation model. This basically results in obtaining an estimate that represents the joint and indistinguishable effect of the linear terms of tenure and actual working experience. Hence, we cannot derive the ten-year effect of either employer-tenure or actual labour market experience. Summarising our discussion in this section, we see that the analysis suggests that individuals accumulate in work skills that are specific to their occupations. This kind of transferable and competitive skills prove to be quite valuable in workers' earnings profiles, since employers appreciate and reward them accordingly. The evidence on industry specificity is not conclusive, but even if it exists, its effect is dominated by occupational expertise in a wage equation model.

[10] The estimates remain fairly similar when I use full-time and part-time employment spells for the

5. A closer examination on occupational and industry experience

The discussion in the previous section clearly indicates that occupational experience is an important determinant of an individual's earnings profile. The more experienced an individual is in a particular occupation, the higher her wages are going to be. In other words, the workers who, in a way, stay loyal to their "career plan" and seek and acquire specific knowledge and experience in their chosen occupation are likely to be more rewarded by their employers, ceteris paribus. One question though that the analysis above does not answer is whether this finding is uniform across the different occupations or not. We know that individuals will choose their occupation based on their comparative advantage, i.e. they will choose a career that best suits and emphasises their strengths. Therefore, it is quite useful to know whether there is homogeneity in the accumulation rate and the returns to occupation-specific human capital across various occupations, or there are different patterns dictated by the nature of each occupation. One will probably expect the effect of occupational-experience to be rather high in those occupations that require and attract high-ability workers, and quite limited or insignificant in the not so demanding occupations. This is probably due to the "anybody-can-do-it" effect of the latter occupations (Roy, 1951), which says that if anyone is as good as anybody else to perform a particular task, then that occupation is more likely to be chosen by individuals of average or below average ability. In this section therefore, I explore whether there are significant differences in the way occupational-experience is rewarded across the various occupations. There are two obvious ways to pursuit this idea, either run separate regressions according for each occupation or include interaction terms between occupational-experience and occupational dummies in the wage equation model. The author is in favour of the second approach since dividing the sample according to occupational choice would result to sub-samples of rather limited size that would probably make the estimation process difficult and not very accurate. Therefore in the analysis that follows I re-estimate the wage-equation model where alongside the other regressors used above (summarised in **Table A1**) I include interaction terms between

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construction of actual labour market experience.

occupational dummies[11] (1-digit SOC classification) and employer-tenure, potential labour market experience and occupational experience polynomials.

The findings on the male and female sample are summarised in **Tables 4** and **5**, respectively. Each column in these tables refers to a choice of different estimator (OLS, GLS or FE) and each row represents the returns to ten years of experience of the human capital variables of interest. In addition a test is performed where we formally examine whether the observed variation in the estimated effect of a particular human capital variable across different occupations is statistically significant or not. Starting our discussion with the male sample (**Table 4**) we see that there is some fluctuation in the returns to ten-year of employer tenure depending on the occupation reported by the individual. Although tenure appears to have an insignificant effect in many occupations, there are a few cases where it actually appears to have a noticeable effect on earnings. In particular, the findings suggest that seniority and employer-specific skills have a strong positive effect mainly in *clerical and secretarial* occupations and in *craft and related* occupations, with an estimated ten-year impact of above 10% on average. However, the performed test implies that this variation in the returns to tenure is only significant when GLS estimators are employed. Similarly, according to the test on the effect of ten-year of potential working experience, general labour market skills are equally rewarded across the various occupations, despite the derived fluctuation in our estimates. Industry experience, which is assumed not to vary over the different occupations (hence no interaction terms are used) is estimated to have only a modest positive effect on earnings that does not exceed the 4% (ten-year effect). Finally, the findings on occupational experience are quite interesting and insightful. In the previous section we demonstrated that occupational specificity plays a rather important role in the wage determination process. Here our estimates suggest that the previous findings are actually driven by some particular occupations and are not uniform over the whole "landscape" of occupational choices. We see that there is a quite strong impact for those individuals who have *managerial*, *professional* or *associate professional* or *technical* occupations (SOC: 1,2,3). This is particularly true though for the *managers*

[11] **Tables A4** and **A5** in the Appendix provide a detailed "map" on how male and female employees are distributed across the various occupations and industry sectors (1-digit level of classification) in my sample.

and administrators. Acquiring a ten-year experience in this occupation (SOC: 1) appears to have an effect between 15 and 30% (depending on the estimator used) and that on average is even higher than the effect of general labour market skills, traditionally considered as the human capital variable with the highest returns. *Managers and administrators* are far better off when they focus on developing their "expertise" rather than investing in any other kind of human capital. Furthermore, estimates on OLS and GLS (II) imply that there are significant returns to *sales* associated occupational experience. It seems that the more experience an individual acquires as a *salesman*, the more persuasive that he is, hence the higher his earnings are going to be (assuming sales are directly related to his wage). Apart though from these occupations outlined above, there is no evidence to support something similar for the rest if the occupations, where their returns appear to be negligible. One final comment, the performed test verifies that these observed patterns between the various occupations are indeed significant, providing a further support to our discussion above.

Table 4

Occupational Interaction Terms (Male Employees)

	OLS	**GLS (I)**[†]	**GLS (II)**[‡]	**FE (I)**[†]	**FE (II)**[‡]
T10 (soc1)[*]	-.003	-.041	-.074	.005	-.028
	(.092)	(.034)	(.038)	(.035)	(.048)
T10 (soc2)	.080	.077	.038	.112	.055
	(.079)	(.043)	(.047)	(.043)	(.053)
T10 (soc3)	.014	.017	.007	.021	6.92e-04
	(.072)	(.044)	(.049)	(.044)	(.054)
T10 (soc4)	.128	.130	.106	.146	.069
	(.087)	(.049)	(.052)	(.049)	(.057)
T10 (soc5)	.151	.104	.141	.072	.059
	(.057)	(.036)	(.039)	(.037)	(.047)
T10 (soc6)	.170	.112	.106	.049	-.011
	(.134)	(.067)	(.068)	(.070)	(.074)
T10 (soc7)	.040	.018	.017	.056	-.023
	(.124)	(.071)	(.076)	(.072)	(.087)
T10 (soc8)	.035	.079	.058	.076	-.016
	(.061)	(.037)	(.040)	(.037)	(.047)
T10 (soc9)	.197	.036	.008	-.055	-.155
	(.085)	(.071)	(.073)	(.072)	(.079)
Test (p-value)	0.671	0.072	0.073	0.116	0.261
PotExp10 (soc1)	.287	.220	.200		
	(.081)	(.050)	(.051)		
PotExp10 (soc2)	.198	.261	.196		
	(.088)	(.056)	(.059)		
PotExp10 (soc3)	.148	.186	.153		
	(.089)	(.053)	(.054)		
PotExp10 (soc4)	.324	.312	.298		
	(.069)	(.055)	(.056)		
PotExp10 (soc5)	.209	.267	.244		

	(.060)	(.044)	(.044)		
PotExp10 (soc6)	.394	.336	.292		
	(.137)	(.084)	(.083)		
PotExp10 (soc7)	.299	.368	.367		
	(.118)	(.081)	(.081)		
PotExp10 (soc8)	.053	.180	.183		
	(.075)	(.049)	(.050)		
PotExp10 (soc9)	.134	.201	.196		
	(.074)	(.085)	(.086)		
Test (p-value)	0.099	0.205	0.224		
Ind10	.028	.039	.034	.036	.026
	(.028)	(.016)	(.017)	(.017)	(.018)
Occ10 (soc1)	.303	.257	.268	.184	.168
	(.071)	(.034)	(.035)	(.036)	(.039)
Occ10 (soc2)	.143	.088	.060	.045	.007
	(.078)	(.044)	(.045)	(.046)	(.049)
Occ10 (soc3)	.149	.073	.060	.035	.012
	(.070)	(.042)	(.042)	(.044)	(.045)
Occ10 (soc4)	-.082	.017	.013	.042	.053
	(.081)	(.047)	(.048)	(.048)	(.050)
Occ10 (soc5)	.015	.010	-.013	.037	.007
	(.062)	(.040)	(.040)	(.042)	(.043)
Occ10 (soc6)	-.100	-.043	-.026	-.032	-.019
	(.116)	(.066)	(.065)	(.070)	(.070)
Occ10 (soc7)	.291	.113	.150	.019	.064
	(.127)	(.074)	(.073)	(.073)	(.077)
Occ10 (soc8)	-.014	.025	-.005	.030	-.026
	(.054)	(.037)	(.038)	(.039)	(.040)
Occ10 (soc9)	-.012	-.064	-.071	.021	.035
	(.076)	(.068)	(.067)	(.075)	(.075)
Test (p-value)	0.001	0.000	0.000	0.028	0.021

*: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.
•: Classification of Occupations in Appendix

Table 5

Occupational Interaction Terms (Female Employees)

	OLS	GLS (I)†	GLS (II)‡	FE (I)†	FE (II)‡
T10 (soc1)•	-.107	-.041	-.054	-.039	-.004
	(.087)	(.042)	(.046)	(.043)	(.063)
T10 (soc2)	-.123	.020	.028	.071	.164
	(.102)	(.048)	(.050)	(.050)	(.059)
T10 (soc3)	.098	.089	.109	.057	.137
	(.088)	(.042)	(.044)	(.043)	(.059)
T10 (soc4)	.006	.019	.035	-.020	.055
	(.051)	(.031)	(.035)	(.033)	(.055)
T10 (soc5)	-.067	-.121	.025	-.114	.054
	(.145)	(.104)	(.114)	(.097)	(.116)
T10 (soc6)	.176	.002	.044	-.035	.029
	(.123)	(.055)	(.061)	(.058)	(.078)
T10 (soc7)	.191	.071	.122	-.043	.056
	(.105)	(.088)	(.089)	(.084)	(.097)
T10 (soc8)	.112	.136	.148	-.003	-.044
	(.162)	(.100)	(.108)	(.103)	(.124)
T10 (soc9)	-.057	.004	.065	-.027	.052
	(.163)	(.122)	(.123)	(.119)	(.127)
Test (p-value)	0.177	0.240	0.180	0.419	0.189

PotExp10 (soc1)	.224	.136	.124		
	(.096)	(.048)	(.049)		
PotExp10 (soc2)	.209	.181	.197		
	(.118)	(.058)	(.060)		
PotExp10 (soc3)	-.021	.024	.030		
	(.067)	(.042)	(.044)		
PotExp10 (soc4)	.215	.083	.088		
	(.073)	(.040)	(.040)		
PotExp10 (soc5)	-.014	.173	.104		
	(.094)	(.113)	(.113)		
PotExp10 (soc6)	-.142	.062	.021		
	(.113)	(.062)	(.062)		
PotExp10 (soc7)	-.114	.037	-.023		
	(.102)	(.089)	(.097)		
PotExp10 (soc8)	-.150	.003	.084		
	(.121)	(.105)	(.108)		
PotExp10 (soc9)	-.043	-.016	-.032		
	(.098)	(.090)	(.092)		
Test (p-value)	0.045	0.139	0.073		
Ind10	.049	.032	.043	.008	.016
	(.038)	(.021)	(.021)	(.022)	(.023)
Occ10 (soc1)	.269	.086	.111	-.028	.013
	(.077)	(.041)	(.043)	(.045)	(.048)
Occ10 (soc2)	.175	.115	.129	-.008	-.039
	(.094)	(.054)	(.055)	(.057)	(.062)
Occ10 (soc3)	.148	.172	.153	.138	.097
	(.087)	(.042)	(.042)	(.045)	(.047)
Occ10 (soc4)	.105	.067	.047	.073	.030
	(.059)	(.045)	(.047)	(.043)	(.047)
Occ10 (soc5)	.029	-.021	-.016	-.110	-.094
	(.143)	(.102)	(.105)	(.111)	(.125)
Occ10 (soc6)	.213	.077	.056	.078	.050
	(.141)	(.060)	(.060)	(.059)	(.060)
Occ10 (soc7)	-.045	-.040	-.078	-.028	-.057
	(.116)	(.083)	(.083)	(.085)	(.085)
Occ10 (soc8)	-.309	-.143	-.039	.024	.181
	(.113)	(.096)	(.104)	(.099)	(.115)
Occ10 (soc9)	.341	.034	.032	-.080	-.075
	(.165)	(.129)	(.127)	(.136)	(.134)
Test (p-value)	0.002	0.041	0.169	0.118	0.361

*: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.
•: Classification of Occupations in Appendix

The findings in **Table 5** tell us a slightly different story for the female workers. Employer-tenure is uniformly estimated to have an insignificant effect on earnings over the various occupational choices. On the contrary, there appears to be a noticeable variation in the returns to potential labour market experience depending on the individuals' occupations, which is verified to be significant in the case of OLS and GLS (II). According to these findings, general labour market skills are highly rewarded only in the prestigious *managerial and professional* occupations and in the, popular to female employees, *secretarial* occupations. In the rest of the occupations, potential working experience does not appear to have any significant impact on individuals' earnings profiles[12]. Industry specificity as well appears to be unimportant, apart from the case of GLS (II), in the wage determination process. Finally, the picture on occupational experience is not very clear. Although the findings suggest that there is some variation in the returns to occupational expertise, the performed tests imply that this is true only in the case of OLS and GLS (I). Similar to the estimates on the male employees, occupational experience seems to be significant mainly in the case of the highly–esteemed *managerial*, *professional* and *technical* occupations (SOC: 1,2,3), where their ten-year effect is calculated to be around 15% on average. Overall, the main conclusion that we can draw from **Tables 4** and **5** is that there is heterogeneity in the returns to occupational experience across the various occupational choices. The estimated impact of occupational expertise appears to be driven by the more prestigious and highly paid occupations, while in the other occupations it is estimated to have a negligible and insignificant contribution on earnings.

Although the analysis in section 4 provides only weak evidence on the importance of industry specificity in the earnings profiles, we believe it is interesting to explore whether the significance of its role varies across the industry sectors. Therefore, in what follows we address this question by re-estimating a wage equation model with industry sector interaction terms. In particular, similar to what we did above, we consider an earnings equation where we include alongside the other regressors, interaction terms between the industry sectors (1-digit SIC classification) and the tenure, potential experience and industry experience polynomials. The findings are summarised in **Tables 6** and **7**, where the estimated ten-year effects of the human capital variables of interest are presented. In addition, the p-value of a test that examines the significance of the variation (across the different industry sectors) in the estimates for each variable of interest is included as well. The results on the male workers in **Table 6** suggest some rather interesting patterns. The significance of seniority and employer-specific skills appears to vary across the industry sectors. The

[12] The wage equation models are re-estimated this time using actual labour market experience instead of potential working experience. The findings (not presented in the paper) suggest that general labour market skills have a significant and positive effect of around 20% (ten-year effect) which however does not vary across the different occupations. The estimates on the other variables of interest remain similar to those presented in **Table 5**.

results almost uniformly suggest that tenure has a strong positive effect on earnings in the *agricultural*, the *energy* and the *mineral extraction* and *manufacture of metal and mineral products* industries. In addition there is weak evidence for the *construction* and *transport and communication* industries as well as for *other services*. Tenure in the other industry sectors does not appear to have any significant contribution on the earnings determination. Finally, the test verifies that indeed the observed variation of tenure effect across the industries is significant. Overall, we see that the role of employer tenure crucially depends on the industry sector the individual is employed in. Particularly, employer-specific skills are highly rewarded mainly in "blue-collar" industries. About the returns to potential working experience, the findings suggest that despite the slight fluctuation in the estimated effects of the general labour market skills, their contribution in an earnings equation appears to be rather homogeneous across the various industry sectors. Industry experience in the majority of industries seems to play an insignificant role on workers' wages. However, there are two distinct cases where industry specificity truly matters, but with opposite effects. Accumulated industry experience in the *metal goods, engineering and vehicles* industries is estimated to have a strong, negative though effect. We believe that the interpretation of this finding does not lie on the human capital theory but on some story associated with industry rents or business cycle. Although in our wage equation model we include industry dummy variables in order to capture any industry effect that may influence earnings, it is possible that the returns to industry experience, in this particular case, are in a way "contaminated" by what is happening that period in this specific industry sector. The negative returns to industry experience, for instance, may actually be reflecting the fact that a particular industry is going through a recession. One possible interpretation may be that this is a declining industry, where junior workers either are laid off or quit and senior workers (generally considered less mobile) are in a way "trapped" in their current sector. In this case, the negative industry experience contribution probably captures the effect of those senior workers who are unable to find a new job in a more prosperous industry[13]. On the other hand,

[13] In order to further explore this issue, we re-estimated this wage equation model (the results are not presented in the paper) including alternatively industry interaction terms with the time trend and the employment growth rate (over the last five years) of the individual's current industry sector. Although we anticipated that the inclusion of these variables would "correct" the negative industry experience effect, the results were practically identical to the previous estimates. Overall, the findings from both the earnings equations remained fairly similar to those presented in **Table 6** (and **Table 7** for the female employees below).

the findings suggest that the accumulated industry-specific human capital in the *banking* sector has a significant positive effect on an individual's earnings profile. Finally, occupational experience is estimated to have a significant and positive impact in all cases examined. Moving to the results on the female employees in **Table 7** we see that despite the variation in the estimates, employer tenure and potential labour market experience have a rather homogeneous impact on wages across the various industry sectors, as the performed tests suggest[14]. The role of industry experience, on the contrary, appears to vary across the different sectors. In particular, acquired industry-specific skills in the *banking* sector and in *other services* have a strong and positive effect on earnings, while in the majority of the other sectors it seems that industry specificity does not matter at all. Similar to the case of male employees, occupational experience is estimated to have a positive effect on earnings. Based on our discussion above, one conclusion that we may draw, concerning industry experience, is that on both male and female employees the banking sector seems to represent the main sector where industry specificity truly matters in the wage determination process. Concluding the discussion, the findings suggest a particular pattern concerning the returns to accumulated occupation and industry specific skills. Although the analysis may not be exhaustive, the evidence presented in this section implies that occupational and industry specificity are mainly significant and noticeable in the more prestigious and high-paid occupations and industry sectors. Apparently, workers' expertise and consequently true productivity is what governs employees' earnings profiles in the more antagonistic and demanding sectors and occupations.

Table 6

Industry Interaction Terms (Male Employees)

	OLS	**GLS (I)†**	**GLS (II)‡**	**FE (I)†**	**FE (II)‡**
T10 (sic1)•	.116	.168	.221	.156	.127
	(.107)	(.070)	(.073)	(.072)	(.082)
T10 (sic2)	.020	.099	.153	.133	.227
	(.110)	(.064)	(.073)	(.063)	(.083)
T10 (sic3)	-.063	-.001	.015	.037	.027
	(.060)	(.037)	(.041)	(.039)	(.050)
T10 (sic4)	-.058	-.020	-5.66e-04	-.005	-.033
	(.076)	(.043)	(.047)	(.043)	(.056)
T10 (sic5)	.245	.112	.066	.101	.007
	(.093)	(.067)	(.069)	(.067)	(.074)

[14] The picture remains fairly identical when actual experience is included, instead of potential experience, in the wage equation model. Its estimated effect though is higher in this case.

T10 (sic6)	.198	.045	.042	.016	-.061
	(.091)	(.045)	(.048)	(.047)	(.057)
T10 (sic7)	.034	.172	.085	.203	.034
	(.083)	(.053)	(.058)	(.055)	(.067)
T10 (sic8)	.114	.019	-.049	.031	-.041
	(.129)	(.046)	(.050)	(.047)	(.058)
T10 (sic9)	.087	.082	.087	.054	.021
	(.058)	(.034)	(.037)	(.036)	(.047)
Test (p-value)	0.054	0.037	0.046	0.043	0.039
PotExp10 (sic1)	.135	.189	.094		
	(.130)	(.091)	(.093)		
PotExp10 (sic2)	.179	.274	.234		
	(.115)	(.077)	(.078)		
PotExp10 (sic3)	.251	.310	.284		
	(.058)	(.047)	(.049)		
PotExp10 (sic4)	.144	.235	.234		
	(.086)	(.050)	(.051)		
PotExp10 (sic5)	.249	.190	.195		
	(.107)	(.074)	(.075)		
PotExp10 (sic6)	.346	.367	.390		
	(.078)	(.051)	(.052)		
PotExp10 (sic7)	.166	.228	.190		
	(.116)	(.068)	(.072)		
PotExp10 (sic8)	.214	.263	.199		
	(.096)	(.059)	(.062)		
PotExp10 (sic9)	.207	.198	.178		
	(.073)	(.047)	(.048)		
Test (p-value)	0.690	0.282	0.046		
Ind10 (sic1)	.240	.062	.001	.090	.027
	(.108)	(.079)	(.080)	(.083)	(.085)
Ind10 (sic2)	.296	.049	.059	-.052	-.114
	(.113)	(.070)	(.069)	(.070)	(.072)
Ind10 (sic3)	-.155	-.130	-.140	-.082	-.094
	(.055)	(.043)	(.043)	(.046)	(.048)
Ind10 (sic4)	.021	.040	.028	.029	.021
	(.065)	(.044)	(.045)	(.047)	(.049)
Ind10 (sic5)	-.121	.042	.029	.053	.058
	(.079)	(.065)	(.066)	(.067)	(.069)
Ind10 (sic6)	-.097	.003	.003	.083	.119
	(.086)	(.049)	(.050)	(.052)	(.054)
Ind10 (sic7)	-.029	-.072	-.033	-.105	-.077
	(.082)	(.057)	(.060)	(.063)	(.072)
Ind10 (sic8)	.086	.178	.230	.103	.080
	(.126)	(.050)	(.051)	(.054)	(.060)
Ind10 (sic9)	-.016	.043	.019	.078	.042
	(.070)	(.040)	(.040)	(.045)	(.047)
Test (p-value)	0.002	0.001	0.000	0.052	0.042
Occ10	.107	.076	.068	.059	.038
	(.025)	(.015)	(.015)	(.015)	(.016)

*: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.
•: Classification of Industry in Appendix

Table 7

Industry Interaction Terms (Female Employees)

	OLS	GLS (I)†	GLS (II)‡	FE (I)†	FE (II)‡
T10 (sic1)*	.310	.285	.229	.156	.148
	(.148)	(.127)	(.138)	(.133)	(.160)
T10 (sic2)	-.071	.095	.048	.054	-.035
	(.203)	(.153)	(.163)	(.170)	(.208)
T10 (sic3)	-.053	-.016	.073	.014	.173
	(.106)	(.069)	(.079)	(.071)	(.098)
T10 (sic4)	-.214	-.009	.057	-.041	.079
	(.123)	(.074)	(.077)	(.076)	(.092)
T10 (sic5)	-.140	.473	.558	.691	.836
	(.256)	(.376)	(.373)	(.327)	(.326)
T10 (sic6)	.064	.117	.138	.048	.080
	(.071)	(.044)	(.048)	(.047)	(.068)
T10 (sic7)	.340	.076	.076	.352	.557
	(.221)	(.124)	(.139)	(.149)	(.219)
T10 (sic8)	.003	.036	.050	-.005	.051
	(.091)	(.046)	(.050)	(.051)	(.075)
T10 (sic9)	-.012	-.040	-.005	-.041	.079
	(.050)	(.027)	(.031)	(.031)	(.047)
Test (p-value)	0.119	0.259	0.676	0.127	0.128
PotExp10 (sic1)	-.078	-.128	.243		
	(.266)	(.164)	(.202)		
PotExp10 (sic2)	.091	.088	-.024		
	(.170)	(.145)	(.152)		
PotExp10 (sic3)	.348	.167	.056		
	(.108)	(.080)	(.084)		
PotExp10 (sic4)	.135	.078	.081		
	(.109)	(.068)	(.075)		
PotExp10 (sic5)	.449	.176	.053		
	(.241)	(.322)	(.318)		
PotExp10 (sic6)	-.055	.044	.013		
	(.094)	(.047)	(.049)		
PotExp10 (sic7)	-.351	-2.53e-04	-.026		
	(.277)	(.143)	(.159)		
PotExp10 (sic8)	.201	.154	.166		
	(.076)	(.049)	(.052)		
PotExp10 (sic9)	.074	.066	.060		
	(.056)	(.033)	(.033)		
Test (p-value)	0.030	0.505	0.467		
Ind10 (sic1)	-.028	.016	.081	.025	.092
	(.158)	(.117)	(.131)	(.127)	(.165)
Ind10 (sic2)	-.153	.070	.159	.163	.335
	(.166)	(.122)	(.137)	(.132)	(.178)
Ind10 (sic3)	-.113	-.111	.002	-.164	-.153
	(.112)	(.080)	(.085)	(.084)	(.104)
Ind10 (sic4)	.063	-.018	-.010	-.037	.003
	(.087)	(.073)	(.075)	(.078)	(.081)
Ind10 (sic5)	-2.45	.940	.769	1.68	1.47
	(2.89)	(2.84)	(2.77)	(2.61)	(2.54)
Ind10 (sic6)	-.048	-.092	-.102	-.058	-8.24e-04
	(.128)	(.051)	(.052)	(.052)	(.056)
Ind10 (sic7)	.062	.102	.075	-.257	-.336
	(.201)	(.139)	(.145)	(.180)	(.234)
Ind10 (sic8)	.188	.173	.188	.138	.130
	(.084)	(.052)	(.054)	(.055)	(.063)
Ind10 (sic9)	.116	.106	.106	.032	-.004

	(.055)	(.037)	(.038)	(.042)	(.046)
Test (p-value)	0.339	0.012	0.018	0.027	0.127
Occ10	.152	.071	.072	.040	.034
	(.032)	(.018)	(.018)	(.018)	(.019)

*: Standard errors in parentheses.
†: Identification unit, the individual.
‡: Identification unit, the individual working for a particular employer.
•: Classification of Industry in Appendix

6. Conclusion

In this paper the author departed form the dichotomous assumption on the transferability of accumulated human capital that divides human capital into employer-specific and general labour market skills and pursued the idea of possible industry or occupational specificity. For the purpose of our analysis we introduce two new variables, the industry and occupational experience that represent the accumulation of relevant skills and expertise over the years of employment. Their inclusion in a Mincer wage equation proves to be quite insightful on the workers' human capital-earnings paths. Occupation specific skills are estimated to have a rather important contribution on wages, highlighting the importance of "specialisation" in earnings profiles. The evidence, on the other hand, on industry specificity is not so strong and in some cases inconclusive. In addition, a further examination on occupational and industry specificity indicates that the observed patterns are actually driven by some particular occupations and industries, rejecting the assumption of homogeneity across them. Specifically, the findings outline that industry and occupational expertise is truly important on individuals' earnings in industry sectors and occupations that are characterised by high-paid, prestigious but competitive and antagonistic, at the same time, jobs, like *professional* and *managerial* jobs or jobs in the *banking* and *finance* sector. This study clearly provides evidence that supports the importance of, especially, occupational experience, that has been wrongly overlooked in the literature, and suggests some rather interesting patterns in the workers' earnings profiles.

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Appendix

1. Tables

Table A1

Regressors
Employer tenure (cubic)
Total labour market experience (quadratic)
Industry experience (cubic)
Occupational experience (cubic)
Age left education
Individual's skills (dummies)
Time trend
Region (dummies)
Industry (1-digit dummies)
Establishment size (dummies)
Occupation (dummies)
Qualification (dummies)
Union Coverage (dummy)
Union Membership (dummy)

Table A2

	Industry Classification (1-digit)
1	Agriculture, Forestry & Fishing; Energy & Water Supplies
2	Extraction of Minerals & Ores (other than fuels); Manufacture of Metals, Mineral Products & Chemicals
3	Metal Goods, Engineering & Vehicles Industries
4	Other Manufacturing Industries
5	Construction
6	Distribution, Hotels & Catering (Repairs)
7	Transport & Communication
8	Banking, Finance, Insurance, Business Services & Leasing
9	Other Services

Table A3

	Occupational Classification (1-digit)
1	Managers & Administrators
2	Professional Occupations
3	Associate Professional & Technical Occupations
4	Clerical & Secretarial Occupations
5	Craft & Related Occupations
6	Personal & Protective Service Occupations
7	Sales Occupations
8	Plant & Machine Operatives
9	Other Occupations

Table A4

Industry and Occupational Choices (Male)

	SIC1	SIC2	SIC3	SIC4	SIC5	SIC6	SIC7	SIC8	SIC9	Total	%
SOC1	25	37	113	82	54	148	86	137	192	874	17.4
SOC2	18	9	124	8	18	5	8	101	301	592	11.8
SOC3	15	16	58	35	14	6	40	128	220	532	10.6
SOC4	35	24	27	24	10	79	30	76	79	384	7.6
SOC5	98	63	265	214	89	130	47	7	64	977	19.4
SOC6	3	0	1	22	0	35	15	26	283	385	7.7
SOC7	0	9	39	19	6	90	3	30	0	196	3.9
SOC8	37	90	158	247	15	62	123	12	45	789	15.7
SOC9	73	3	6	5	20	12	144	3	32	298	5.9
Total	304	251	791	656	226	567	496	520	1216	5027	
%	6.1	5.0	15.7	13.0	4.5	11.3	9.9	10.3	24.2		100

Table A5

Industry and Occupational Choices (Female)

	SIC1	SIC2	SIC3	SIC4	SIC5	SIC6	SIC7	SIC8	SIC9	Total	%
SOC1	5	6	18	36	3	125	8	82	200	483	13.4
SOC2	1	2	4	3	2	4	3	37	406	462	12.9
SOC3	2	5	25	17	4	15	3	58	389	518	14.4
SOC4	45	21	100	83	9	152	79	311	441	1241	34.6
SOC5	1	16	5	83	0	3	0	0	9	117	3.3
SOC6	0	0	0	0	1	44	7	7	296	355	9.9
SOC7	3	1	1	4	0	120	0	6	4	139	3.9
SOC8	1	25	54	40	0	10	1	0	2	133	3.7
SOC9	5	8	3	7	0	32	14	4	66	139	3.9
Total	63	84	210	273	19	505	115	505	1813	3587	
%	1.8	2.3	5.9	7.6	0.5	14.1	3.2	14.1	50.5		100

2. Construction of Industry & Occupational Experience

1st Step

Wave: C
Record(s): CLIFEJOB

This is a record that contains information about jobs held in employment spells, covering the period from the time individuals first left full-time education since the 1st September 1990, where the collection of data in the main panel began (***AJOBHIST*** record). ***CLIFEJOB*** record is restricted to respondents that were interviewed at ***Wave B*** and had another (full-time or part-time) paid job (with different employer than the one in their previous employment spell) at ***Wave C***, that lasted more than one month. The construction of industry experience is based on this record since it is the only lifetime employment status history record in **BHPS** that provides information on the industry respondents were employed[15]. Therefore, industry experience can be constructed only for those individuals included in the ***CLIFEJOB*** record.

Methodology

I restrict my attention to those who reported being either part-time or full-time employees, excluding the self-employed respondents. Then I calculate the employment spells based on the recorded length of job history spells, or based on the information about the beginning and the end of these spells. When seasons are reported, they are replaced with months. Information on the industry is collected when reported. In the case of missing information, I check the ***CINDRESP*** record, only though when the starting date of employment matches between these two records, or when the current job in ***CINDRESP*** began before the employment spell of interest in the ***CLIFEJOB***. Alternatively, I gather this information from the following waves (***D-H***). The criterion is that the starting date of the reported current employment spell should coincide or be before the date the spell in ***CLIFEJOB*** began. Finally, I check whether the starting date of current job in ***Waves A & B*** matches exactly with the date the employment spell in ***CLIFEJOB*** has began, since I can get information on industry from these waves. After constructing the employment spells and collecting the related information on industry, I add up the spells by industry for each respondent separately in order to construct the industry experience and keep the most recent one, since individuals may be repeated in the sample. In the next step, I use the already calculated industry experience as the basis for the construction of industry experience in ***Wave A***.

2nd Step

Wave: A
Record(s): AJOBHIST & AINDRESP

In the 1st step I constructed a variable that measures industry-experience from the time individuals first left full-time education since their last employment spell, given that it started before 1st September 1990. However, this last spell may have ended either before or after the ***Wave A*** interview. Therefore I need to identify which is the case, for each individual, and based on this information and the already constructed variable above to measure the industry experience up to the time of ***Wave A*** interview.

Methodology

Based on the ***AJOBHIST*** record, which contains information from the employment history over the period from 1st September of the year before to the date of interview, the sample is divided into four groups, according to the individual's status type of the last job history record. This is quite informative on what to expect in the following waves.

***Not Last Spell*:**

---

[15] The ***BLIFEMST*** record which contains information about employment status spells, covering the period since the respondent first left full-time education, does not provide any information on the industry the individual was employed.

- ✘ If the most recent employment spell (in a different job but with the same employer, or with a different employer) in ***AJOBHIST*** ended when the last employment spell in ***CLIFEJOB*** terminated, or afterwards but before the ***Wave A*** interview, then the industry-experience variable in ***Wave A*** is the one calculated in step one.
- ✘ If it ended after the ***Wave A*** interview, then the period between the end of the last employment spell (in ***CLIFEJOB*** record) and the date of interview is subtracted from the measured above variable.
- ✘ If the last employment spell in ***CLIFEJOB*** ended before the most recent one in ***AJOBHIST***, then the duration of any additional employment spells from the latter record is included in the variable of step one and that gives the ***Wave A*** industry-experience.

Last Job Ever:

- ✘ If the most recent job spell in ***AJOBHIST*** did not end after the date the last employment status in ***CLIFEJOB*** ended or the ***Wave A*** interview, the industry-experience in that wave coincides with the one already measured above.
- ✘ Otherwise, the duration between the date of interview and the termination of the ***CLIFEJOB*** last job spell should be subtracted from the variable of step one.

Began After 1.9.90

- ✘ If at the most recent employment spell in ***AJOBHIST*** the end date is before or at the same time that the last spell in ***CLIFEJOB*** began, then Wave A industry experience is equal to the one already calculated after subtracting the duration of this last spell.
- ✘ If the beginning though of the most recent spell in ***AJOBHIST*** matches with the beginning of the last spell in ***CLIFEJOB***, then industry experience in ***Wave A*** should be equal to the already calculated industry experience minus the period between the ***Wave A*** and ***C*** interviews.

Present Job (Started) Before 1.9.90

Similar to the previous case.

For the remained individuals, the construction of industry-experience is based on ***AINDRESP*** record, the main ***Wave A*** record. The sample is divided into three main groups according to their employment status.

- If individuals not currently employed, then industry-experience is equal to the one calculated in the 1st step.
- If the beginning of the current employment in ***Wave A*** matches with the beginning of the last spell in ***CLIFEJOB***, then industry experience in this wave is equal to the one already estimated, minus the duration of this last spell, plus the period between the beginning of the current job and the ***Wave A*** interview.
- The last group of interest contains those individuals whose current job began after the date the last spell in ***CLIFEJOB*** started. There are six sub-cases considered here. If the last spell in ***CLIFEJOB***:
  - Finished after the ***Wave A*** interview, then industry experience is equal to the step-one industry experience, minus the last spell, plus the period between the end of this last spell and the ***Wave A*** interview.
  - Finished before or during the beginning of the current employment in ***Wave A***, then industry experience is equal to the calculated one, plus the period between the start of current job and the ***Wave A*** interview.
  - Started after the beginning of the current employment, but before the date of interview, then ***Wave A*** industry experience is equal to the variable from step one, minus this last spell, plus the period between the beginning of this last spell and the ***Wave A*** interview.
  - Ended before or during the ***Wave A*** interview, then industry experience is equal to the one measured in the first step, plus the period between the end of this last spell and the date of interview.
  - Ended after the ***Wave A*** interview, then industry experience is equal to the industry experience based on step-one, minus the period between the date of interview and the end of this last spell.

For the remained individuals, industry experience is equal to the one estimated before, minus the last spell in that record, plus the period between the start of current job in ***Wave A*** and the date of interview.

The construction of the ***Wave A*** industry experience is completed here. The calculation of industry experience for the following waves is based on this one.

3rd Step

Wave: B

Record(s): BJOBHIST & BINDRESP

The methodology employed for the construction of the industry experience for the remaining waves is the same for all of them. Therefore, I only discuss how to proceed on ***Wave B*** and exactly similar should be the analysis for the rest of the waves (***C-H***).

Methodology

Focusing first on the ***BJOBHIST*** record, the individuals of interest here are those in a different job but with the same employer or those working full-time or part-time for a different employer. The first group of respondents includes those, whose least recent employment spell in ***BJOBHIST*** began before and ended after or during the ***Wave A*** date of interview. Industry experience is equal to the one in ***Wave A*** plus the period between the ***Wave A*** interview and the end of this employment spell, the duration of the following spells of employment and the period between the beginning of the current employment spell, reported in ***BINDRESP***, and the date of ***Wave B*** interview. The second group contains the respondents who did not report any employment spell in ***BJOBHIST***. For those individuals, industry experience is equal to the one in ***Wave A*** if they reported not employed as well in ***BINDRESP***. Otherwise in the case of employment, it should be equal to the ***Wave A*** industry experience plus the period between the beginning of their current employment and the ***Wave B*** interview. For the remained individuals in record ***BINDRESP***, industry experience is equal to the ***Wave A*** industry experience plus the period between ***Wave A*** and ***B*** interviews if they reported employed and equal to the ***Wave A*** industry experience if they were not currently working. The construction of industry experience for the remained waves is exactly the same as the one described above.

Comment

Occupational experience is constructed on equivalent way to industry experience. The spells are identified in a similar pattern and the only difference is that instead of using information on the industry individuals are working in, here I use the occupation of the individual reported in each employment spell, in order to estimate the period of time spent in each occupation.