The sources of interindustry wage differentials.*

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Abstract

We analyse the nature of interindustry wage differentials using Portuguese data. Estimates from models controlling for observed worker and firm characteristics reveal significant and persistent raw interindustry differentials, which questions the competitive model of the labour market. However, the estimated interindustry wage structure is greatly attenuated when controlling for unobserved worker heterogeneity, suggesting that the raw differentials are due to the concentration of high wage workers in certain industries and not to genuine differences in compensation across industries. Nevertheless, conclusions based on this model are incomplete. A complete decomposition, obtained from models that control for unobserved worker, firm, and match heterogeneity simultaneously, shows that (i) firm effects on average explain 70% of the industry wage premia observed in cross sectional data, and (ii) genuine and sizeable interindustry wage differentials exist. These differentials are shown to increase the time to separation from firms, and are therefore compatible with the competitive model.

Keywords: interindustry wage differentials; unobserved worker firm and match effects; job mobility

JEL Classification: C33, J21, J31, J62, J63.

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1 Introduction

Empirical analysis using cross-sectional data commonly finds significant wage differentials across industries. That is, some industries appear to pay higher wages than others to observably equal workers employed in observably equal firms. However, in a perfectly competitive labour market with homogeneous workers and firms these differences should not exist as wage differences across industries will prompt the mobility of workers that equalises wages. To the extent that interindustry wage differentials may reflect the existence of noncompetitive mechanisms, they are an empirical finding difficult to explain in labour economics. Noncompetitive mechanisms, however, are not the only possible explanation for these differentials. Such a wage structure can arise, for example, because our observed measures of the qualities of workers are imperfect. Therefore, high wage industries can either be hiring high wage workers or be composed of high wage firms, or have a combination of both. This means that substantial wage differences across industries can be either a consequence of the type of workers employed, or of different compensation policies of firms. A first purpose of this paper is to investigate the existence and sources of interindustry wage differentials. Are cross-sectional industry effects true wage differences or are they simply a consequence of unobserved individual heterogeneity? What is the relative importance of unobserved worker, firm and match effects in explaining differences in wages across industries? These questions are only possible to answer if we have appropriate longitudinal linked employer and employee data. The Portuguese data set used in this study, *Quadros de Pessoal*, has such characteristics. Hence, we are able to estimate worker, firm and match unobserved effects using the techniques developed in Abowd et al. [AKM] (1999) and Woodcock (2007), and to decompose the interindustry wage differentials into proportions attributable to each of these unmeasured components. Due to lack of appropriate data, decompositions of wage differentials are not common in the literature. Therefore, our analysis contributes to the ongoing debate on the sources of the industry wage structure, and adds to the existing evidence for France and the U.S..

If interindustry wage differentials exist and persist over time, even after controlling for worker and firm characteristics, then wages are playing roles other than providing signals for labour reallocation. That is, wages are not reflecting temporary differences in productivity caused by shifts in the relative demand for labour between industries. There are two possible explanations for the existence of wage differences across industries. Either firms are not maximising profits, or firms find it profitable to pay higher wages. The latter is the main hypothesis of efficiency wage models, which argue that higher wages can increase output and so wages above opportunity costs are profit maximising. Although efficiency wage models can be grouped in categories such as shirking, turnover, adverse selection and fair wages, these alternative explanations are not mutually exclusive. Firms may be paying higher wages to accomplish a combination of objectives. However, we can use them separately to test the competitive model. One possibility is to analyse the relationship between the industry wage premia and turnover. Krueger and Summers (1988) suggest that if workers in high wage industries truly receive economic rents then we could expect to find a negative relationship between turnover and interindustry wage differentials. In this case the cost of higher wages would be at least partially offset by the benefits derived from reduced turnover rates. In this context the second aim of this paper is to investigate the relationship between the industry wage premia and separations from firms. This analysis is done using duration models in which the dependent variable is the time to separation from firms, and where the industry wage premia is included amongst the explanatory variables.

Our main findings can be summarised as follows. Firstly, we find that wages differ across industries in Portugal and that their dispersion is fairly stable over time. Hence, temporary variations in productivity are not the main force driving the industry wage structure. Secondly, our decomposition of the raw interindustry wage differentials into components due to worker, firm and match effects reveals that firm effects are the major source of the observed differences in wages. Therefore, interindustry job mobility can have a large impact on the wages received as the nature of the differences is not due to a portable component of compensation (worker effects), but to different compensation policies across firms. Thirdly, we find that the industry wage premia reduces the time to separation from firms. This suggests that the mechanisms generating wage dispersion across industries are not completely incompatible with predictions of the competitive model, insofar as it can be profit maximising for firms to pay higher wages in order to reduce turnover costs.

The paper is structured as follows. In section 2, we document cross-sectional differences in wages across industries and identify their sources. In section 3, we test the competitive model by analysing the relationship between the time workers take to separate from firms and the industry wage premia identified in the previous section. Summary and conclusions are presented in section 4.

2 Interindustry wage differentials

In a competitive model where all workers and jobs are homogeneous, where information and search costs are low, and where issues of worker motivation and risk shifting are not important, the long run labour market equilibrium is characterized by identical wages for all workers and little unemployment. Transitory wage differentials that reflect differentials in labour productivity (caused by demand fluctuations at the firm level, or at any labour market segment level) induce labour mobility. As there is no reason for workers to form attachments to specific firms or industries, they will respond to wage differentials and move between segments, equalizing productivity and restoring wage equality across segments. Therefore, in equilibrium, the competitive model with perfect information entails all workers with the same worker/job match characteristics obtaining the same wage. The model implies the nonexistence of unemployment, because wages adjust until the demand for workers equals their supply and the labour market clears. This suggests that wage dispersion and unemployment appear to be intimately related. Differences in wages generate worker flows across firms, and the transition between jobs can involve a period of unemployment. The model also predicts the nonexistence of wage differentials associated with the industry where the worker is employed, except if these are compensating differentials for nonpecuniary aspects of the job. However, reality appears not to comply with these predictions, as typically introducing the industry of employment adds explanatory power to a wage equation which attempts to explain wages solely in terms of worker, firm and worker/firm match characteristics. The existence and persistence of wage differentials leads us to the question of how wages are determined. This is an important issue, because understanding the wage determination process is fundamental to understanding labour mobility and unemployment.

Responses in the literature to observed interindustry wage differentials range from denial of their existence to accepting that these differences are true. The first approach complies with the competitive model and argues that observed cross-sectional wage differences between industries is illusory rather than reflecting true industry differences in compensation. According to this view the observed wage structure is generated by unobserved heterogeneity of workers, firms and job characteristics. Higher wage industries may be compensating workers for their unmeasured labour quality, or for some less desirable working conditions or job characteristics that affect the utility of workers. If measures of worker's productive abilities are imperfect and if workers in high wage industries have more productive ability than others, then the industry wage premia could simply be reflecting the earnings capacity of its workers. In this case, changing industries will not be associated to wage gains or losses for workers because the observed differences are due to a portable component of compensation that will follow the worker to whatever industry he moves to.

The second approach accepts that there are interindustry wage differentials even when controlling for the nature of work and the quality of workers. One possible cause of such wage differentials is the existence of worker-firm attachments. These appear if efficiencies are gained when workers remain with specific firms or industries for extended periods. If efficiencies outweigh the gains in productivity that might come from reallocating labour in response to every transitory demand shock, then the labour market structure, employment rules, and wage structures adjust to encourage long-term attachments and to limit day-to-day competition in the labour market. The result is a segmented labour market where market competition is limited, and workers become attached to specific firms or industries with competition taking place only at limited ports of entry to internal labour markets. If workers do not compete in a single aggregate labour market, the labour market is expected to adjust less rapidly than suggested by the neoclassical model because wages play roles other than providing signals for labour reallocation. Efficiency wage models give some alternative explanations for the existence of industry specific wages. Krueger and Summers (1988) and Thaler (1989) group these models into four categories: i) in shirking models high wage industries should be those with high monitoring costs and that have relatively higher costs of employee shirking; ii) in turnover models high wage industries are those in which turnover costs are highest; iii) in adverse selection models high wage industries are those more sensitive to labour quality differences or have higher costs of measuring quality; iv) in fair wage models, if workers believe that fairness requires firms to share rents, industries with high profits will pay higher wages. Therefore, despite predictions from the competitive model that a profit maximising firm offers wages equal to marginal productivity, there can be reasons why firms pay supra competitive wages and create incentives for long term attachments of its workforce. These can be part of a profit maximising strategy of firms, and hence not fully incompatible with the neoclassical model.

Given the availability of longitudinal data on workers, within-worker transformations and first differenced regressions were commonly applied in empirical studies of interindustry wage differentials in the eighties and early nineties to eliminate the effect of worker unobserved heterogeneity and identify the sources of the industry effects estimated using cross-sectional data. The results are as varied as the predictions of the models discussed. Murphy and Topel (1987) find evidence that two thirds of the observed differential can be explained by unmeasured worker characteristics. On the other hand, despite not identifying the sources of interindustry wage differentials, Krueger and Summers (1987) find empirical regularities that lead them to conclude that unmeasured worker characteristics cannot explain such differentials. These regularities include evidence suggesting that i) by changing industries workers receive wage changes similar to the industry effects found in cross-sectional data, ii) the industry premia/penalty is similar for different types of quality of workers, and iii) wage differentials can be explained by product market characteristics. Blackburn and Neumark (1992) by includin measures of worker abilities (test scores) in their parameterizations conclude that ability can only account for a small portion (10%) of interindustry wage differences observed in cross-sectional analysis. Gibbons and Katz (1992) conclude that a major proportion of interindustry wage differences cannot be explained by the sorting of workers across industries by unobserved productive ability.

More recently, questions of the sources of the industry wage structure have resurfaced due to the emergence of longitudinal linked employer-employee data. Yet, the results using this type of data remain varied. Using French data, Goux and Maurin (1999) find that the wage structure is mainly due to unmeasured labour quality and that the potential wage gains from switching industries would be less than 3%. Furthermore, the authors conclude that these remaining true differentials do not persist over time. Also using French data, AKM (1999) conclude that person effects are relatively more important in explaining the differentials found in cross-sectional analysis. The same result is obtained by Abowd, Finer and Kramarz (1999) with data for the State of Washington and applying the same decomposition as AKM (1999). Woodcock (2008) using American data finds that, controlling for match effects, firm effects are responsible for 72% of the variance in raw interindustry wage differentials.[1] The difference between the findings of Goux and Maurin (1999) and other papers using matched worker-firm data might be essentially due to the different techniques applied. The other studies use similar statistical methods to decompose the raw interindustry wage differentials found in cross-sectional data, and all provide evidence of the existence of pure interindustry wage differentials. This paper will add to the small empirical literature that controls for measured and unmeasured characteristics of both sides of the labour market. The methodology developed in AKM (1999) is used to distinguish between the two leading explanations of the industry wage structure found in cross-sectional analysis. The data used is described in the following section.

2.1 The data set: *Quadros de Pessoal*

The data for our analysis comes from the *Quadros de Pessoal.* This is a longitudinal data set with matched information on workers and firms in Portugal. Since 1985, the survey has been annually collected (in March until 1993, and in October from 1994 onwards) by the Portuguese Ministry of Employment and the participation of firms with registered employees is compulsory. The data includes all firms (about 200 thousand per year) and employees (about two million per year) within the Portuguese private sector. Although the survey is still ongoing, the data available for analysis starts in 1985 and ends in 2000. The present analysis covers the period from 1986 through 2000, with 1990 excluded because the database was not built in that year. Each firm and each worker has a unique registration number which allows them to be traced over time. All information – on both firms and workers – is reported by the firm. In general, the

[1] In contrast with the other studies using linked employer-employee that disaggregate industry coding to a detailed level (more than 90 industries) Woodcock (2008) uses only 8 SIC Major Divisions.

information refers to the situation observed in the month when the survey is collected. In some cases, namely information on dates, reported data may be retrospective but limited to the past within that specific firm. Information on workers includes, for example, gender, age, education, level of skill, occupation, date of admission in the firm, date of last promotion, monthly wages and hours of work. Firm level data include, for example, the industry, location, number of workers, number of establishments, sales volume, and legal setting. Due to data processing and analysis limitations, a random sample – clustered by worker – of 10% was drawn from the original panel data set.[2] In this sample, observations related to employers and to workers for whom we cannot compute seniority at the firm were deleted. This sample contains 1,823,572 observations related to 377,866 workers, 98,438 firms and 589,826 matches over time. In all our specifications we control for worker and firm observed characteristics. Worker related variables include the type of job mobility experienced by the worker within the last year (automatic or merit promotion, entry to the firm after a short or long period of non-employment), gender, seniority and its square, potential labour market experience and its square, hours of work and its square, education (up to ISCED 1, ISCED 2, ISCED 3, ISCED 5/6), skill level split into 3 categories (low, medium, high), occupation (9 categories), and a dummy for part time or full time work.[3] Firm related covariates include percentage of foreign capital, size of firm (micro, small, medium or large), ownership type (public firm - ruled by private sector laws, sole partnership, anonymous partnership, limited liability partnership and other), instrument of collective regulation (5 categories), and region (20 categories). Macroeconomic conditions are controlled for by inclusion of year indicators. The central variable of our analysis is the industry affiliation of the firm. The classification of industries in Portugal follows the European Standard Industrial Classification (SIC codes). However, until 1994 (inclusive) the coding followed a revision approved in 1978, and from 1995 onwards the coding follows a revision approved in 1993. This change in the coding system makes harmonization over the period difficult and the highest level of disaggregation possible with the data results in 43 different industries. Descriptive statistics of the variables are presented in table 1.

[2] Details on the procedure followed to clean the original panel data set, as well as descriptive statistics of the sample, can be found in Ferreira (2006).

[3] Occupations are recorded in accordance to the National Classification of Occupations 1994 (compatible with the International Standard Classification of Occupations 1988).

2.2 The importance of industry affiliation in wage variation

In the competitive model the wages of workers do not depend on firm or industry affiliation. This prediction is usually tested by defining a wage function as follows:

$$y_{ijt} = x_{\cdot t}\beta + k_{(j(i,t))}\kappa + \epsilon_{ij} \tag{1}$$

where y_{ijt} is the logarithm of real monthly wages of worker $i = 1, ..., N$ in firm $j = 1, ..., J$ in period $t = 1, ..., T$; $x_{\cdot t}$ is the vector of observed time varying covariates of workers and firms; $k = 1, ..., K$ is a vector of mutually exclusive dummy variables indicating the industry affiliation of firm j, and ϵ_{ij} is the idiosyncratic error. β and κ are the parameters to estimate. If wages do not depend on industry affiliation, then the parameters κ should be jointly equal to zero. In what follows, we test this prediction of the competitive model.

To assess the existence and stability of relative wages across industries we regress model (1) on the annual data for the period from 1986 to 2000. The vector X includes covariates on workers and firms as listed in subsection 2.1, and k assigns each firm to each of the $K = 43$ defined industries. The cross-sectional results for the period 1986-2000 are shown in tables 2 and 3. These suggest the existence of important interindustry wage differentials. Industry parameters are, in general, individually statistically significant and, contrary to the competitive prediction, the hypothesis of simultaneously null κ coefficients is rejected (see F-statistics in the tables). Therefore, workers with the same observed characteristics working in firms with observably equal characteristics have different wages depending on the industry in which they are employed. The identified wage differences are considerable, with some industries paying wages that are more than 41% above the economy average while others pay wages that are more than 26% below the average. Amongst the industries paying the lowest wages we find the Manufacture of furniture, Textiles, Clothing and Restaurants and cafés, manufactures. The wage penalty in these industries ranges from 8% to 26% below the economy average. The industries paying the highest wages tend to be related to financial intermediation like Banking or Insurance, the Electricity, gas and water supply services, and Productive services such as transports. The wage premia paid by these industries ranged between 8% to 41% above the economy average. There is considerable dispersion in this wage structure, the estimated employment-weighted standard deviations of the industry coefficients range from 8% to 11% in the period. This suggests that interindustry mobility can have a large impact on wages.[4]

[Tables 2 and 3 about here]

The estimated industry wage structure, however, can be partially transitory and therefore not stable over time. That is, due to demand fluctuations some industries may lower wages relative to the wages paid elsewhere without leading workers to switch to expanding industries. We assess the role of transitory shocks by analysing the degree of linear association between the industry wage premia observed in one point in time, with those observed in other points in time. For this purpose we compute correlations between the 43 industry coefficients observed in each year with those observed in 1986. As is shown in table 4, the industry wage structure was fairly stable in the period 1986-2000. Weighted correlations between relative wages in 1986 and all of the subsequent years range from 0.76 to 0.98 which suggests that the structure barely changed in the 15 year period analysed.[5] Therefore, we conclude that temporary variations in productivity do not seem to drive the structure of wages between industries.[6]

[Table 4 about here]

Taken with the previous results, we see that industry affiliation is a significant and stable determinant of wages. We now determine its relative importance in explaining observed wage dispersion using analysis of covariance. In model (1) the total proportion of wage variation explained by the covariates (X) and industry affiliation (k) is given by the R^2 of the regression. If X and k were not correlated, regressions of log wages on each of the covariates alone would give a unique decomposition of the contribution of each set of variables to the total explained variation. The possible collinearity between the two sets implies there is no unique variance

[4]The magnitudes of the weighted standard deviations are comparable to those obtained by Krueger and Summers (1988) and Goux and Maurin (1999).

[5]Note that we observe a discrete drop (of about 0.05) in the strength of the correlation between 1994 and 1995, this drop is most likely to have been caused by the change in the industry coding system than by an effective decrease in the correlations between the wage structure observed in the years post 1994 with that observed in 1986.

[6]And According to Krueger and Summers (1987) the structure persists and changes only moderately over longer intervals.

decomposition. We can, however, identify the bounds of the share of variance explained by each set of variables. The share of wage variation unambiguously associated to k is given by the increase in the explanatory power arising from adding industry dummies to a wage regression already including X. This marginal contribution of k corresponds to the minimum estimate of the relative size of the variance contributed by k. The upper bound for the importance of the industry effects is given by the R^2 of a wage equation including only industry dummies.

For this analysis (and that which follows) the observations for the period from 1986 to 2000 are pooled together.[7] The basic decomposition of the sources of wage dispersion is presented in table 5. The proportion of the variance in wages explained by the covariates and industry affiliation together is 72%. The covariates (industry) first specification allows identification of the portion of wage variation associated unambiguously to the industry (covariates) effects. Therefore, the minimum estimates of the relative size of the variance contributed by industry and covariates is 2% and 43%, respectively. The upper bound is 29% for industry effects and 70% for the covariates. The large range in the explanatory power (e.g., industry effects account for between 2% and 29% of wage variation) arises from the large degree of collinearity between industry and the covariates. These results are in line with those obtained by Dickens and Katz (1987) for the U.S., who find that industry effects account for between 7% to 30% of wage variation using 1983 CPS data. They suggest that industry affiliation is an important factor explaining wage dispersion and that noncompetitive mechanisms may be at work in the labour market.

[Table 5 about here]

A non-competitive labour market, however, is not the only possible explanation for the observed interindustry wage differentials resulting from model (1). It is possible that some individual- (ability), firm- (compensation policies) or match-related (production complementarities) determinants of wages are not being captured by the data. This unobserved heterogeneity explanation is more difficult to evaluate and requires a data set that has information on

[7] For all the specifications in which the data is poolled the right hand side and left hand side variables are coded in deviations from the grand means. Where the grand mean of y_{ijt}, for example, is given by: $\overline{y}_{...} = \sum_{i=1}^{N}\sum_{j=1}^{J}\frac{T_{ij}\overline{y}_{ij.}}{T}$

the demand and supply sides of the labour market. Our data set allows us to test whether the industry wage structure remains after we control for worker, firm and match effects. Therefore, we can investigate if true interindustry wage differentials exist or if the differentials observed in cross-sectional data simply reflect an unequal distribution of unmeasured heterogeneity across industries. Before considering the simultaneous impact of the three types of unobserved effects, we first analyse, with the pooled data, how interindustry wage differentials change as we gradually control for worker and firm heterogeneity. These results are shown in table 6, and each of its columns includes additional controls. Column (1) displays the results of a model that controls only for industry affiliation and time effects. This column gives us the unadjusted wage differentials between industries, i.e., the difference between average wages in the industry and the economy wide average of wages. Column (2) adds to the model observed worker characteristics, this column gives us interindustry wage differentials adjusted for worker characteristics. In column (3) observed firm characteristics are added as controls. The differentials observed in this column are what we will, henceforth, call raw interindustry wage differentials. That is, it is the industry wage structure adjusted for all the worker and firm characteristics that we can observe in the data. Column (4) additionally controls for unobserved worker heterogeneity using the within-worker transformation.

From column (1) we conclude that, similar to our previous cross-sectional results, the industries paying the highest wages are Banking, and Insurance, Electricity, gas and water supply services for which the unadjusted wage premia are above 66%. Those paying the lowest wages are Clothing, Furniture and shoes manufactures, for which the unadjusted wage penalty is above 40%. With no controls for any type of heterogeneity, the standard deviation of the estimated industry wage premia is 29%, which suggests substantial wage growth can be realized by changing industries. However, results are very sensitive to controls for worker observed heterogeneity. As we can see from column (2), the explanatory power of the model increases significantly (from 33% to 68%) when we control for measured worker characteristics, while the dispersion of wages across industries is almost halved (the standard deviation is now 0.15). Adding firm observed characteristics (column 3) further increases the explanatory power of the model (to 72%). While in some industries adding observed characteristics of firms hardly affects the estimated industry effect (compared to the model in column 2), in some others it substantially reduces it. This is reflected in inter-industry wage dispersion, as the standard deviation of the interindustry wage effects falls from 0.15 to 0.10. Thus, it seems that observed characteristics of workers and firms explain much of the observed differences in wages across industries.[8] If unmeasured ability is time invariant and equally rewarded in all industries, unobserved productive ability is an individual fixed effect which disappears using the within-worker transformation.[9] The results of the model that applies this transformation are presented in column (4). In this model the explanatory power of observed worker and firm characteristics is greatly reduced, the R^2 is now 47%. This suggests that unmeasured labour quality is correlated with measured characteristics and shows the importance of controlling for unobserved effects. Furthermore, much less variation in wages across industries remains. The standard deviation of wages across industries is now 0.06, which means that workers who change industries experience small wage changes. These results are in line with those obtained, for example, by Goux and Maurin (1999) and Carruth et al. (2004) after controlling for person unobserved heterogeneity.

[Table 6 about here]

To this point, our findings suggest that wages may be being set competitively but more able workers are concentrated in certain industries, making wages appear to be larger in some industries than in others. That is, industries paying higher wages are different from other industries in that they hire a higher proportion of high wage workers. This could drive us to conclude, as Murphy and Topel (1987), that most of the raw interindustry wage differentials (in column 3) are due to unobserved worker heterogeneity and not to true differences in firm compensation policies across industries. However, to this point we have ignored unobserved characteristics of firms, despite firms being the wage determining units. If we add to this the idea that industry is a wage contour, defined by Dunlop (1964, pp. 17) as a stable group of

[8] Using the 2002 European Structure of Earnings Survey, Magda et al. (2008) find similar results for the dispersion of interindustry wage differentials presented in columns 1, 2 and 3 of table 6. In a group of 11 Eastern and Western European countries, Portugal was found to be one of the countries with highest dispersion in the interindustry wage structure when controls for observed worker and firm characteristics are included.

[9] Note that the condition that ability is rewarded equally in every industry is what makes it a worker-specific fixed effect, otherwise there is matching (Gibbons and Katz, 1992). If matching exists, the ability of the worker is of the same level in every industry, but the quality of the match (hence compensation) may differ across industries.

firms "[...] which are so linked together by (a) similarity of product markets, (b) by resort to similar sources of labour force, or (c) by common labour market organization that they have common wage making characteristics", ignoring compensation policies of firms in a study of interindustry wage differentials is a major weakness. Moreover, as Goux and Maurin (1999, pp. 506) suggest, "If the interindustry differentials are not measured as an average of firm effects, an uncertainty over the correct interpretation of estimated industry effects will persist." This means that the analysis cannot be complete until we disentangle the roles of workers and firms in defining the industry wage structure. If firms are an important factor in explaining interindustry wage differences then, as Krueger and Summers (1987) suggest, the dispersion in wages between industries must be decomposed into three parts, the part due to person effects, the part due to firm effects and the part due to the covariance between the two. To do this we use AKM's (1999) exact decomposition.

2.3 Contribution of unobserved heterogeneity to interindustry wage differentials

In the previous section we specified a competitive model of wage determination that only considers observed characteristics of workers and firms, and unobserved worker characteristics as determinants of wages. We now specify a match effects model that considers not only observed characteristics, but also unmeasured worker, firm and match effects.[10] This will allow the estimation and decomposition of interindustry wage differences into parts attributable to unobserved individual, firm, and worker-firm match heterogeneity. The match effects model estimates a wage equation of the type:

$$y = X\beta + D\theta + F\psi + G\gamma + \xi \qquad (2)$$

where $X_{(N^* \times Z)}$ is the matrix of observable time varying covariates (in deviations from the grand means); $D_{(N^* \times N)}$ is the matrix of indicators for worker $i = 1, ..., N$; $F_{(N^* \times J)}$ is the matrix of indicators for the firm at which worker i works at period t; and $G_{(N^* \times M)}$ is the matrix of

[10] This section follows very closely the framework developed in AKM (1999).

indicators of worker-firm matches. y is a $(N^* \times 1)$ vector of log monthly real wages (also in deviations from the grand means).[11] The set of parameters to estimate are β, the $Z \times 1$ vector of coefficients on the covariates; θ, the $N \times 1$ vector of worker effects; ψ, the $J \times 1$ vector of firm effects; and γ the $M \times 1$ vector of unobserved match effects.

Based on the concept of industry as a wage contour, an industry effect is defined as a characteristic of the firm and the pure interindustry wage differential, conditional on the same information as in equation (2), is defined as κ_k for some industry classification $k = 1, ..., K$.[12] Being a characteristic of the firm, it follows that the definition of the pure industry effect (κ_k) is the aggregation of the pure firm effects (ψ) within the industry, that is

$$\kappa_k \equiv \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\frac{\mathbf{1}(\mathrm{K}(\mathrm{J}(i,t)) = k)\psi_{\mathrm{J}(i,t)}}{N_k}\right] \tag{3}$$

where

$$N_k \equiv \sum_{j=1}^{J}\mathbf{1}(\mathrm{K}(j) = k)N_j$$

and $\mathbf{K}(j)$ is a function denoting the industry affiliation of firm j. This aggregation of J firm effects into κ_k industry effects, weighted so as to be representative of individuals, corresponds to including industry indicator variables in equation (2), $\kappa_{\mathrm{K}(\mathrm{J}(i,t))}$, and defining what is left of the pure firm effect as a deviation from industry effects, $\psi_{J(i,t)} - \kappa_{\mathrm{K}(\mathrm{J}(i,t))}$.[13] In matrix notation:

$$y = X\beta + D\theta + FA\kappa + (F\psi - FA\kappa) + G\gamma + \xi \tag{4}$$

where the matrix A, $J \times K$, with element $a_{jk} = 1$ if $\mathrm{K}(j) = k$, classifies each of the J firms into one of the K industries. The parameter vector κ, $K \times 1$, is the weighted average of the pure firm effects. $(F\psi - FA\kappa)$ is the firm effect net of industry effects. This effect can also be expressed

[11] In the presence of an unbalanced panel dataset (as we have here) where both workers and firms can enter or exit the panel during the period of analysis, the total number of observations per worker is $N^* = \sum_{i=1}^{T} T_i$.

[12] Model (1) does not consider firm effects. Therefore, it involves the aggregation of firm effects into industry dummy indicators.

[13] Authors attempt to use industry classifications as detailed as to have more than 90 industry codes. The reason for decomposing industrial aggregates into the most detailed level possible is related to the possibility that average compensation policies of firms may vary across finer levels of classification and not within aggregates, and so estimates can be subject to aggregation biases. The pure industry effects, however, are not subject to this bias because they are computed from firm-level estimates.

as $M_{FA}F\psi$, where M_{FA} is the matrix that obtains deviations from industry means. In the classical least squares estimates of equation (4) there are no biases due to omitted variables or to aggregation as it only decomposes $F\psi$ into two orthogonal components: the industry effects $FA\kappa$, and what is left of the firm effect after removing the industry effect $(F\psi - FA\kappa)$. It is worth noticing that, because industry affiliation is defined as a characteristic of the firm, we do not have to actually run model (4). Pure industry effects, $FA\kappa$, are standard (duration-weighted) averages of firm effects within the industry, as shown in (3). An alternative method of computing these averages (and to make the orthogonal decomposition of the pure firm effects) is to specify a model that regresses the pure firm effects $(F\psi)$, estimated from equation (2), on the set of mutually exclusive dummy variables for the K industries.[14]

If wages are in fact determined according to specification (2), that is, if the expected values or probability limit of worker, firm and match effects are non-zero, then the estimated returns to the observed characteristics, industry affiliation included, are biased if we use parameterization (1).[15] AKM (1999) discuss the biases that arise due to omitted residual firm effects (column (4) of table 6), and to omitted person and residual firm effects (column 3 of table 6) when we specify the wage equation as a function of unobserved person and firm heterogeneity only (that is, the match effect $(G\gamma)$ is included in the error term). Woodcock (2007) extends this discussion by deriving the biases caused by the omission of match effects when wages are also determined by match unobserved heterogeneity.

Understanding the nature and composition of these biases is the tool for decomposing the raw interindustry wage differentials (column (3) of table 6) into the contributions due to worker, firm and match effects. Consequently, in the next section we revise the biases generated by the omission of the three components of unobserved heterogeneity, focussing solely on the industry coefficients, and explain the procedure to identify the relative importance of each unobserved effect in explaining the raw interindustry wage differentials.[16]

[14]To clarify, we know that in a model without a constant: $Y_i = \beta X_i + u_i \Leftrightarrow Y_i = E[Y|X_i] + u_i$. Therefore, the coefficients obtained are the pure industry effects $(FA\kappa)$, or average firm effects within the industry, and the residual from this regression is the remaining, or residual, firm effect $(F\psi - FA\kappa)$. [This result is true because industry dummies are mutually exclusive and their covariance is zero.]

[15]In the case where person, firm and match effects have non-zero expectation, the bias would not exist only if these components were orthogonal to the observed covariates, which is unlikely.

[16]The focus on industry coefficients is for clarity of reasoning, naturally the β parameters suffer from the same biases and so this discussion also applies to them.

2.3.1 Omission of person, firm and match effects

If the true data generation process is given by equation (2) but estimates of industry effects are based upon a model that omits person, firm and match effects (and so we estimate some κ^{**}, instead of the pure industry effect, κ), this implies that $D\theta$, $(F\psi - FA\kappa)$ and $G\gamma$ of model (4) are moved into the error term and our model takes the form

$$y = X\beta^{**} + FA\kappa^{**} + \varepsilon \tag{5}$$

where $\varepsilon = (F\psi - FA\kappa) + D\theta + G\gamma + \xi$. Because the set of regressors can be broken up in two groups, in this case X (observed characteristics of workers and firms) and FA (industry effects), we can transform (5) as follows

$$y = P_W y + M_W y = X\beta^{**} + FA\kappa^{**} + M_W y \tag{6}$$

where $W = [X \quad FA]$; $P_W = X(X'X)^{-1}X'$, is the matrix that averages the observations across time for each individual and has typical element $\overline{u}_{i.}$; and $M_W = I - P_W$, is the matrix that obtains the deviations from individual means and has typical element $u_{it} - \overline{u}_{i.}$. β^{**} and κ^{**} are the least squares estimates obtained from (5). Premultiplying (6) by $(FA)'M_X$ we obtain

$$A'F'M_X y = A'F'M_X FA\kappa^{**}$$

and solving with respect to κ^{**} we obtain the estimator of industry effects[17]

$$\kappa^{**} = (A'F'M_X FA)^{-1}A'F'M_X y. \tag{7}$$

Under the assumption that κ^{**} is uncorrelated with ξ (but correlated with the other components of the error term of (5)), and because M_X annihilates X (that is, $M_X X = 0$), the expectation

[17] These estimates are obtained from a Frisch-Waugh-Lovell (FWL) regression. In a model in which the regressors can be split into two groups, and these are transformed to be mutually orthogonal, then OLS estimates of the parameter of interest obtained either from the original specification or from the modified model are numerically identical. See Davidson and MacKinnon (2004) for a thorough presentation of the FWL theorem.

of (7) is

$$E[\kappa^{**}] = \kappa + \left(A'F'M_X FA\right)^{-1} A'F'M_X \left(M_{FA}F\psi + D\theta + G\gamma\right)$$

that is the estimator κ^{**} is equal to the pure industry effects, κ, plus the sum of the employment-duration weighted average of the residual firm effect, the person and match effects inside the industry, given X. This means that the bias is equal to the sum of the weighted portion of firm, person and match effects that is explained by the included covariates. Given that the pure firm effect, $F\psi$, is equal to the sum of the pure industry effect, $FA\kappa$, with the residual firm effect, $F\psi - FA\kappa$, we can rearrange the previous equation and obtain

$$\begin{aligned} E[\kappa^{**}] \quad &= \quad \left(A'F'M_X FA\right)^{-1} A'F'M_X F\psi + \left(A'F'M_X FA\right)^{-1} A'F'M_X D\theta + \\ &\quad + \left(A'F'M_X FA\right)^{-1} A'F'M_X G\gamma. \end{aligned} \tag{8}$$

This expression shows that the raw interindustry wage differential, i.e. the differential obtained in a model that does not include unobserved worker, firm and match effects, can be decomposed into the sum of the industry average firm effect, the industry average person effect and the industry average match effect, each of these averages conditional on X. These averages are the expectation of the least squares estimator in auxiliary regressions of each of the omitted regressors on the included regressors.[18] Equation (8) is exact if the values of θ and ψ and γ are known in which case we can have a consistent estimate of the decomposition based in (8). The decomposition is done in the following section.

2.3.2 Empirical results: the sources of interindustry wage differentials

In this section we decompose the raw interindustry wage differentials into proportions due to person, firm and match effects, as shown in equation (8). The raw wage differentials, κ^{**}, are estimated using model (1). The person, θ, firm, ψ, and match, γ, effects are estimated from the match effects specification (2). The estimation of this model involves a three-step procedure. Firstly, β is estimated after transforming (2) into deviations from match-specific means. Results from partitioned regression imply that $\widehat{\beta}$ is a consistent estimate of β. Secondly, $\widehat{\theta}$ and $\widehat{\psi}$ are

[18] This is easier to recognise if we compare the expression of each component of equation (8), with the logic that connects equations (5) and (7).

computed using the person and firm effects model (a model without unobserved match effects as in AKM, 1999).[19] Finally, the match effects estimator is defined as the error of the regression of worker-firm matches on a constant and on the person and firm effects estimated previously.[20] This match effect can be correlated with the observed covariates, but is orthogonal to the person and firm effects.

Before moving to the exact decomposition of the raw interindustry wage differentials we present the resulting industry wage structure when we control for person and firm effects, and when we estimate the match effects model of equation (2). We are thus able to establish whether true interindustry wage differentials exist after we control for all types of measured and unmeasured heterogeneity. These results are shown in table 7. To the extent that it adds further controls for unobserved heterogeneity, this table can be considered a continuation of table 6. Compared to a parameterization that includes only unobserved worker characteristics (table 6, column 4), the interindustry wage dispersion doubles when we also consider person and firm effects (table 7, column 1) or when we control for person, firm and match effects (table 7, column 2) which are the unbiased estimates of interindustry wage differentials. The adjusted standard deviation is now 0.15, which suggests that unobserved abilities of workers are not the sole factor influencing productivity, hence wages, and that compensation policies of firms vary across industries.

[Table 7 about here]

The wage structure reported in table 7 corresponds to our estimate of the pure interindustry wage differentials. These results, however, are an average for the 1986-2000 period and do not allow us to verify the persistence of the pure interindustry wage structure over the 14 year period. To assess how transitory these pure differentials are, we computed the annual average of firm effects within industries and correlated the yearly industry coefficients with that observed in 1986. Our results show that the magnitude of the weighted correlations of the pure industry

[19] These were estimated using the exact least squares solution (instead of the approximate method of AKM, 1999) as developed by Abowd, Creecy and Kramarz (2002), see Ferreira (2007).

[20] That is, we estimate the following model: $\widehat{\overline{y}}_{ij\cdot} = \sum_{t=1}^{Tij} \frac{y_{ijt} - x_{ijt}\widehat{\beta}}{T_{ij}} = (\widehat{u} + \widehat{\theta}_i + \widehat{\psi}_j + \widehat{\gamma}_{ij})$, where $\widehat{\beta}$ is the within-match estimator of β, and $\widehat{\theta}$ and $\widehat{\psi}$ are the worker and firm unobserved effects previously identified using the person and firm effects model.

effects in 1986 with those of the following years ranges from 0.92 in 2000 to 0.999 in 1987 (see table 8). Therefore, the pure interindustry wage differentials are unlikely to be caused by transitory shocks. Given the persistence and large dispersion of the pure interindustry wage structure we understand that changing industries can in fact lead to considerable wage growth.

[Table 8 about here]

We now proceed with the decomposition of the raw interindustry wage differentials into a part due to person effects, a part due to firm effects and another part due to match effects as shown in equation (8). The raw industry effects, κ^{**}, estimated from equation (1), are presented in column 3 of table 6. The other components of equation (8), that is the industry average firm effect (the first component of the equation) the industry average person effect (the second component), and the industry average match effect (the third component) were estimated using model (2). Results for the estimated version of equation (8), both when we are in the context of a person and firm effects model or in the context of a match effects model, are presented in table 9. These regressions, see column (1), yield an R^2 of 1 and the coefficients on the industry average person and firm effects are very close to 1 (the same is not true for the coefficient of the average match effects, suggesting less precision in its estimate).[21] This means that these components fully account for the raw industry effects and that the estimates of the interindustry wage differentials are sufficiently precise to allow an accurate decomposition. Since the industry average person, firm, and match effects are centered to have a zero sample mean, the terms high wage-worker, -firm, or -match mean, respectively, workers, firms or matches whose effect is greater than the economy-wide average of zero. The same interpretation applies to the raw interindustry wage differentials. The R^2 in columns (2) through (4) show results for the upper bound of the share of person, firm and match effects, respectively, in explaining the raw interindustry wage differentials. With the estimated version of equation (8) we find that industry average person effects are able to explain at most 31% while the industry average firm effects explain a maximum of 90% of the observed dispersion in wages across industries.[22]

[21] The estimated unobserved effect should have an impact equal to its size in the regression, therefore, its coefficient should be one.

[22] Note that, similar to AKM (1999), the person and firm effects are weakly correlated (correlation below 0.10) and so we expect little of the person effect to be explained by the firm effect.

In table 10 we present the exact decomposition of raw interindustry wage differentials for both the person and firm effects model and the match effects model. This decomposition is done in proportional terms as follows

$$\text{share of } \kappa^{**} \text{ due to individual effects} = \frac{\left(A'F'M_XFA\right)^{-1}A'F'M_XD\theta}{\kappa^{**}} \tag{a}$$

$$\text{share of } \kappa^{**} \text{ due to firm effects} = \frac{\left(A'F'M_XFA\right)^{-1}A'F'M_XF\psi}{\kappa^{**}} \tag{b}$$

and

$$\text{share of } \kappa^{**} \text{ due to match effects} = \frac{\left(A'F'M_XFA\right)^{-1}A'F'M_XG\gamma}{\kappa^{**}}. \tag{c}$$

In the case of the person and firm effects model, (a) and (b) (shown in columns 2 and 3, respectively) must add to 1, whilst in the case of the match effects model, (a), (b) and (c) (shown in columns 4, 5 and 6, respectively) add up to 1. Regardless of the model used, the average proportion of raw interindustry wage differentials due to industry average person effects is about 30%, while the average proportion of raw differentials due to the industry average firm effects is close to 70%. Match effects have a smaller role in explaining the raw industry wage premia (3%). One could think that the low proportion explained by the match effects is due to the assumption that they are orthogonal to person and firm effects. However, Woodcock (2008) reaches similar negligible interindustry variation in the match effects despite not assuming orthogonality. We have also checked whether the average proportion explained by each component would differ for the group industries paying wages above the economy average and those paying wages below the economy average. The results remained unchanged. Both in the case of high wage industries and low wage industries, industry average firm effects explain close to 70% of the estimated raw differential.

Our last exercise is to compute the correlation between the industry average person effects and the industry average firm effects. Using the person and firm effects model we obtain a positive correlation (0.45) between these two components, which means that across industries we have either high wage workers working in high wage firms, or low wage workers in low wage firms. Therefore, from the person and firm effects model we conclude that the nature of the raw interindustry wage differentials is related to positive assortative matching, and that the forces that sort person effects are correlated with the forces that sort firm effects within industries. This result contrasts with that obtained by Abowd et al. (2005), who find weak positive correlations between industry average person and firm effects, and Woodcock (2008) who, when using the person and firm effects model, finds this correlation to be weak and negative (-0.10). However, Woodcock (2008) finds a positive correlation (0.60) between these two components when using estimates from a hybrid match effects model.

Our main findings can now be summarized as follows. We conclude that the raw interindustry wage differentials are not a temporary disequilibrium in the labour market and are not due to systematic differences in unobserved labour quality across industries. Differences in compensation policies of firms are the main source of the differentials found in cross-sectional analysis. The pure interindustry wage structure (computed as the average firm effects within industry), on the other hand, shows considerable dispersion (weighted standard deviation of 0.15) and is also very persistent. Therefore, and against the predictions of the competitive model, different firms pay different wages to workers with the same characteristics (measured or unmeasured), and mobility across industries can generate substantial wage growth.

3 Testing the competitive model: interindustry wage differentials and labour mobility

Our evidence that true interindustry wage differentials exist in the Portuguese economy. However, it is not yet clear whether non-competitive forces are at work in the economy, or whether these differentials are caused by mechanisms compatible with the competitive model such as rent-sharing or efficiency wage explanations. The hypothesis of rent sharing between firms and workers is consistent with the fact that the wage premia received by workers in a particular industry extends over many occupations within the industry. It is also consistent with a positive relationship between profitability and wages (Blanchflower, Oswald and Sanfey 1996); and with a negative correlation between turnover and wage premia (Krueger and Summers, 1988). Efficiency wage hypotheses are also consistent with a negative association between industry wage differences and turnover. One mechanism that would generate this association is the existence of firm (or industry) specific skills and training. If some firms have more specific skills than others and if they are providing training to their workers, then they increase the productivity of its workforce and make workers more costly to replace. This raises the threshold of the firm in terms of labour turnover, and provides incentives to increase wages in order to reduce the likelihood of separation (Krause, 2000). If industry specific skills are more important than firm specific skills, then all firms within a certain industry will be acting in similar way thus levelling up wages within the industry.[23] If, on the other hand, the industry wage structure is generated by compensating differentials for unobserved working conditions, no association is expected to be found between industry wage premia and quits. Therefore, the relationship between the industry wage premia and separations from firms provides a test of the competitive model of industry wage determination.

In this section we examine the relationship between the industry wage structure identified in the previous section and the time workers take to separate from firms. In the literature, this analysis is typically done using worker-initiated separations, that is quits. We cannot make such a distinction with our data. However, we have noticed in previous work (Ferreira, 2007) that separations followed by short gaps (less than 1 year) of non-employment seem to be ruled by a process different from that ruling separations followed by long gaps (longer than 1 year) of non-employment. In particular, we have concluded that the former group is more likely to be formed by quits and the latter by layoffs. Hence, we use such a distinction in the present analysis of the association between interindustry wage differentials and separations.[24] We estimate parametric duration models where the dependent variable is the time to separate from firms, and the independent variable of interest is the pure industry effect (the effect obtained after controlling for all types of observed and unobserved heterogeneity).

[23]Parent (2000), e.g., finds that industry specific skills are more important then firm-specific skills in determining wage growth.

[24]Although, for robustness checks we also estimate models considering all separations together and separations followed by long periods of non-employment.

3.1 Empirical results: Industry wage structure and separations from firms.

In this subsection we present the results obtained from estimating a duration model of the time to quit a firm assuming that time follows a loglogistic distribution.[25] As well as the industry wage premia estimated in the previous section (estimated in the previous section), we also include the previously estimated residual firm effects, person and match effects to control for worker unobserved ability, firm compensation policies and match quality. The vector of observed covariates includes the age of the worker (and its square), gender, educational level, skill level, occupation, part-time or full-time work, dummy for having previously changed firms, type of instrument of collective regulation, size of firm, growth of firm, type of ownership of the firm, percentage of foreign capital, region and year. Estimates of the effects of industry wage premia on the time to quit the firm are presented in table 11. Given the functional form of the model, these coefficients measure relative changes in survival time for a given absolute change in the regressors. Therefore, a positive coefficient indicates that survival time is lengthened, while a negative coefficient indicates that the survival time is shortened. Because industry effects are measured in deviation from the grand means, these effects are measured against an economy wide average of zero.

The average effect of interindustry wage differentials on the time to separation is positive and significant, which means that the higher the industry wage premia, the longer workers take to change firms. In the case of quits (changes of firm which involve a period of non-employment of less than a year) increasing the industry wage premia by one lengthens the time to quit the industry by 37%. The coefficient on the industry wage premia is also positive and significant when we consider layoffs (.51) and all separations together (0.41).[26] Our result is consistent with a context in which firm or industry specific skills are important and where the gains of keeping workers for long periods outweigh the gains in productivity resulting from adjusting the labour force to every transitory demand shock. That is, firms find it optimal to pay wages

[25] Where a quit is separation that is followed by a period of non-employment that lasted less than one year.

[26] There are two potential explanations for the larger effect found for layoffs than for quits. On the one hand, if a worker is fired, a signal about his quality might be being sent to other firms within the industry, hence it takes longer to find a job. On the other hand, having worked for a high wage industry, workers have a high reservation wage. Hence, it takes longer to find a matching offer and/or to adjust expectations.

above the competitive level in order to provide incentives for workers to remain at the firm. If the benefits firms extract from this longer term attachment offset the costs of higher wages, then this can be a profit maximising strategy. Therefore, the industry wage differentials found in our data might not be totally incompatible with the competitive model.

4 Summary and conclusions

Departing from the predictions of the neoclassic model this paper examines the sources of interindustry wage differentials. In a competitive labour market, in the long run, homogeneous workers working in similar firms are paid similar wages. Wage differences across segments of the labour market, be it firms or industries, are due to temporary differences in productivity and are a signal for labour mobility. The flow of workers across segments equalizes wages. However, cross-sectional analysis of wages typically find that there are significant and persistent differences in wages across industries. Unsurprisingly, our analysis using Portuguese data confirms these results. The industry wage structure in Portugal shows high dispersion at points in time and the differentials persist over time. These findings raise issues about the competitiveness of the labour market and prompt the question of what explains the existence of a structure of wages across industries.

The two most common explanations for the identified cross-sectional interindustry wage differentials are that either the results obtained are not genuine differences, and the structure we find is due to imperfect measures of labour quality. Alternatively, genuine interindustry wage differentials do exist, hence compensation policies of firms vary across industries. If the industry wage premia are real then noncompetitive mechanisms may be at work in the labour market, because by paying supracompetitive wages firms might not be maximising their profits. On the other hand, and compatible with a competitive model, firms may find it profitable to pay wages above the competitive level.

We examined the sources of interindustry wage differentials using panel data over a 15 year period. Our models control for observed worker and firm characteristics, but also for unobserved worker, firm and match heterogeneity. Results show that after controlling for all types of heterogeneity the true interindustry wage differentials are sizeable and persistent. This means that compensation policies of firms vary across industries and that by changing industries workers enjoy substantial wage growth. Furthermore, we conclude that firm compensation policies are the main source of the differentials found in cross-sectional analysis and explain, on average, about 70% of the raw industry wage structure. Unmeasured worker abilities are not as important and account for about a third of such structure. We thus conclude that interindustry wage differentials are not a trick caused by unmeasured labour productive quality and are not a temporary disequilibrium in the labour market, they reflect different treats given by firms across industries.

Why might firms treat their workers by paying them supra-competitive wages? We focus on the turnover strand of efficiency wage models to investigate if the industry wage structure is caused by mechanisms compatible with the competitive model, by testing the effect of the pure wage premia on the time workers take to separate from firms. Our results indicate that the effect of the industry wage premia on the time to quit firms is positive and significant. This is consistent consistent with a labour market in which industry specific skills are important and where efficiencies are gained from creating incentives to worker-firm attachments.

In this study we identify the relative importance of worker and firm effects in generating the observed wage structure across industries, and conclude that the wage premia is compatible with the competitive model. However, some questions remain unanswered and demand further insight into the black box of the firm. What differs in production functions that makes the labour input more valuable in some industries? Which of the potential efficiency wage explanations is more powerful in shaping compensation policies of firms across industries? What causality can we establish between these wage contours and characteristics of the product market? Answers to questions such as these would allow us to understand the mechanisms determining why firms pay noncompetitive wages and why that happens with greater intensity in some industries than others.

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Tables

Table 1: Descriptive statistics of variables

Variable	Mean	Variable	Mean
Log monthly real wage	6.3	Percentage of foreign capital	9.1
Seniority (years)	8.7	Region	20 Districts
Experience (years)	22	Year	1986-2000
Hours of work (monthly)	170		
Yearly gap	0.14		
Gender		Industry	
Men	61.7	Agriculture	1.20
Women	38.4	Silviculture	0.09
Education		Fishing	0.21
ISCED 1	71.6	Mining	0.73
ISCED 2	11.3	Food products	3.92
ISCED 3	12.6	Beverages	0.67
ISCED 5/6	4.6	Tobacco	0.09
Occupations		Textiles	7.45
Directors	1.7	Clothing	6.53
Intellectual and scientific specialists	2.0	Leather	0.33
Professional, technical (intermediate)	8.3	Shoes	3.05
Administrative and managerial workers	14.1	Wood and cork	2.01
Clerical and sales workers	8.5	Furniture	1.45
Agriculture, silviculture and fishing	1.26	Pulp, paper, paper prod.	0.88
Production and related workers	25.6	Publishing and printing	1.33
Equipment operators and labourers	13.9	Industrial chemicals	0.64
Unqualified workers	18.0	Other chemicals	1.01
Skill Level		Petrol, rubber, plastics	1.42
High	18.4	Ceramics	1.30
Medium	43.5	Glass	0.52
low	38.1	Other non-met min prod.	1.60
Type of work		Base metals	0.92
Full time	91.5	Metallic products	3.38
Part time	8.4	Non-electric materials	1.80
Event		Electric materials	2.19
Automatic promotion	7.7	Motor vehicles	2.09
Merit promotion	2.9	Professional instruments	0.25
Separation, small gap	1.6	Other manufacturing	0.39
Separation, big gap	3.1	Elect., gas and water	1.31
Size of firm		Building	9.38
Micro	9.2	Wholesale trade	7.28
Small	25.0	Retail trade	7.84
Medium	29.2	Restaurants and cafes	2.83
Large	36.6	Hotels	1.87
Instrument of collective regulation		Transport	5.05
Collective agreement	4.0	Communications	1.97
Collective contract	82.7	Banking	3.06
Regulating law	3.8	Insurance	0.92
Firm agreement	8.7	Real estate	3.73
Ownership type		Productive serv - transp.	0.84
Public (Private market law)	4.8	Other productive serv.	0.79
Sole partnership	5.3	Social services	3.66
Anonymous partnership	29.0	Personal services	2.00
Limited liability partnership	55.2		

Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 2: Cross-sectional interindustry wage differences, 1986-1993

Industry	1986	1987	1988	1989	1991	1992	1993
Agriculture	-0.186	-0.20	-0.167	-0.153	-0.106	-0.126	-0.122
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
Silviculture	-0.071	-0.046	-0.041	-0.054	-0.012	-0.075	-0.023
	(0.038)	(0.032)	(0.023)	(0.020)	(0.029)	(0.031)	(0.033)
Fishing	-0.135	-0.114	-0.181	-0.271	-0.185	-0.217	-0.243
	(0.021)	(0.022)	(0.032)	(0.025)	(0.028)	(0.033)	(0.033)
Mining	0.031	0.007	0.025	0.033	0.076	0.099	0.112
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Food products	-0.064	-0.073	-0.078	-0.089	-0.076	-0.078	-0.069
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Beverages	-0.095	-0.104	-0.107	-0.120	-0.123	-0.112	-0.106
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Tobacco	-0.102	-0.077	-0.028	0.046	0.117	0.003	0.034
	(0.019)	(0.019)	(0.020)	(0.021)	(0.024)	(0.027)	(0.027)
Textiles	-0.081	-0.075	-0.108	-0.115	-0.119	-0.123	-0.138
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Clothing	-0.124	-0.095	-0.108	-0.112	-0.113	-0.128	-0.149
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Leather	-0.005	0.021	0.018	-0.008	-0.028	-0.006	0.002
	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)
Shoes	-0.087	-0.071	-0.084	-0.108	-0.135	-0.114	-0.114
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Wood and cork	-0.120	-0.109	-0.114	-0.095	-0.083	-0.096	-0.091
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Furniture	-0.239	-0.246	-0.247	-0.229	-0.234	-0.219	-0.261
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Pulp, paper, paper prod.	0.047	0.053	0.036	0.038	0.075	0.034	0.030
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Publishing and printing	-0.041	-0.046	-0.049	-0.031	0.019	0.014	0.033
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Industrial chemicals	0.073	0.067	0.105	0.094	0.052	0.066	0.086
	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)	(0.010)	(0.011)
Other chemicals	0.043	0.034	0.081	0.058	0.058	0.067	0.058
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Petrol, rubber, plastics	0.009	-0.012	0.091	0.115	0.101	0.073	0.074
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Ceramics	0.021	0.037	0.041	0.029	0.033	0.029	0.011
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Glass	0.205	0.205	0.168	0.152	0.118	0.098	0.099
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Other non-met min prod.	0.003	0.013	-0.000	0.035	0.054	0.041	0.025
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Base metals	-0.013	-0.026	-0.010	-0.012	-0.023	-0.016	-0.004
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Metallic products	-0.066	-0.047	-0.055	-0.047	-0.039	-0.028	-0.019
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Non-electric materials	-0.073	-0.070	-0.051	-0.048	-0.033	-0.030	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Electric materials	0.056	0.065	0.084	0.067	0.073	0.074	0.071
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Motor vehicles	0.008	0.043	0.005	0.005	0.087	0.078	0.086
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Professional instruments	-0.031	-0.026	-0.061	-0.048	-0.044	0.015	-0.049
	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)

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Table 2: (– continued from previous page)

Industry	1986	1987	1988	1989	1991	1992	1993
Other manufacturing	-0.095	-0.098	-0.112	-0.100	-0.084	-0.054	-0.057
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.012)	(0.013)
Elect., gas and water	0.258	0.246	0.232	0.247	0.245	0.259	0.236
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Building	-0.052	-0.068	-0.074	-0.060	-0.068	-0.076	-0.086
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wholesale trade	0.014	0.009	0.012	0.012	0.020	0.030	0.029
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Retail trade	-0.049	-0.045	-0.048	-0.037	-0.034	-0.028	-0.009
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Restaurants and cafes	-0.091	-0.110	-0.127	-0.121	-0.121	-0.120	-0.130
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Hotels	0.031	0.020	-0.001	0.020	-0.006	-0.028	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Transport	0.109	0.126	0.110	0.108	0.050	0.045	0.047
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Communications	0.091	-0.021	0.131	0.022	-0.016	0.019	0.046
	(0.006)	(0.021)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Banking	0.289	0.266	0.305	0.369	0.243	0.295	0.265
	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
Insurance	0.413	0.398	0.360	0.348	0.263	0.313	0.255
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Real estate	0.102	0.092	0.064	0.041	0.017	0.041	0.030
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Productive services - transp	0.287	0.348	0.267	0.335	0.277	0.254	0.259
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Other productive services	-0.096	-0.108	-0.130	-0.149	-0.146	-0.143	-0.127
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
Social services	-0.088	-0.094	-0.086	-0.111	-0.100	-0.093	-0.065
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Personal services	-0.088	-0.068	-0.068	-0.055	-0.049	-0.038	-0.029
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
F-stat	227.81	250.50	231.79	275.61	216.49	224.71	220.92
Weighted SD	0.104	0.103	0.104	0.108	0.102	0.109	0.107
No. of obs	103,925	104,893	109,632	119,886	128,766	132,284	130,095

Note.- i) Given that the model does not include a constant the resulting coefficients are proportionate differences in wages between a worker in a given industry and the average worker in the economy. ii) Standard errors in parenthesis. iii) Weights are industry employment shares for each year. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 3: Cross-sectional interindustry wage differences, 1994-2000

Industry	1994	1995	1996	1997	1998	1999	2000
Agriculture	-0.140	-0.110	-0.129	-0.118	-0.109	-0.090	-0.078
	(0.011)	(0.011)	(0.011)	(0.010)	(0.10)	(0.010)	(0.010)
Silviculture	-0.011	-0.083	-0.024	-0.013	-0.019	0.055	0.076
	(0.031)	(0.026)	(0.025)	(0.023)	(0.023)	(0.022)	(0.024)
Fishing	0.121	-0.051	-0.089	-0.095	-0.150	-0.071	-0.172
	(0.031)	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.023)
Mining	0.046	0.060	0.077	0.066	0.082	0.084	0.102
	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Food products	-0.086	-0.086	-0.085	-0.090	-0.090	-0.097	-0.103
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Beverages	-0.104	-0.072	-0.104	-0.079	-0.051	-0.055	-0.042
	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tobacco	0.056	0.059	0.047	0.034	0.104	0.181	0.048
	(0.029)	(0.031)	(0.032)	(0.031)	(0.029)	(0.027)	(0.027)
Textiles	-0.158	-0.162	-0.165	-0.163	-0.158	-0.178	-0.151
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Clothing	-0.181	-0.174	-0.173	-0.169	-0.160	-0.174	-0.156
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Leather	0.036	0.046	0.084	0.057	0.100	0.020	0.068
	(0.013)	(0.014)	(0.013)	(0.014)	(0.015)	(0.015)	(0.016)
Shoes	-0.133	-0.131	-0.138	-0.116	-0.109	-0.129	-0.123
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Wood and cork	-0.109	-0.077	-0.074	-0.066	-0.058	-0.047	-0.026
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Furniture	-0.248	-0.221	-0.198	-0.193	-0.169	-0.180	-0.165
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Pulp, paper, paper prod.	0.049	0.062	0.063	0.098	0.084	0.078	0.043
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Publishing and printing	0.007	-0.008	-0.009	0.012	0.001	0.010	0.026
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Industrial chemicals	0.091	0.120	0.105	0.095	0.060	0.062	0.073
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Other chemicals	0.074	0.083	0.088	0.076	0.065	0.059	0.064
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Petrol, rubber, plastics	0.059	0.052	0.040	0.012	0.037	0.026	0.047
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ceramics	-0.030	-0.006	-0.040	-0.017	-0.025	-0.021	-0.090
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Glass	0.097	0.069	0.111	0.084	0.138	0.158	0.140
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)
Other non-met min prod.	0.038	0.028	0.039	0.033	0.025	0.037	0.045
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Base metals	0.015	-0.018	-0.008	0.004	-0.006	-0.017	0.022
	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
Metallic products	-0.033	-0.054	-0.047	-0.034	-0.024	-0.020	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Non-electric materials	-0.021	-0.004	0.008	0.017	0.021	0.027	0.064
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Electric materials	0.099	0.048	0.010	0.018	0.050	0.031	0.008
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Motor vehicles	0.067	0.078	0.047	0.048	0.044	0.005	0.023
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Professional instruments	-0.122	-0.074	-0.060	-0.079	-0.106	-0.040	-0.073
	(0.017)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)

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Table 3: (– continued from previous page)

Industry	1994	1995	1996	1997	1998	1999	2000
Other manufacturing	-0.071	-0.107	-0.103	-0.111	-0.113	-0.130	-0.081
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Elect., gas and water	0.301	0.277	0.230	0.239	0.200	0.199	0.103
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Building	-0.086	-0.088	-0.089	-0.084	-0.088	-0.081	-0.061
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wholesale trade	0.031	0.009	0.009	0.003	0.002	-0.002	0.026
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Retail trade	-0.029	-0.025	-0.024	-0.017	-0.026	-0.024	-0.007
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Restaurants and cafes	-0.151	-0.168	-0.181	-0.166	-0.154	-0.157	-0.135
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Hotels	0.001	-0.013	-0.012	-0.027	-0.038	-0.034	-0.015
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
Transport	0.021	-0.018	-0.016	0.020	0.023	0.050	0.070
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Communications	0.071	0.131	0.128	0.130	0.087	0.052	0.037
	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Banking	0.235	0.238	0.251	0.191	0.157	0.165	0.117
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Insurance	0.223	0.279	0.285	0.300	0.282	0.257	0.281
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Real estate	0.016	-0.072	-0.075	-0.074	-0.069	-0.079	-0.057
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Productive services - transp	0.217	0.214	0.238	0.205	0.167	0.104	0.083
	(0.011)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Other productive services	-0.160	0.047	0.062	0.047	0.037	0.026	0.016
	(0.007)	(0.014)	(0.013)	(0.012)	(0.011)	(0.011)	(0.010)
Social services	-0.069	-0.060	-0.058	-0.068	-0.058	-0.067	-0.036
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
Personal services	-0.032	-0.018	-0.022	-0.010	0.013	0.006	-0.015
	(0.005)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)
F-Stat	227.19	238.22	241.78	233.22	223.73	224.50	200.48
Weighted SD	0.110	0.108	0.108	0.099	0.090	0.091	0.08
No. of obs	130,439	134,981	134,284	142,809	146,159	150,921	154,498

Note.- i) Given that the model does not include a constant the resulting coefficients are proportionate differences in wages between a worker in a given industry and the average worker in the economy. ii) Standard errors in parenthesis. iii) Weights are industry employment shares for each year. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 4: Persistence of the raw interindustry wage structure, k^{**}, between 1986 and 2000

Year	Weighted correlation with 1986
1986	1.00
1987	0.979
1988	0.979
1989	0.962
1991	0.921
1992	0.938
1993	0.914
1994	0.891
1995	0.839
1996	0.839
1997	0.838
1998	0.822
1999	0.807
2000	0.761

Note.- Weights are average employment shares of each industry in the period from 1986 to 2000. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 5: Analysis of sources of wage variation

Source of wage variation	Share of TSS
Covariates and industry (A)	0.718
Error (1-A)	0.282
Covariates first	
Covariates (B)	0.699
Industry (A-B)	0.019
Industry first	
Industry (C)	0.292
Covariates (A-C)	0.426
Variance of log wage	0.276
Mean of log wage	0
Total no. of observations	1,823,572
No. of industry cells	43
No. of covariates	74

Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 6: Estimated interindustry wage differentials with differing controls

Industry	Industry & time (1)	Add worker obs. effects (2)	Add firm obs. effects, κ^{**} (3)	Add worker unobs. effects (4)
Agriculture	-0.456	-0.234	-0.144	-0.091
	(0.003)	(0.003)	(0.003)	(0.004)
Silviculture	-0.348	-0.117	-0.030	-0.035
	(0.011)	(0.007)	(0.007)	(0.008)
Fishing	-0.220	-0.075	-0.112	-0.003
	(0.007)	(0.007)	(0.007)	(0.008)
Mining	0.007	0.030	0.070	0.053
	(0.004)	(0.003)	(0.002)	(0.004)
Food products	-0.180	-0.105	-0.082	-0.040
	(0.002)	(0.001)	(0.001)	(0.002)
Beverages	0.042	-0.060	-0.093	-0.025
	(0.004)	(0.003)	(0.003)	(0.004)
Tobacco	0.360	0.175	0.021	0.063
	(0.010)	(0.007)	(0.007)	(0.019)
Textiles	-0.283	-0.181	-0.126	-0.045
	(0.001)	(0.001)	(0.001)	(0.002)
Clothing	-0.444	-0.193	-0.140	-0.073
	(0.001)	(0.001)	(0.001)	(0.002)
Leather	-0.193	-0.049	0.028	-0.017
	(0.005)	(0.004)	(0.004)	(0.006)
Shoes	-0.403	-0.148	-0.112	-0.103
	(0.002)	(0.001)	(0.001)	(0.003)
Wood and cork	-0.265	-0.153	-0.081	-0.063
	(0.002)	(0.002)	(0.002)	(0.003)
Furniture	-0.430	-0.306	-0.213	-0.111
	(0.003)	(0.002)	(0.002)	(0.003)
Pulp, paper, paper prod.	0.177	0.089	0.056	0.000
	(0.003)	(0.002)	(0.002)	(0.004)
Publishing and printing	0.046	-0.038	-0.000	-0.025
	(0.003)	(0.002)	(0.002)	(0.003)
Industrial chemicals	0.400	0.162	0.082	0.061
	(0.004)	(0.003)	(0.003)	(0.004)
Other chemicals	0.276	0.092	0.064	0.004
	(0.003)	(0.002)	(0.002)	(0.003)
Petrol, rubber, plastics	0.128	0.053	0.051	0.035
	(0.003)	(0.002)	(0.002)	(0.003)
Ceramics	-0.170	-0.023	-0.004	0.023
	(0.003)	(0.002)	(0.002)	(0.004)
Glass	0.179	0.155	0.135	0.107
	(0.004)	(0.003)	(0.003)	(0.006)
Other non-met min prod.	-0.020	-0.003	0.032	0.034
	(0.003)	(0.002)	(0.002)	(0.003)
Base metals	0.100	0.008	-0.010	-0.026
	(0.003)	(0.002)	(0.002)	(0.003)
Metallic products	-0.138	-0.088	-0.034	-0.042
	(0.002)	(0.001)	(0.001)	(0.002)
Non-electric materials	-0.007	-0.038	-0.010	-0.016
	(0.002)	(0.002)	(0.002)	(0.002)
Electric materials	0.105	0.123	0.057	0.033
	(0.002)	(0.002)	(0.002)	(0.002)
Motor vehicles	0.169	0.081	0.046	0.002
	(0.002)	(0.002)	(0.002)	(0.002)

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Table 6: (– continued from previous page)

Industry	Industry & time (1)	Add worker obs. effects (2)	Add firm obs. effects, κ^{**} (3)	Add worker unobs. effects (4)
Professional instruments	-0.009	-0.017	-0.050	-0.011
	(0.006)	(0.004)	(0.004)	(0.007)
Other manufacturing	-0.249	-0.147	-0.093	-0.046
	(0.005)	(0.003)	(0.003)	(0.004)
Elect., gas and water	0.656	0.405	0.251	0.117
	(0.003)	(0.002)	(0.002)	(0.007)
Building	-0.184	-0.120	-0.074	-0.050
	(0.001)	(0.001)	(0.001)	(0.001)
Wholesale trade	0.056	-0.020	0.016	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)
Retail trade	-0.163	-0.087	-0.024	-0.035
	(0.001)	(0.001)	(0.001)	(0.001)
Restaurants and cafes	-0.418	-0.213	-0.141	-0.102
	(0.002)	(0.001)	(0.001)	(0.002)
Hotels	-0.063	0.006	-0.008	-0.003
	(0.002)	(0.002)	(0.002)	(0.003)
Transport	0.278	0.147	0.056	0.041
	(0.002)	(0.001)	(0.001)	(0.002)
Communications	0.509	0.263	0.083	0.086
	(0.002)	(0.002)	(0.002)	(0.005)
Banking	0.719	0.384	0.250	0.184
	(0.002)	(0.001)	(0.002)	(0.004)
Insurance	0.663	0.340	0.309	0.236
	(0.003)	(0.002)	(0.002)	(0.007)
Real estate	-0.095	-0.026	-0.042	-0.032
	(0.002)	(0.001)	(0.001)	(0.002)
Productive services - transp	0.356	0.204	0.205	0.051
	(0.003)	(0.002)	(0.002)	(0.003)
Other productive services	-0.339	-0.085	-0.087	-0.021
	(0.004)	(0.002)	(0.002)	(0.003)
Social services	-0.127	-0.134	-0.077	-0.051
	(0.002)	(0.001)	(0.001)	(0.003)
Personal services	-0.024	-0.055	-0.025	-0.056
	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.33	0.68	0.72	0.47
Weighted SD	0.287	0.153	0.100	0.064

Note.- i) Given that the model does not include a constant the resulting coefficients are proportionate differences in wages between a worker in a given industry and the average worker in the economy. ii) Standard errors in parenthesis. iii) Weights are industry average shares of employment in the period 1986-2000. iv) The no. of observations is 1,823,572. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 7: Estimated interindustry wage differentials with differing controls

	Industry effect given X and:	
	person and firm effects, κ^*	person, firm and match effects, κ
Industry	(1)	(2)
Agriculture	-0.244	-0.253
	(0.001)	(0.002)
Silviculture	-0.167	-0.173
	(0.005)	(0.006)
Fishing	-0.010	-0.010
	(0.004)	(0.004)
Mining	0.025	0.025
	(0.002)	(0.002)
Food products	-0.090	-0.093
	(0.001)	(0.001)
Beverages	-0.027	-0.028
	(0.002)	(0.002)
Tobacco	0.202	0.209
	(0.005)	(0.006)
Textiles	-0.123	-0.127
	(0.001)	(0.001)
Clothing	-0.186	-0.193
	(0.001)	(0.001)
Leather	-0.024	-0.025
	(0.003)	(0.003)
Shoes	-0.216	-0.223
	(0.001)	(0.001)
Wood and cork	-0.135	-0.140
	(0.001)	(0.001)
Furniture	-0.291	-0.301
	(0.001)	(0.001)
Pulp, paper, paper prod.	0.100	0.104
	(0.002)	(0.002)
Publishing and printing	-0.044	-0.046
	(0.001)	(0.001)
Industrial chemicals	0.203	0.210
	(0.002)	(0.002)
Other chemicals	0.116	0.120
	(0.002)	(0.002)
Petrol, rubber, plastics	0.101	0.104
	(0.001)	(0.001)
Ceramics	-0.056	-0.058
	(0.001)	(0.001)
Glass	0.186	0.193
	(0.002)	(0.002)
Other non-met min prod.	0.004	0.004
	(0.001)	(0.001)
Base metals	0.037	0.039
	(0.002)	(0.002)
Metallic products	-0.114	-0.118
	(0.001)	(0.001)
Non-electric materials	-0.081	-0.084
	(0.001)	(0.001)
Electric materials	0.090	0.093
	(0.001)	(0.001)
Motor vehicles	0.053	0.055

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Table 7: (– continued from previous page)

	Industry effect given X and:	
	person and firm effects, κ^*	person, firm and match effects, κ
Industry	(1)	(2)
	(0.001)	(0.001)
Professional instruments	-0.044	-0.045
	(0.003)	(0.003)
Other manufacturing	-0.107	-0.111
	(0.003)	(0.003)
Elect., gas and water	0.316	0.328
	(0.001)	(0.001)
Building	-0.145	-0.150
	(0.001)	(0.001)
Wholesale trade	-0.017	-0.018
	(0.001)	(0.001)
Retail trade	-0.106	-0.110
	(0.001)	(0.001)
Restaurants and cafes	-0.223	-0.231
	(0.001)	(0.001)
Hotels	-0.028	-0.029
	(0.001)	(0.001)
Transport	0.101	0.105
	(0.001)	(0.001)
Communications	0.212	0.220
	(0.001)	(0.001)
Banking	0.383	0.397
	(0.001)	(0.001)
Insurance	0.357	0.370
	(0.002)	(0.002)
Real estate	-0.035	-0.036
	(0.001)	(0.001)
Productive services - transp	0.201	0.208
	(0.002)	(0.002)
Other productive services	-0.055	-0.057
	(0.002)	(0.002)
Social services	-0.072	-0.075
	(0.001)	(0.001)
Personal services	-0.050	-0.052
	(0.001)	(0.001)
Constant	-0.039	-0.041
	(0.000)	(0.000)
R^2	0.92	0.94
Weighted SD	0.145	0.150

Note.- i) Given that the model does not include a constant the resulting coefficients are proportionate differences in wages between a worker in a given industry and the average worker in the economy. ii) Standard errors in parenthesis. iii) Weights are industry average shares of employment in the period 1986-2000. iv) The no. of observations is 1,823,572. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 8: Persistence of the pure interindustry wage structure, k, between 1986 and 2000

Year	Weighted correlation with 1986
1986	1.00
1987	0.999
1988	0.998
1989	0.995
1991	0.989
1992	0.988
1993	0.984
1994	0.978
1995	0.945
1996	0.943
1997	0.935
1998	0.935
1999	0.923
2000	0.922

Note.- Weights are average employment shares of each industry in the period from 1986 to 2000. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 9: Estimates of the relation between the raw interindustry wage structure and industry average person, firm and match effects

Independent variables	Coefficients:			
Person and firm effects model:	(1)	(2)	(3)	(4)
Industry average person effect	0.996	1.692		
	(0.007)	(0.391)		
Industry average firm effect	0.998		1.100	
	(0.002)		(0.058)	
R^2	1.000	0.313	0.899	
Match effects model:				
Industry average person effect	1.057	1.618		
	(0.012)	(0.374)		
Industry average firm effect	1.047		1.061	
	(0.009)		(0.055)	
Industry average match effect	2.343			-25.014
	(0.257)			(0.591)
R^2	1.000	0.313	0.899	0.978

Note: Standard errors in parenthesis. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 10: Sources of raw inter industry wage differentials

	Pooled OLS Raw differential (κ^{**})	Person and firm effects model, proportion of κ^{**} due to:		Match effects model proportion of κ^{**} due to:		
		Person eff.	Firm eff.	Person eff.	Firm eff.	Match eff.
Industry	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.144	0.007	0.993	0.007	0.960	0.033
Silviculture	-0.030	0.348	0.652	0.347	0.644	0.009
Fishing	-0.112	0.709	0.291	0.680	0.276	0.044
Mining	0.070	0.039	0.961	0.0379	0.929	0.033
Food products	-0.082	0.361	0.639	0.349	0.613	0.037
Beverages	-0.093	0.209	0.791	0.203	0.762	0.035
Tobacco	0.021	0.362	0.638	0.362	0.633	0.005
Textiles	-0.126	0.465	0.535	0.450	0.513	0.037
Clothing	-0.140	0.309	0.691	0.300	0.664	0.036
Leather	0.028	0.344	0.656	0.342	0.648	0.010
Shoes	-0.112	0.164	0.836	0.162	0.817	0.021
Wood and cork	-0.081	0.292	0.708	0.284	0.682	0.034
Furniture	-0.213	0.135	0.865	0.131	0.834	0.035
Pulp, paper, paper prod.	0.056	0.135	0.865	0.133	0.843	0.024
Publishing and printing	-0.000	0.500	0.500	0.499	0.494	0.007
Industrial chemicals	0.082	0.222	0.778	0.220	0.763	0.016
Other chemicals	0.064	0.120	0.880	0.117	0.852	0.030
Petrol, Rubber, Plastics	0.051	0.322	0.678	0.321	0.670	0.009
Ceramics	-0.004	0.329	0.671	0.329	0.666	0.005
Glass	0.135	0.223	0.777	0.221	0.761	0.018
Other non-met min prod.	0.032	0.227	0.773	0.225	0.759	0.016
Base metals	-0.010	0.561	0.439	0.562	0.435	0.003
Metallic products	-0.034	0.231	0.769	0.230	0.759	0.011
Non-electric materials	-0.010	0.413	0.587	0.414	0.582	0.004
Electric materials	0.057	0.244	0.756	0.237	0.727	0.036
Motor vehicles	0.046	0.398	0.602	0.387	0.580	0.033
Professional instruments	-0.050	0.186	0.814	0.184	0.797	0.019
Other manufacturing	-0.093	0.526	0.474	0.510	0.455	0.035
Elect., gas and water	0.251	0.423	0.577	0.409	0.554	0.038
Building	-0.074	0.075	0.925	0.073	0.900	0.027
Wholesale trade	0.016	0.789	0.211	0.756	0.200	0.044
Retail trade	-0.024	0.283	0.717	0.281	0.706	0.014
Restaurants and cafes	-0.141	0.105	0.895	0.102	0.863	0.035
Hotels	-0.008	0.367	0.633	0.366	0.626	0.008
Transport	0.056	0.616	0.384	0.600	0.368	0.036
Communications	0.083	0.584	0.416	0.563	0.398	0.039
Banking	0.250	0.263	0.737	0.255	0.709	0.036
Insurance	0.309	0.188	0.812	0.182	0.782	0.036
Real estate	-0.042	0.143	0.857	0.142	0.843	0.014
Productive serv - transp.	0.205	0.220	0.780	0.212	0.748	0.040
Other productive serv.	-0.087	0.184	0.816	0.173	0.762	0.065
Social services	-0.077	0.132	0.868	0.130	0.845	0.025
Personal services	-0.025	0.328	0.672	0.329	0.666	0.005
Average Proportion		30.4%	69.6%	29.8%	67.7%	2.5%

Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 11: Interindustry wage differentials and time to separation

	Quits (small gap)	Layoffs (big gap)	All separations
Industry premia	0.366	0.512	0.410
	(0.063)	(0.050)	(0.040)
No. obs	639,829	639,533	639,829
% separating	6.20	11.84	18.03

Note.- The average industry effect is estimated from a regression in which the pure interindustry wage differential is taken as a continuous variable. Source: Own calculations based on Quadros de Pessoal (1986-2000).