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Returns to Job Mobility: The Role of Observed and Unobserved Factors

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Non-technical summary

Earnings profiles of individuals depend not only on the characteristics of workers and their employers, which may be both observable and unobservable, but also on the quality of the match between the two. The quality of the match is determined when the worker enters the firm and while successful matches are likely to continue, unsuccessful ones are likely to result in separations of workers from the firm. Both good and bad matches are at risk of job mobility. Good matches may lead to internal mobility (promotions) while bad matches lead to permanent separations from firms.

Typically, analyses of the impact of job mobility on wages focus either on moves within a firm, or between firms, making it difficult to compare changes in wages associated with each type. Furthermore, although much of the differences in wages are not explained by what we can observe, the nature of most data sets does not allow us to identify the effect of unmeasured factors relating to the worker, the firm and the match between the two. We make three main contributions to the existing literature. Firstly, using the same data set we compare the impact on wages of promotions within firms and of moving between firms, and therefore provide a direct comparison of the returns to both forms of job mobility. Second, we include observable characteristics of both workers and firms as determinants of wages. Third, we separate the total unobserved effect in order to identify and compare the shares of wage variation that are due to unobservable worker, firm and match effects across types of job mobility.

Our results suggest that more than 90% of the total variation in wages can be explained by observed and unobserved characteristics of workers and firms. Taken together, worker and firm unobserved effects explain more than half of the variation of wages for all types of job mobility. Although unobserved match effects explain little of the variation in wages of promoted workers, they are more important in explaining entry wages of workers that have experienced between firm mobility. Despite finding little difference between automatic and merit promotions, we identify observed wage premiums to promotions generally and establish that promoted workers are high wage workers employed in high wage firms with which they match well. Differences appear for workers that have separated from firms. Workers that enter a new firm within one year of separation from their old firm are improving their position by moving to higher paying firms with which they match better. Workers that enter a new firm more than one year from separation have the worst outcomes: they move to lower paying firms with which they match worse. These differences suggest that these separations are driven by two distinct processes. Workers that find a new job within one year are more likely to have been quits, whereas those that take more than 12 months to do so are more likely to have been laid off from firms.

Returns to job mobility: the role of observed and unobserved factors.*

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Abstract

We investigate the returns to promotions and separations from firms using Portuguese linked employer-employee data. More than 90% of the total variation in wages can be explained by observed and unobserved characteristics of workers and firms. Taken together, worker and firm unobserved effects explain more than half of the variation of wages for all types of job mobility. Our results suggest that promoted workers are high wage workers in high wage firms. Movers are inherently lower wage workers, in lower wage firms. However, on average, workers that find a new job within one year enter firms that pay higher wages. This is not true for workers that take more than a year to find a new job.

Keywords: promotions; separations; wages; estimation of unobserved worker, firm and match heterogeneity.

JEL Classification: C33, J31, J41, J62, J63.

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1 Introduction

Earnings profiles of individuals depend not only on the characteristics of workers and their employers, which may be both observable and unobservable, but also on the quality of the match between the two. The quality of the match is determined when the worker enters the firm and while successful matches are likely to continue, unsuccessful ones are likely to result in separations of workers from the firm. Both good and bad matches are at risk of job mobility. Good matches may lead to internal mobility (promotions) while bad matches lead to permanent separations from firms.

Typically, analyses of the impact of job mobility on wages focus either on within-firm or between-firm mobility, making it difficult to compare changes in wages associated with each type. Furthermore, although much of the dispersion in wages is not explained by observable characteristics (Mortensen, 2003), the nature of most data sets does not allow us to identify unobserved worker, firm and match effects. We make three main contributions to the existing literature. Firstly, using the same data set we compare the impact on wages of promotions within firms and of moving between firms, and therefore provide a direct comparison of the returns to both forms of job mobility. Second, we include observable characteristics of both workers and firms as determinants of wages. Third, we decompose the total unobserved effect (as represented by the stochastic error term) in order to identify and compare the shares of wage variation that are due to unobservable worker, firm and match effects across types of job mobility.

Using the *Quadros de Pessoal* data, our statistical approach starts with the simple OLS specification of a wage equation, in which we assume that all coefficients are constant across time and units and that the error term captures remaining differences. This also assumes that the composite error is orthogonal to the covariates. If this assumption is violated then OLS estimates are biased and inconsistent. We compare the results from several approaches designed to deal with unobserved effects, such as standard random effects and within-groups fixed effects models; the Abowd, Kramarz and Margolis [AKM] (1999) decomposition that permits separate identification of firm and worker effects; and, Woodcock's (2008) orthogonal match effects method which permits identification of unobserved match heterogeneity in addition to unobserved person and firm effects.

Models that control for either worker or firm effects, and worker, firm and match effects show only small differences in the coefficients of observed characteristics and in the proportion of variance in wages attributable to each component. Merit promotions are the type of job mobility with highest rewards, with an associated wage premium of 3%, while workers with automatic promotions have a wage premium of 2% relative to workers that do not experience any job mobility.

Promoted workers have above average unobserved individual effects and are in firms with above average unobserved effects, and the correlation between these two effects is positive. We therefore conclude that these are the best workers, employed in the best firms. In contrast, workers who entered a firm in the last year have a below average individual effect and work in firms with a below average effect. That is, these are lower wage workers in lower wage firms. However by changing firms, workers who have had short spells of non-employment move, on average, improve the quality of their match. This suggests that on-the-job search plays an important role in identifying suitable employment opportunities. On the other hand, workers who have experienced a long period of non-employment before entering a new firm have their situation worsened. Match effects are relatively more important in explaining the wage dispersion of workers who move between firms than of promoted workers.

The paper is organized as follows. The next section discusses the literature on within- and between firm job-mobility. Section 3 presents the empirical approach for estimating the unobserved worker, firm and match effects. The data set used is described in Section 4, and results are discussed in Section 5. Summary and conclusions are derived in Section 6

2 Theoretical background

Several authors model the mechanisms that prompt mobility of workers in the labour market. A transition from unemployment to employment is typically analysed by search models; turnover caused by permanent separations from firms is typically analysed by matching models; and mobility within firms is often analysed in the context of matching models and personnel economics. Given that traditional search models are particularly useful to explain the duration of unemployment, they will not receive much attention in this study. However, search models have been extended to incorporate on-the-job search and these extensions will be discussed here. Our analysis relies mostly on matching models that focus on job-to-job transitions but also relate to mobility from employment to unemployment.

Job matching models emphasize the importance of match heterogeneity in explaining phenomena that are commonly found in empirical studies of the labour market. These include the decline in separation probability with job tenure and the positive relationship between wages and job tenure. These correlations were typically explained by the human capital model which attributes them to the accumulation of firm-specific human capital. Within this context, if workers and firms share the returns to specific training, the wages of workers rise with seniority at the firm and the incentive of both workers and firms to separate as tenure increases is reduced.[1] The job matching model, however, argues that workers differ in their suitability to different firms and that this is the central mechanism driving separations from firms. Well matched workers receive higher wages and are unlikely to separate, whereas poorly matched workers have lower wages and are more likely to separate. As the quality of the match is identified early, separations are most prevalent among those with shorter tenures. Therefore high wages are associated with high tenure even if wages do not increase because of accumulated seniority in the firm. Thus, matching models rely on imperfect information, and job mobility is caused by the acquisition of information either about the current match, or about possible alternative matches. If separations are caused by the former, the match is an experience good. If mobility is caused by the latter the match is a search good.

Johnson (1978), Jovanovic (1979a), and Viscusi (1980) consider the match as an experience good and show that for any given mean return, the worker will prefer the job with higher earnings variance because the mean value for its upper tail is higher. This is all that matters to the worker as the possibility of changing jobs eliminates the lower tail. Since wages always equal expected marginal products for all similar workers, the model generates (on average) wage growth over the life-cycle.[2] The separation probability is a decreasing function of job tenure because a mismatch between a worker and his employer is likely to be detected earlier than

[1] See Parsons (1972) for a review of human capital models.

[2] That is, as low wage workers quit and high wage workers stay, the model implies that the average wage of a cohort of workers increases with tenure.

later. As mismatches lead to lower wages and early separations, holding experience in the labour market constant, average past earnings are likely to be lower for a worker who has experienced many job separations. Also within a matching context, McLaughlin (1991) establishes that the quit (worker initiated separations)-layoff (firm initiated separations) distinction is compatible with efficient turnover. In a matching framework with partially flexible wages, informational asymmetries create incentives to revise the wage and, if a separation occurs, the side initiating the wage revision determines the label. Implications from this structural model are that workers who quit go to for higher paying jobs and workers who are laid off go to lower paying jobs.[3]

Burdett (1978), Mortensen (1978) and Jovanovic (1979b) consider the match to be a search good. Mortensen's (1978) model differs from previous models in that the rents of the match are shared between the worker and the firm and the existence of better prospective matches will motivate search by both. Therefore some separations will be quits and others layoffs, and are related to the search strategies chosen by workers and firms. In each case the search strategy has two components, a criterion for accepting alternative matching opportunities and a measure of search intensity that determines the frequency with which such alternatives are received. Hence, turnover is a process by which worker-firm matches are improved and the decline in separation probability with tenure is a consequence of an exogenously growing match-specific human capital. By also creating complementarities between the quality of the match and investment in specific human capital, Jovanovic (1979b) develops a model that has two distinct implications. First, holding constant the quality of the match, the likelihood of a match terminating falls with the amount of firm-specific capital. Second, the better the match, the larger the investment in human capital, all else constant. The reason for these complementarities is the uncertainty about the duration of the current match caused by the possibility of an offer of a more attractive match. This model implies that workers's search intensity is inversely related to match quality and to the amount of training received. The most intense searchers will predominantly be young workers who have been unlucky in their search for a good job match and who have a short job tenure. The amount of time devoted to search for alternative jobs decreases with the total value of the match. Therefore those that are well matched and

[3] Another implication of this model is that separations to the non-market sector are never labeled quits. However, we cannot distinguish workers' fates if they are absent from the database, and cannot test this implication.

that have more specific human capital spend less time searching, which lowers the probability of separations.

Burdett (1978) generalizes the search model to allow workers to search on the job, and assumes that workers do not accumulate human capital and know everything about the job before entry. A worker employed at a wage less than another worker of the same age is more likely to quit for two reasons. First, the lower paid worker is more likely to obtain an offer greater than the current wage. Second, the lower paid worker will choose to work and search at least as much as the other worker. While in the human capital model older workers receive higher wages through accumulation of human capital while working, in Burdett's model this happens because they have obtained more job offers and so have higher probability of receiving a higher wage offer. In contrast, Jovanovic (1984) generalizes matching models and combines a search model with a matching model. He considers the possibility that, due to changes in the perceived value of market opportunities, a worker may change jobs but can also move from employment to unemployment.[4] Therefore, the worker has three reservation wages, one for job-to-job transitions, another for unemployment-to-job movements, and the third for job-to-unemployment.[5] In this model, the worker and firm are equally informed about the quality of the match which, although initially unknown, is revealed as the match produces output. With no other information, a worker and his employer regard the quality of their match as having been drawn from a normal distribution. Their beliefs are updated as information becomes available, either as the firm screens the worker or by direct observation of the output of the match. If the current match is a disappointment and if acceptable new offers do not arrive, the worker may choose unemployment. In this model, an increase in the current wage reduces the probability that the worker will leave the firm for two reasons. First, the higher the current wage, the less likely it is to fall to the point at which worker chooses unemployment. Second, the higher the wage, the less likely it is that the worker will be bid away by another firm.

[4]Typically theories assume that workers can choose unemployment due to changes in non-market opportunities. In this case an alternative view is developed in which movements into unemployment are driven by changes in perceived values of market opportunities.

[5]For job-to-job transitions the individual would give up a job with a stable wage in favor of a job with a lower initial wage if the new job offered the possibility of wage growth (higher variance). If the worker's wage is held constant while his general abilities grow, his alternative wage will rise and he will become more likely to leave. The worker is least demanding when he is unemployed, because unemployment is a state the worker can always choose.

Therefore, both types of transition are more likely for lower paid workers.

Matching models explain not only separations from firms but also explain the existence of promotions. For example, Jovanovic (1979a, b) allows employers to establish individual contracts with their workers. Examples of individual contracting include a system of promotions or delayed pay increases based on the quality of the worker's performance on the job over a period of time. In this setting the employer is able to reward the employee with whom he matches well by paying him relatively more. Hence individual contracting creates a structure of rewards that provides proper signals for the attainment of optimal matches. Promotions can also arise within a scheme of counter offers (Mortensen, 1978) intended to elicit cooperative behaviour between workers and firms when potential alternative matches are found. In the personnel economics literature, however, instead of promotions being just a reward to good matching, they are part of a scheme of incentives for workers to exert effort, and a premium to good performance. As personnel economics is more interested in analysing how several events impact on the outcomes of the firm, it is less comprehensive in explaining separations from firms, and focuses more on how firing costs may condition hiring decisions and overall levels of employment.[6]

Matching models suggest that biases arise when estimating the determinants of wages or quit rates due to the presence of match, firm or individual unobserved heterogeneity. Some authors have tried to test the empirical importance of job matching in determining wages, for example Topel (1986, 1991), Flinn (1986), Altonji and Shakotko (1987), Abraham and Farber (1987), and Mortensen (1988). All have the difficult task of testing hypotheses about unobserved effects, which becomes even more difficult when most of the data available initially was cross-sectional. Longitudinal data on workers allowed investigators to control for unobserved characteristics of workers (perhaps mixed with unobserved characteristics of their firms). Other studies focus on data on one single firm and therefore have information on workers and firms, but have the limitation of being difficult to generalize to the economy (Baker *et al.* 1994a,b). More recently, longitudinal linked employer-employee data has allowed researchers to control for unobserved worker and firm effects, and match effects. Our contribution is to this new and expanding literature, as we analyse the returns to promotions and separations from firms while controlling

[6] See Lazear and Oyer (2007) for a review of the personnel economics literature.

for observed and unobserved characteristics of workers and firms as well as for unobserved match quality.

3 Empirical model

The choice of method for estimating a wage equation requires assumptions about the intercept, slope coefficients and the error term. Here we compare the results obtained under several different assumptions.

3.1 Standard estimation techniques

Pooled OLS is the simplest specification of a wage equation. In this model, we assume that all coefficients (slope and intercept) are constant across time and units (individuals and firms) and that the error term captures remaining differences between them. We can specify the wage equation in the following way:

$$y_{ijt} = u + (x_{it} + x_{j(i,t)t})\beta + \mu_i \eta + q_{j(i,t)}\rho + \varepsilon_{ijt} \tag{1}$$

where y_{ijt} is the logarithm of real monthly wages of worker $i = 1, ..., N$ in firm $j = 1, ..., J$ in period $t = 1, ..., T$; u is the general mean; x_{it} is the vector of time varying characteristics of worker i in period t; $x_{j(\cdot)t}$ is the vector of time varying characteristics of firm j in which worker i is employed at period t; μ_i and $q_{j(\cdot)}$ are the vectors of time invariant covariates of workers and firms, respectively; ε_{ijt} is a composite error which, in this study, includes the vectors of time-, worker-, firm- and match-specific unobserved effects, and an idiosyncratic error.[7]

Besides assuming that the intercepts are the same for every worker and firm, and that the slope coefficients are equal for all units, the statistical properties of the pooled OLS model depend on the assumption that the composite error is orthogonal to the covariates, and therefore that each of its components (time, worker, firm and match unobserved heterogeneity, and the idiosyncratic error) are all orthogonal to the covariates. However, if the unobserved effects are

[7] The general mean of y_{ijt} is given by: $u = \overline{y}_{...} = \sum_{i=1}^{N}\sum_{j=1}^{J} \frac{T_{ij}\overline{y}_{ij.}}{T}$, where T is the total number of observations.

correlated with the covariates, pooled OLS estimates are biased and inconsistent. Furthermore, even if the orthogonality assumption holds, the composite errors are serially correlated due to the presence of time-invariant unobserved effects in each period.

Random effects methods recognize unobserved effects as components of the error term and exploit the serial correlation in the composite error using a generalized least squares approach. Random effects models assume (i) that the error term has zero mean conditional on past, present and future values of the regressors (strict exogeneity), (ii) orthogonality between unobserved effects and covariates, and (iii) that the conditional variance of the composite error is constant and that the conditional covariances are zero. The random effects estimator is consistent under assumptions (i) and (ii) and efficient in the class of estimators consistent under the strict exogeneity assumption. However, it is usual to expect that the unobserved effects are correlated with the explanatory variables. If this is the case, random-effects estimators are inconsistent and other methods of estimation are required.

Within-group fixed effects methods also rely on the assumption of strict exogeneity but allow the unobserved effects to be arbitrarily correlated with the covariates. Equations are transformed in order to eliminate the unobserved effects by time-demeaning the original specification.[8] Under the strict exogeneity assumption and the assumption that the disturbance terms are homoscedastic and nonautocorrelated (spherical) the within-groups estimator is unbiased, although not necessarily the most efficient estimator in the class of estimators consistent under the strict exogeneity assumption.

If we are not interested in estimating the unobserved effects of workers and firms, we could obtain consistent estimates of the parameters by time-demeaning within-match (worker-firm interaction). This transformation would eliminate unobserved worker, firm, and match heterogeneity.[9] One potential disadvantage of the within-groups fixed effects approach is that we cannot identify all the time-invariant unobserved effects, separately. We also lose the information provided by the time-invariant observed covariates whose parameters (η and ρ) may be of interest for the analysis. If we are interested in estimating the time-invariant observed and unobserved parameters, non-standard econometric approaches have to be used. The person

[8] That is, transforming the variables to be deviations from their means over time.

[9] AKM (1999) label this procedure as the "consistent method", Andrews et al. (2006a) labelled it as "spell fixed effects".

and firm effects model and the match effects model are examples of such estimation techniques.

3.2 The person and firm effects model

The person and firm effects model of AKM (1999) contrasts with random effects and within-groups fixed effects models in that it allows the unobserved effects to be estimated.[10] This is important as workers can sort into firms non-randomly, and we are interested in identifying and comparing the unobserved effects across types of job mobility. Within this context equation (1) can be restated as:

$$y_{ijt} = u + (x_{it} + x_{j(i,t)t})\beta + \theta_i + \psi_{j(i,t)} + \epsilon_{ijt} \tag{2}$$

where y_{ijt} is the logarithm of real monthly wages of worker $i = 1, ..., N$ in firm $j = 1, ..., J$ in period $t = 1, ..., T$. u is the general mean; $x_{\cdot t}$ are the vectors of observed time varying covariates; θ_i and $\psi_{j(\cdot)}$ are the vectors of time-invariant (observable and unobservable) covariates related to worker and firms, respectively; ϵ_{ijt} is the idiosyncratic error. In this specification, two error components (θ_i and $\psi_{j(\cdot)}$) are stated explicitly, the time effects (one of the error components) are included in the vector of time varying covariates as categorical variables.[11] Additionally, we can make an orthogonal decomposition of the time invariant individual effects (θ) into observable (μ) and unobservable (α) components as follows:

$$\theta_i = \alpha_i + \mu_i \eta \tag{3}$$

and a similar decomposition can be made for the time invariant firm effects.

One way of estimating the unobserved components as parameters is achieved by introducing N dummy variables for each unit of analysis. This is called the least squares dummy variable approach, and allows us to obtain estimates for both the β (which coincide with the within groups estimator) and the unobserved worker and firm effects. However, estimation of these two unobserved effects involves very high dimensional factors. If we restate equation (2) in

[10] The exposition made in this section is draws heavily from sections 2 and 3 of AKM (1999).

[11] This model relies on the assumption of strict exogeneity and that the errors are spherical, *i.e.* $\varepsilon \sim N(0, \sigma_\varepsilon^2 \mathbf{I})$.

matrix notation our model would be of the type

$$y = u + X\beta + D\theta + F\psi + \epsilon \tag{4}$$

where $X_{(N^* \times K)}$ is the matrix of observable time varying covariates; $D_{(N^* \times N)}$ is the matrix of indicators for worker $i = 1, ..., N$, and $F_{(N^* \times J)}$ is the matrix of indicators for the firm at which worker i works at period t. y is a $(N^* \times 1)$ vector of monthly real wages, u is the $(N^* \times 1)$ mean vector.[12] The set of parameters to estimate are β, the $K \times 1$ vector of coefficients on the covariates; θ, the $N \times 1$ vector of worker effects; and ψ, the $J \times 1$ vector of firm effects. Overall, we want to estimate $K + N + J$ parameters. Given equation (4) the least squares estimation problem is to solve the following equations for all identified effects

$$\begin{bmatrix} \widehat{\beta} \\ \widehat{\theta} \\ \widehat{\psi} \end{bmatrix} = \begin{bmatrix} X'X & X'D & X'F \\ D'X & D'D & D'F \\ F'X & F'D & F'F \end{bmatrix}^{-1} \begin{bmatrix} X'y \\ D'y \\ F'y \end{bmatrix}. \tag{5}$$

Due to the large number of individual and firm unobserved effects (over 0.5 million in this study), the inversion necessary in (5) is not computationally possible and different estimation techniques have to be used. Abowd *et al.* (2002) show that the identification of the unobserved effects using fixed effects techniques can be obtained by constructing groups of connected workers and firms. Mobility of workers across firms is necessary for constructing such groups, each of which contains all workers who have ever worked for any particular firm and all the firms at which any particular worker was ever employed. Figure 1 illustrates graphically the concept of connectedness of workers and firms.

[Figure 1 about here]

We can understand the importance of connectedness as follows. Suppose that we have two high dimension vectors of unobserved effects, one associated with workers, the other with firms. To estimate these effects we can make a within-worker transformation and include dummies for

[12] 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 $N^* = \sum_{i=1}^{T} T_i$. Equation (4) corresponds to equation (2.2) in AKM (1999).

the firms. Under this setting the within-worker transformation eliminates from the specification all the time invariant components associated to workers, including the firm dummy if the worker does not change firms. In Figure 1, we have 5 workers and 5 firms. If we consider each worker in turn, worker 1 has been in firms 1 and 2, and for this worker one of the firm effects will be set as the reference category (say, firm 2) and the effect for firm 1 can be estimated. Worker 2 has only been employed in firm 1. Given the within transformation we would usually be unable to identify the firm effect for worker 2. However, the effect for firm 1 has already been identified using the information for worker 1. The employment history of worker 3 shows that he has been employed by firms 2 and 3 and, if we set firm 2 as the base category, the effect for firm 3 can be estimated. Worker 4 works only in firm 3, but is connected to all the previous workers because worker 3 has also worked in that firm. In this case, workers 1 to 4 and firms 1 to 3 are connected and form group 1. Worker 5 was employed in firms different to those the other workers have belonged to and so forms a different group, that is group 2. Therefore, as long as there is sufficient mobility that connects workers and firms, within each connected group of workers and firms we are able to estimate $N-1$ firm effects regardless of the fact that not all workers have changed firms. These effects are comparable within each group, because they are all computed relative to the same firm (firm 2 in the example), but not between groups.[13]

Thus, the first step in the estimation is to assign workers and firms into G mutually exclusive groups of connected workers and firms. Within each connected group, the group mean of y is estimable and the unobserved person and firm effects are identified up to one constraint – that is the person effects are normalized to have zero mean within each group and the last firm effect is zero (Ouazad, 2007a). Consequently, the estimated effects are not comparable across connected groups of workers and firms because the constraints for each of them are different. Abowd *et al.* (2002) show that under these grouping conditions we can identify $N+J-G$ effects and they point out that solving the identification problems does not simplify the estimation because one of the groups will be of almost the same size as the entire sample. Given the high dimension of the equations, the authors developed a variant of the conjugate gradient algorithm, which is an iterative method that makes direct least squares estimation of the full model by fixed-effects

[13] Cornelissen (2008) develops a Stata module to estimate two-way fixed effects models and presents some examples to demonstrate the importance of connectedness.

methods feasible.[14] The standard errors of the parameters cannot be estimated because they require an estimate of the variance-covariance matrix (which also involves the inversion of a matrix such as the one presented in (5)).

Once we have estimated the worker and firm effects in this way, we can recover the effects of the time invariant observed characteristics (η) by estimating equation (3). Having obtained $\widehat{\eta}$, the estimator of the individual effect is given by

$$\widehat{\alpha}_i = \widehat{\theta}_i - \mu_i \widehat{\eta} \tag{6}$$

the authors state that $\widehat{\alpha}_i$ is unbiased and asymptotic in T_i.

3.3 The match effects model

As discussed previously, several authors have developed theoretical models in which job mobility depends on the worker-firm interaction or match. If match quality affects job mobility, it can also affect wages within firms. In the person and firm effects model the match effect is a part of the stochastic error but, if this effect is not zero and if it is correlated with the observable characteristics, estimates obtained from equation (2) can be biased because the strict exogeneity assumption is violated. Therefore, it is important to understand how much variation in wages is due to this component of unobserved heterogeneity. In a matching model the logarithm of monthly real wages of the i^{th} worker at the j^{th} firm at time t is given by:

$$y_{ijt} = u + (x_{it} + x_{j(i,t)t})\beta + \theta_i + \psi_{j(i,t)} + \gamma_{ij(i,t)} + \xi_{ijt} \tag{7}$$

where all the components are as in equation (2), except for $\boldsymbol{\gamma}_{ij(\cdot)}$ which is the unobserved match effect (which can be the worker-firm specific productivity, a production complementarities component, or performance on the job, for example) and measures the time-invariant heterogeneity associated to the match of a worker with a firm; and for ξ_{ijt} which is the white noise (in the person and firm effects model ϵ_{ijt} is a composite error should the match effects not be equal

[14] The conjugate gradient method was invented to minimise quadratic functions, which is equivalent to finding x by solving a linear system of the type $\mathbf{Ax} + \mathbf{b} = \mathbf{0}$, where $\mathbf{A}$ is symmetric positive definite. With this method, the only operation involving $\mathbf{A}$ is its multiplication with a vector. See Schewchuk (1994) for an "almost painless introduction" to the conjugate gradient method.

to zero, and $\epsilon_{ijt} = \xi_{ijt}$ in the absence of match effects).[15] Woodcock (2008) argues that the match effects model corrects for potential bias in the person and firm effects model, either in the estimates of the coefficients on the observable characteristics or in the estimates of the person and firm effects themselves.[16] Restating equation (7) in matrix notation, we have:

$$y = u + X\beta + D\theta + F\psi + G\gamma + \xi \tag{8}$$

where all components remain the same as in equation (4) and $G_{(N^* \times M)}$ is the matrix of indicators for worker-firm matches and γ is an $M \times 1$ vector of unobserved match effects. Therefore, in the match effects model we wish to estimate $K + N + J + M$ parameters.

Within a match effects model, the individual effects (θ) measure persistent differences in wages between workers, conditional on time varying characteristics, firm effects and match quality. The firm effects (ψ) measure persistent differences in wages, conditional on time varying covariates, worker effects and match quality. The match effects (γ) measure unobserved differences in wages of workers with the same observed characteristics and the same unobserved effect, within firms with the same observed characteristics with the same unmeasured effect.[17]

Estimation and identification of all the parameters within the context of a match effects model, as with the person and firm effects model, is non-trivial. We have $K = 88$, $N = 377,866$, $J = 98,438$, and $M = 589,826$, which means that the number of parameters to estimate is $1,066,216$.

Of the parameters to estimate, the vector β can be identified in a straightforward manner. The potential correlation of the unobserved effects with the columns of X is overcome by eliminating the unobserved effects through transforming the data into deviations from match-specific means. With this transformation, the subset of observable covariates becomes orthogonal to the

[15] This specification can be considered an extension to Flinn's (1986) matching model. This extension is done by incorporating firm unobserved heterogeneity in the specification. Firm effects were excluded from Flinn's model because of lack of demand side data. This inclusion has no impact on the main assumptions and conclusions of the original model in which the components α, ψ, γ and ε are unobservable, assumed to possess a continuous distribution, and are independently distributed across workers, firms, and time. Wages are assumed to be bounded which implies that all unobservables have bounded support. Workers and firms are assumed to know the value of their permanent unobserved component but they can only observe the sum of the match value $\boldsymbol{\gamma}_{ij(\cdot)}$ and the error $\boldsymbol{\epsilon}_{ijt}$ each period.

[16] The nature of those biases is also derived in Woodcock (2008).

[17] Stochastic changes in these unobserved effects are ignored.

subset of unobserved effects and, in these circumstances, the estimator of β is not affected by the absence of the parameters related to the unobserved effects of workers, firms and matches. Using this result for partitioned regression, the least squares estimator of β is the within match estimator $\widehat{\beta} = (X'Q_{[DFG]}X)^{-1}X'Q_{[DFG]}y$. Where $Q_{[DFG]}$ is the matrix that wipes out the unobserved effects.[18]

After estimating β, it is complicated to separately identify the components of the orthogonal subset of unobserved effects $(u, \theta_i, \psi_j, \gamma_{ij})$ using a fixed effects estimator in a way that allows inter-worker and inter-firm comparisons of person and firm effects. This is because we have $1 + N + J + M$ effects to estimate, but only M worker-firm matches from which to estimate them. To clarify this problem in more detail, think of the information on workers and firms as organized in a two-way layout or an $I \times J$ table, with rows denoting workers (i), and columns denoting firms (j). y_{ijt} is the t^{th} observation of row i and column j for $i = 1, ..., N$, $j = 1, ..., J$ and $t = 1, ..., T_{ij}$ with T_{ij} being the number of observations of worker i in firm j. In our model (7) u is the general mean, β are the effects of characteristic x_{ij} in period t, θ_i is the effect due to the i^{th} row, ψ_j is the effect due to the j^{th} column, γ_{ij} is the effect due to the interaction of the i^{th} row with the j^{th} column, and ξ_{ijt} is the residual. A model such as this involves more parameters $(N + J + M + 1)$ than observed cell means (only $M = ij$ cell means: $\overline{y}_{ij\cdot} = \sum\limits_{t=1}^{Tij} \frac{y_{ijt}}{T_{ij}}$) from where to estimate them. In other words, we have too many parameters to estimate as linear functions of the observed $\overline{y}_{ij\cdot}$ cell means, and neither the grand mean, nor the row or column means help in solving this issue because they are linear functions of the cell means.[19]

[18] β is estimated from a regression of $\widetilde{y} = Qy$ with typical element $(y_{ijt} - \overline{y}_{ij\cdot})$ on $\widetilde{X} = QX$ with typical element $(X_{ijt,k} - X_{ij\cdot,k})$ for the k^{th} regressor, $k = 1, 2, ..., K$. With this transformation we are eliminating not only the match effects, but also the person and firm effects because these effects do not vary for each worker-firm combination (match). (For further details, see Baltagi (2008) section 2.2.)

[19] If we define the number of observations in row i as $T_{i\cdot} = \sum\limits_{j=1}^{J} T_{ij}$, and the number of observations in column j as $T_{\cdot j} = \sum\limits_{i=1}^{N} T_{ij}$, and the total number of observations as $T = T_{\cdot\cdot} = \sum\limits_{i=1}^{N}\sum\limits_{j=1}^{J} T_{ij} = \sum\limits_{i=1}^{N} T_{i\cdot} = \sum\limits_{j=1}^{J} T_{\cdot j}$. The grand mean is given by: $\overline{y}_{\cdot\cdot\cdot} = \sum\limits_{i=1}^{N}\sum\limits_{j=1}^{J} \frac{T_{ij}\overline{y}_{ij\cdot}}{T}$; the row mean is given by: $\overline{y}_{i\cdot\cdot} = \sum\limits_{j=1}^{J} \frac{T_{ij}\overline{y}_{ij\cdot}}{T_{i\cdot}}$; and the column mean is given by: $\overline{y}_{\cdot j\cdot} = \sum\limits_{i=1}^{N} \frac{T_{ij}\overline{y}_{ij\cdot}}{T\cdot j}$. (See Searle, 1987, for more details.)

Coming back to our model we can rearrange equation (7) in terms of cell means as follows:

$$\overline{y}_{ij\cdot} = \sum_{t=1}^{Tij} \frac{y_{ijt}}{T_{ij}} = u + \sum_{t=1}^{Tij} \frac{x_{ijt}\beta}{T_{ij}} + \theta_i + \psi_j + \gamma_{ij} + \sum_{t=1}^{Tij} \frac{\xi_{ijt}}{T_{ij}}. \tag{9}$$

Having estimated $\widehat{\beta}$, there are only M distinct elements in the vector of predicted values, which are the sample means

$$\widehat{\overline{y}}_{ij\cdot} = \sum_{t=1}^{Tij} \frac{y_{ijt} - x_{ijt}\widehat{\beta}}{T_{ij}} = (\widehat{u} + \widehat{\theta}_i + \widehat{\psi}_j + \widehat{\gamma}_{ij}). \tag{10}$$

From equation (10) it is possible to understand that the least squares estimator of the subset of equations orthogonal to $X\beta$ is equivalent to regressing $y - X\widehat{\beta}$ on D, F, G and an intercept. But given that only the sample means are identified, the 1+ $N + J + M$ parameters related to u, θ, ψ, γ do not have an unique solution unless we make additional identifying restrictions. One possible restriction is to assume that the match effects are orthogonal to the person and firm effects.[20]

Under the assumption that the match effects are orthogonal to the person and firm effects, the implementation of the matching model is, as Woodcock (2008) shows, relatively straightforward once we have been able to compute the person and firm effects model without match effects. The orthogonal match effects estimator is defined by the regression of worker-firm matches (as defined in equation (10) and where $\widehat{\beta}$ is the within-match estimator of β) on an intercept, and on the worker $(\widehat{\theta})$ and firm $(\widehat{\psi})$ unobserved effects previously identified using the person and firm effects model. The least squares estimate of the orthogonal match effect is the vector of residuals obtained from this regression.[21] That is:

$$\widehat{\gamma}_{ij} = \widehat{\overline{y}}_{ij\cdot} - \widehat{u} - \widehat{\theta}_i + \widehat{\psi}_j. \tag{11}$$

Hence, the estimation of the match effects model is slightly more cumbersome than the

[20] See Woodcock (2008) for a discussion of other alternatives to separately identify the unobserved effects in a match effects model.

[21] In so doing we are implicitly assuming that $\gamma \sim N(0, \sigma^2_\gamma)$. This is similar to the match effect derived in Flinn (1986). Consequently, as in Flinn's model, the proportion of wage variability attributable to worker-firm heterogeneity is expected to decline as individuals sort into good matches.

estimation of the person and firm effects model. In the person and firm effects model the parameters are estimated simultaneously from one single specification. The estimation of the match effects model involves a three-step procedure where β is estimated after transforming (7) into deviations from match-specific means. Results from partitioned regression imply that $\widehat{\beta}$ is a consistent estimate of β. $\widehat{\theta}$ and $\widehat{\psi}$ are computed using the person and firm effects model (without match effects). Finally, the match effect is retrieved as is shown in (11). This match effect can be correlated with the observed covariates, but is assumed to be orthogonal to the person and firm effects. The components of the estimated individual effects (α_i and η) are recovered in a way similar to that explained for the person and firm effects model.

4 Data

The data used in this analysis is the *Quadros de Pessoal* (Lists of Personnel) from Portugal. The *Quadros de Pessoal* is a longitudinal data set with matched information on workers and firms. 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 include all firms (about 200 thousand per year) and employees (about two million per year) within the Portuguese private sector. The analyses in this paper are derived from data collections for each year from 1986 to 2000, with 1990 excluded because the database was not built in that year. Although the survey continues, the data currently available for analysis ends in 2000. 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 information refers to the situation observed in the month when the survey is collected. In some cases, namely information on dates, reported data may refer to dates in the past (*i.e.*, before the data collection month or to previous years) but is limited to the past within the specific firm where the worker is employed. Information on workers includes, for example, gender, age, education level, level of skill, occupation, date of admission in the firm, date of last promotion, monthly wages (split into some of its components) and monthly hours of work. Firm level data include, for example, the industry, location, number of workers, number of establishments, and legal structure.

Some data management was carried out before implementing any analysis. First, we converted the data from a set of time series-cross sections into longitudinal panel data format. Second, to overcome computer memory size limitations, a 10% random sample of workers was selected from the cleaned panel data set. The analysis in this paper is based on the 10% sample drawn from *Quadros de Pessoal* that contains information on 520,222 individuals, which corresponds to 2,522,278 observations over time.

To make the data appropriate for this analysis, some checks and cleaning were carried out. To start with, observations related to employers and to workers for whom we cannot compute seniority at the firm (time since entry to the firm) were deleted, the resulting sample that contains 2,337,617 observations relating to 489,702 workers over time. Furthermore, prior to the construction of groups of connected workers and firms, we removed from the sample workers whose wages were in the first and last percentile of the distribution to eliminate possible outliers that may bias the estimated effects in our wage models. The results of applying the algorithm to group connected workers and firms to the pooled data set are presented in Table 1.[22] This shows that 87% of worker-year observations are connected into a single group (the largest group). The second largest group contains only 157 worker-year observations employed in one single firm. All other observations are dispersed over 60,770 groups.

[Table 1 about here]

Given the degree of connectedness obtained in the largest group, and because we are not able to compare the estimated individual and firm effects across groups of connected workers and firms, we will focus our study solely on the largest group. This group contains 81% of workers and 57% of the firms. We will be able to estimate 476,304 unobserved person and firm effects in total.

In the context of within firm career progress, we analyse the returns to automatic and merit promotions. While for between firm job mobility we analyse the wages associated to entries to a firm that follow short (less than 12 months) and long (one year or more) absences from the data set.[23] The distribution of types of job mobility is presented in Table 2. Almost

[22] These groups of conneceted workers and firms were constructed using the "a2group" module for Stata by Ouazad (2007b).

[23] These gaps can be caused by periods of inactivity of the worker, unemployment, self-employment, or

8% of the observations relate to automatic promotions, and 3% to merit promotions, which corresponds to a promotion rate of 11%. In the analysis period, between firm job mobility is less common than within firm job mobility: 3% of observations relate to entries to firms that occur after long periods of non-employment in the private sector and 1.6% after short periods of non-employment in the private sector.

[Table 2 about here]

Some descriptives of the distribution of real monthly wages, measured in euro, over the period 1986–2000 by each type of job mobility are presented in Table 3.[24] On average, the median monthly wage over the period was 476€ with a median wage increase over two consecutive observations of the same worker of 2%. An analysis of the distribution of wages by event is quite revealing. Workers who received a merit promotion have greater wages than any other worker. After a promotion, either automatic or merit, 25% of the workers receive a wage increase of up to 1%. For these workers career progress may be being compensated by means other than wages, for example, associated prestige (Rosenbaum, 1979) or being shifted to a new and longer pay scale. Among promoted workers, those with merit promotions have the greatest median wage increase of 9%. Workers who entered the firm in the previous 12 months have the lowest wages (regardless of the quartile of the distribution analysed). This can arise either because these workers are not as good as others, or because they enter firms that pay lower wages, or both. We test these hypothesis in detail later. Workers that were not registered as employees for twelve months or more have the lowest wages. Separations from firms and reentry to another firm is associated with a wage loss, which is consistent with theories about depreciation of human capital or loss of firm specific human capital, but also with search models that suggest that workers pick the best offers first. 25% of the workers experience a wage loss of at least 8% (11%) in the case of separation followed by short (long) term periods of non-employment in the private sector. For the upper quartiles groups of the

employment in the public sector. Although absences from our datatset can be due to labour market status's different from unemployment, the choice of the 12 month threshold is related to the distinction of unemployment spells officially made in Portugal. Workers are short (long) term unemployed if they are in that employment status for less (more) than one year. For more details in the definition of the types of job mobility see Ferreira (2009).

[24] The base year is 2000.

distribution, the wage growth of workers who have entered the firm within the last year can be considerable. However, given that we are not necessarily analysing two consecutive years, but two consecutive observations for the worker, such growth could be attributable to growth in real wages. Another possible explanation for above average wage growth for these workers is that we are using monthly wages, and workers that change firm may also change their hours of work. Our multivariate analysis controls for these (and other) factors.

In the remainder of the paper, we investigate whether these returns to job mobility hold after allowing for worker and firm characteristics. However, it is well documented in the empirical literature that observable characteristics of workers and firms fail to explain a large proportion (70%) of the variation in wages (Mortensen, 2003). Our empirical strategy allows the identification of worker, firm and match unobserved effects. This has three implications. First, we obtain more precise estimates of the parameters as fewer variables are omitted from our model. Second, we are able to account for a larger proportion of the variation in wages. Third, we can summarize the distribution of each of these effects by type of job mobility and compare their contributions with the total variance of wages. This provides information on the importance of each unobserved effect in explaining the variation in wages associated with each of the different events.

[Table 3 about here]

5 Results

In the sections that follow, we present the results obtained after estimating the models using the techniques discussed previously. In all specifications it is assumed that the parameters associated with the observable characteristics do not vary across mobility groups.[25] Therefore, the only difference we observe is in the intercept terms. All specifications include observed characteristics of workers and firms. The vector of observable characteristics of workers includes gender, education split into four categories (up to ISCED 1, ISCED 2, ISCED 3, ISCED 5/6), skill level split into 3 categories (low, medium, high), occupation (9 categories), scheme

[25] Flinn (1986) finds evidence that they do not. But even if they do, our main objective is not to interpret the effects of each observed covariate but to analyse the importance of unobserved effects in explaining the variation in wages for each type of job mobility.

of work (full time, part time, other), years of seniority at the firm and its square, years of potential labour market experience and its square, monthly hours of work and its square, type of job mobility (automatic or merit promotion, entries to firms after small or big gap of non-employment, and no mobility), and gap length measured in years (to account for the time the worker has been away from the data set). The vector of firm observable covariates is composed of size of firm (micro, small, medium or large), legal structure of the firm (public firm - ruled by private sector laws, sole proprietor, anonymous partnership, limited liability company, and other), type of instrument of collective regulation (4 categories), region (20 categories), and industry (18 categories). One categorical variable was introduced to account for unobserved time effects (14 year dummies). Overall, the specification includes 88 observed covariates whose parameters are to be estimated. Descriptive statistics of these variables are displayed in Table 4.

[Table 4 about here]

5.1 Standard estimation techniques

Estimates obtained from standard regression techniques are shown in Table 5, and are split according to the estimation method (OLS, random effects, and within groups), and to the level at which unobserved heterogeneity is considered (firm, worker, or firm-worker match). The first 3 columns contain the estimates obtained while controlling for firm unobserved effects. The next 2 columns control for unobserved worker heterogeneity, and the last 2 columns control for worker-firm (spell) fixed effects.

Results vary not only with the estimation method but also with the level at which we control for unobserved heterogeneity. In the case of the returns to promotions, the specifications that yield similar estimates are those derived from the model that controls for unobserved person and the model that controls for match effects. In the case of the returns to workers' movements between firms, estimates are closest in value for the specifications that control for firm and match effects. We will interpret only the results obtained for the within match (worker-firm) fixed effects model (the consistent method).

These estimates indicate that there is a wage premium for within-firm job mobility. Merit promotions are the event that results in highest wage growth (3%). Workers that receive an automatic promotion have, on average, a wage increase of 2%. On the other hand, between-firm job mobility seems to have no associated wage premium. Table 5 also reveals that once we control for unobserved heterogeneity the wage variation explained by observables is reduced (compared to the pooled OLS model). We explain less than 55% of the variation in monthly real wages using standard panel data methods.

If there are no payoffs associated with types of between-firm job mobility, the question arises of what drives external job mobility. Some possible explanations include: (i) workers are moving into firms that offer higher wages; or (ii) moving into firms that offer the same wage level but higher wage dispersion, hence the possibility of higher wage growth; or (iii) workers may be sorting into firms in which the value of the match is higher. In each case, the premia are not captured by observed heterogeneity of workers and firms, but instead by unobservable factors. To better understand the relative importance of the unobserved factors we estimate the person and firm effects model, and the match effects model. The former allows identification of the unobserved worker and firm effects; the latter provides further insight on the effect of the interaction of workers and firms. The results are discussed in the following sections.

[Table 5 about here]

5.2 Person and firm effects model

This section presents and discusses the results from the person and firm fixed effects model.[26] In this model, worker effects capture worker time invariant characteristics (*e.g.* ability) that affect his wages in the same way in any firm, it is an unchangeable portable component of compensation. Firm effects capture all fixed characteristics of firms that affect all of its workers in the same way. Table 6 displays the estimated coefficients for the main time varying covariates of interest.[27] Similar to the results obtained from standard estimation techniques, promotions

[26] All variables were included in deviations from their grand means, therefore the coefficients are proportionate differences in wages between a worker in a given economy and the average worker in the economy.

[27] We performed F tests that compare the person and firm (two-way) fixed effects model to one-way models and to a model without any of these two effects. The null hypothesis of the F test is that the coefficients associated to the variable of interest are jointly zero. This hypothesis is rejected in all of the three tests performed. That is, we reject that either the worker fixed effects or the firm fixed effects are jointly zero (F statistics of 5.35 and 4.59, respectively), we also reject the hypothesis that both the person and the firm effects

within firms are associated with greatest wage growth. Workers with merit promotions experience a wage increase of about 1.3% and automatically promoted workers get a wage increase of 1.1%. Mobility between firms is associated to a small negative penalty. Workers that have entered a firm within one year of separating from the previous firm have their wages reduced by about 0.4%. Workers who take one year or more to enter a new firm experience a similar loss in real wages. However this is intensified by the penalty associated to the length of non-employment (gap). If these workers take longer than two years to find a new job their wage reduction will be greater than 1% ($-0.008 + 2 \times (-0.003) = -0.014$). After controlling for firm and worker unobserved heterogeneity, the effects of seniority with the current employer 0.007 per year. This means that a worker who remains with his current employer for 10 years would have a wage 7% higher than that of a worker that has just entered a firm. However, potential experience in the labour market seems to be better rewarded than seniority with the current employer. The wages of workers with 10 years of experience are 15% higher. Part time work, education and skill level are also important factors explaining differences in wages. The wages of part time workers are, on average, 29% lower than the wages of an average worker in the economy. If we focus on levels of skill, all else being equal, the wages of high skilled workers are, on average, 6% larger than those of the economy wide average worker, while low skilled workers have a wage penalty of 5% when compared to that same reference individual. Wages also increase with education level. Workers in micro and small firms experience wage penalties (up to 5%) while those in medium and large firms receive wage a premium (up to 4%) relative to an economy wide average worker.

[Table 6 about here]

We can use the person and firm effects model to identify the contribution of different components to the variance in wages. These components are: (i) the time varying covariates ($X\beta$); (ii) the worker fixed effects (θ) which were decomposed according to equation (3) into the effects of time invariant covariates (η) and the pure individual unobserved heterogeneity (α); and (iii) the firm fixed effects (ψ). Table 7 presents descriptive statistics for each of these components

are simultaneously jointly zero (F statistic of 8.18). Note that we do not compute standard errors because of difficulties in the inversion of matrix (5).

by type of job mobility. Note that although we consider four types of job mobility in our specification − automatic and merit promotions, entries to firm after small and big gaps of non-employment − because both the worker and the firm effects are time-invariant we can also analyse their distribution in the firms from which the workers departed. This is the information contained in the last two columns of Table 7.

For all types of job mobility the standard deviations of person and firm effects are, in general, higher than the ones related to the observable time varying characteristics. This means that the dispersion in the returns to unobserved characteristics is greater than the dispersion in the returns to observed characteristics of workers and firms. That is, unobserved effects induce more variability in wages than observed covariates. If we consider the entire economy, for example, log wages are 0.32 higher for workers whose person-specific time invariant effect is one standard deviation above the mean. Similarly, log wages are 0.27 higher for workers in firms whose specific effect are one standard deviation above the mean.

It is informative to analyse how the average unobserved effects differ between types of job mobility. As mentioned previously the mean worker effect within the mobility group was set to zero for identification purposes. The average firm effect (wage difference) is not subject to such constraint and is estimated to be –0.09, hence a high (low) wage firm is one for which its estimated effect is above (below) –0.9. Regardless of whether we are considering the total worker time invariant fixed effect (θ) or the pure unobserved heterogeneity (α), promoted workers have above average fixed effects. For example, if we consider the pure unobserved heterogeneity of workers ($\widehat{\alpha}$), the average for promoted workers is 0.01. Furthermore, promoted workers are located in firms with above average unobserved heterogeneity. The average unobserved firm effect is 0.05 log points higher for the group of promoted workers. That is, promoted workers will receive above average wages regardless of the firm in which they are employed, and are employed in firms that pay above average wages.

In contrast, workers that move between firms have below average individual portable components of compensation. That is, they are inherently lower wage workers. Furthermore, these workers select themselves into lower wage firms, with average effect of –0.13 and –0.17 for entries after small and long periods of non-employment, respectively, compared to the average firm effect of –0.09 for the economy. However, workers who separate from a firm and enter a new one within the next 12 months move into firms whose specific effects are, on average, greater than those of the firms from which they separate. These workers move from firms that have an average unobserved effect of –0.17 to firms with an average effect of –0.13. Therefore, these workers gain by sorting themselves into higher wage firms. This could signal on-the-job search and worker-initiated separations, in which case workers are able to search and receive offers from better firms.

The same does not happen for separations that involve long gaps of non-employment. In this case, the average effect of the firms from which workers separate is similar to the average firm effect after entry (–0.17). These results are in line with Salop (1973) who develops a model where workers searching for a job sample the most attractive opportunities first and lower their acceptance wage with their duration in unemployment. These workers do not move to firms with a lower wage (as the observed wage change associated to entries to firms is almost zero) but they do seem to lower the threshold in the unobserved quality of the firm.

[Table 7 about here]

We are also interested in identifying how much of the variation in wages is explained by our model, and the relative importance of each of the components of the model in driving wage variability across workers. That is, how much wage variation is accounted not only by the observed characteristics but also by the unobserved worker and firm effects, and how this varies across mobility type. We can use the person and firm effects model to compute a proportional decomposition of the variance in wages as follows:

$$\frac{Cov(y, x\widehat{\beta})}{Var(y)} + \frac{Cov(y, \widehat{\theta})}{Var(y)} + \frac{Cov(y, \widehat{\psi})}{Var(y)} + \frac{Cov(y, \epsilon)}{Var(y)} = \frac{Var(y)}{Var(y)} = 1. \tag{12}$$

The results of this decomposition are presented in Table 8. The variance in log real wages is smaller for workers that have entered the firm within the last year (0.24 and 0.20, for entry to firms after short and long gaps of non-employment, respectively) and larger for promoted workers (0.32 and 0.30, for merit and automatic promotions, respectively). This suggests a greater degree of homogeneity in wages of workers that change firms than of workers that are promoted within firms. Overall, less than 27% of the variation in log real wages is explained by time varying covariates and more than 60% is accounted by worker and firm unobserved heterogeneity. Time varying covariates are relatively more important in explaining wages of workers entering firms (27%) and less so in explaining wages among promoted workers (22%). On the other hand, the unobserved effects of workers and firms are relatively more important in explaining wages of promoted workers than those of workers who have separated from firms and are now entering into new firms. In particular, the effect of the pure unobserved heterogeneity effect of workers ($\widehat{\alpha}$) accounts for 35% of the variation of wages of workers that received a merit promotion and only 25% of the variation in wages of workers who took twelve months or more to enter a new firm. Firm effects follow a different pattern and have similar importance in determining the variation in wages of within and between-firm mobility (31%).

Characteristics of workers and firms account for about 93% of the variation of log real monthly wages for the economy as a whole and for promoted workers, and more than 89% of the variation in wages of workers that have entered firms.

[Table 8 about here]

An advantage of the person and firm effects model is that it allows arbitrary correlation between the unobserved worker and firm effects and the observed time varying characteristics. To identify the nature of these correlations, we compute pair-wise correlations among the components of the wage equation. The results obtained when we consider all workers are shown in Table 9. The pure unobserved person effects and time varying covariates are most highly correlated with real monthly wages (correlations of 0.61 and 0.59, respectively), although the firm effects also have a high linear association with real wages (0.56). These correlations are slightly higher than those reported by Abowd *et al.* (2003) using French data. The person and firm effects are positively correlated with the time varying covariates (0.14 and 0.15, respectively). Therefore estimates that do not take into consideration these effects will suffer from omitted variable bias.[28] Although the unobserved effects are almost uncorrelated with each other (–0.05), the negative correlation suggests that on average low wage workers sort themselves into high wage firms.[29]

[28] AKM (1999) derive the biases that can occur when either person or firm effects are excluded from the specification.

[29] Note that were we to remove micro-firms from the analysis, the correlation between unobserved person and firm effects would have been 0.01. This result would be similar to those obtained in the order-dependent persons

[Table 9 about here]

We then check if these correlations vary according to type of job mobility. Selected results are shown in Table 10 from which we will just highlight differences from the results obtained for the entire sample (Table 9). Regardless of the type of promotion, the time varying covariates and the unobserved worker and firm effects are very highly correlated with the dependent variable (correlation coefficient larger than 0.6). For promoted workers the unobserved effects are also more strongly associated with the observable characteristics, than for workers that have changed firms. Although still relatively weak, the correlation between unobserved worker and firm effects is greater for promoted workers (0.10).[30] Therefore positive assortative matching is more evident for promoted workers. In the case of entries to firms, the correlation between the firm and worker fixed effects is particularly important, especially when compared to that obtained using the data from the firms from which workers have separated. The strength of association between the unobserved worker and firm effects is strongest for workers that move between firms and is above –0.16. For workers who experience short periods of non-employment, the strength of the correlation between worker and firm effects is reduced from –0.19 to –0.16. However, this correlation becomes more negative for workers that have been in non-employment for more than one year (from –0.24 to –0.29).[31]

If we consider the implications from McLaughlin's (1991) model, in which quits separate to higher-paying jobs and layoffs to lower-paying jobs, our results suggest that workers who find a new job within one year are more likely to have been quits, and workers who take a year or more to enter a new firm are more likely to have been layoffs.[32]

[Table 10 about here]

first estimates of AKM (1999) and to those obtained by Abowd, Lengermann and McKinney (2003). Abowd, Finer and Kramarz (1999) find no correlation between these effects and Abowd Kramarz, Lengermann and Pérez-Duarte (2004) find that these correlations are zero for the U.S.A. and negative for France. The authors argue that the weakness in the correlation is not caused by estimation biases resulting from lack of mobility in the data (as suggested, for example, by Andrews et al. 2006b)

[30] These results are similar in magnitude to those obtained in the order-independent estimates of AKM (1999) and those of Maré and Hyslop (2006).

[31] Negative correlations between person and firm effects are also found in Abowd, Creecy and Kramarz (2002) and Woodcock (2007).

[32] If micro firms are excluded from this analysis the strength of correlation between the unobserved person and firm effects is larger for promoted workers and smaller for workers who change firms. However, the signs and relationships remain unchanged.

Additionally, we tested the assumption that the unobserved effects are correlated with the covariates. The person and firm effects model is justified in this case as we are able to identify that the unobserved effects are not only correlated with the covariates, but for some groups of workers are also correlated with themselves. Therefore omitting these effects from the analysis would have resulted in biased estimates. Furthermore, using the person and firm effects model we are able to account for 93% of the variation in wages of promoted workers and more than 89% of the variation in wages of workers that entered firms. Despite this, however, the question remains of why this model is more able to explain wages for promotions than entries into firm, where 9-11% of the variation in wages is accounted by the idiosyncratic error. One possibility is that wages of workers who change firms are explained by the other unobserved component of the error term, the match effect.

5.3 Match effects model

The person and firm effects specification explains the variation in wages of workers who have experienced between-firm job mobility to a lesser extent than it does for those experiencing within-firm job mobility. If promoted workers are already in firms with which they match well and workers that change firms are seeking a better match, then this difference can be understood in terms of job matching models. These models predict that as a cohort of labor market entrants ages, the proportion of wage variability attributable to worker-firm (match) heterogeneity will decline as individuals sort into acceptable matches (Flinn, 1986; Jovanovic, 1979). In this section, we discuss the results obtained from estimating the match effects model and compare them to those obtained from the person and firm effects model.

Descriptive statistics of the components of wages estimated from the match effects model are presented in Table 11. Overall, the statistics related to each component of the wage equation only differ slightly from those obtained from the person and firm effects model (in Table 7), and the relationships between these components remain the same. Therefore, we will concentrate on the results related to the match fixed effects. The average match fixed effect for promoted workers is the same (0.001) for workers that received automatic and merit promotions. The standard deviations of the average match effects of within-firm job mobility types are very small

(0.05), indicating that match effects account for little variation in wages of promoted workers and signals that these workers are allocated into good matches.

Workers who have changed firms have negative match fixed effect, this is –0.003 and –0.024 for workers that have entered a firm after a short/long gaps (respectively) of nonemployment. Match effects induce more variability in the wages of workers who have changed firms, for whom standard deviations of the match are greater than 0.12. According to matching models, this indicates that such workers are still in the process of sorting themselves into good matches. Furthermore, workers that enter a new firm within a short period have improved their match quality. They departed from firms in which the average match effect was –0.015 to enter firms in which the average match effect is very close to the average match effect observed in the economy (–0.003). But workers who take a year or more to find a new job reduce their match quality by separating from firms in which the average match effect was -0.006 and entering firms in which the average match value was -0.024.

Given these results, we conclude that promoted workers are high wage workers (with an above average worker effect), working in high wage firms (with an above average firm effects) with which they form a good match. The group of between-firm job movers is not so homogeneous. Workers entering firms within short periods of time after separating from the previous firm fare somewhat better than workers who experience long periods of non-employment. For the former group of workers changing firms results in an improvement not only in the unobserved effects of the firm, but also in the match quality, and for the latter results in a deterioration in both effects.

[Table 11 about here]

We next analyse the relative importance of each of the components in explaining the variance in log real monthly wages. In the matching model the proportional decomposition of the variance in log monthly real wages is computed as follows:

$$\frac{Cov(y,x\widehat{\beta})}{Var(y)}+\frac{Cov(y,\widehat{\theta})}{Var(y)}+\frac{Cov(y,\widehat{\psi})}{Var(y)}+\frac{Cov(y,\widehat{\gamma})}{Var(y)}+\frac{Cov(y,\epsilon)}{Var(y)}=\frac{Var(y)}{Var(y)}=1. \qquad (13)$$

The results from this decomposition are presented in Table 12, and suggest that the person and firm effects model overestimates the share of the dispersion in wages explained by time varying observed covariates, and underestimates the share of variance accounted by the unobserved person and firm effects (see Table 8). For example, if we compare the results obtained for the entire economy, the person and firm effects model attributes 25% of the variance in wages to time varying covariates, and 35% and 28% to the unobserved worker and firm effects, respectively. The match effects model attributes 21% of the variability in wages to time varying covariates and 36% and 29% to person and firm unobserved effects. Despite the relative importance of each of these components being similar in the match effects and the person and firm effects models, it is noticeable that match effects affect the variation of wages of workers who have changed firms more than those of promoted workers. Match effects account for less than 2% of the dispersion in wages of promoted workers and for at least 6% of the variation in wages of workers who enter a new firm.

Once we control for match effects only a small proportion of the variance in wages is left unexplained for any type of job mobility. We are now able to account for 94% of the variation of wages of promoted workers, and 96% of the variation in wages of workers that move between firms. Therefore, the introduction of the unobserved match effects is the determinant factor in the improvement in the power of the model to explain the wages associated to between-firm job mobility.

[Table 12 about here]

One of the reasons for implementing the match effects specification is to extract the quality of the worker-firm match from the error term of the person and firm effects model. If the quality of the match is not zero and is correlated with the components of the wage regression, then estimates from the person and firm effects model are biased because the assumption of exogenous mobility is violated. Our final contribution is to investigate this by analysing the correlations between the components of the wage equation. These are shown in Table 13. Given that the match effects are, by assumption, orthogonal to the person and firm effects they do not affect the correlations of the person (θ) and firm (ψ) effects with the dependent variable or with themselves. However, unobserved match effects are allowed to be freely correlated with the time varying covariates and therefore will affect any cross correlation with this component

($x\beta$).

Comparing the results obtained from the match effects specification (Table 13) to those obtained with the person and firm effects model (Table 9), the observed characteristics are now less correlated to wages although this correlation is still very strong (0.52). However, the match effects are correlated with wages (0.2) and also with the observed time varying covariates (0.05). This may cause the reduction in the cross correlation of observed covariates and wages and in the variation in wages explained by the covariates in the matching model. That is, part of the explanatory power attributed to the observed covariates in the person and firm effects model was in fact reflecting the influence of the unobserved match quality which, by being incorporated in the residual, was wrongly assumed to be orthogonal to the observed covariates.

[Table 13 about here]

The pattern is very similar when we analyse the cross correlations by type of job mobility (see Table 14). In general, the degree of association between wages and time varying covariates is reduced, and the match effects are positively correlated with wages and with the observed covariates. Match effects are more strongly correlated with the wages of workers that have entered a new firm (correlations above 0.25) than with the wages of promoted workers (correlations of at most 0.14). This is consistent with the results obtained in the decomposition of the variance of wages.

[Table 14 about here]

If we consider the assumption of orthogonality of the unobserved match effects with the unobserved person and firm effects realistic, the match effects model is a helpful tool to further explain wage dispersion, and in particular that of wages of workers who move between firms. This model raises the explanatory power of our parameterization as we are able to account for more than 94% of wage dispersion for all types of job mobility.

6 Summary and conclusions

This paper has analysed the importance of observed and unobserved characteristics of workers and firms in explaining the returns to promotions and separations from firms. In so doing we extended the existing literature in a few number of ways. First, we computed the returns to within firm job mobility and between firm job mobility within the same setting, which makes comparison of the outcomes across types of job mobility possible. Second, the parameterizations controlled for characteristics of workers and firms, the latter are usually are not considered due to lack of available data on the demand side of the labour market. Third, we estimated the components of unobserved heterogeneity of workers and firms within a fixed-effects context, and compared their distributions by type of job mobility. Last, although using more restrictive assumptions, we have also estimated the effect due to the unobserved quality of the match and analyse its importance in explaining wages and its distribution across types of job mobility.

Such an analysis requires a combination of factors namely availability of appropriate data and econometric techniques. As well as containing information on workers and firms the data have to be linked in such a way that it is possible to relate workers to firms, and contain sufficient mobility of workers between firms to permit the creation of groups of connected workers and firms. The data used in this study, Quadros de Pessoal, has such characteristics. Furthermore, the recent development of econometric techniques that allow the estimation of all effects while coping with the problem of the high dimensionality of factors has made this analysis feasible.

The use of models that control for and estimate unobserved effects allows us to obtain more precise estimates of the parameters of interest and raises the explanatory power of the econometric specification. The person and firm effects model explains a greater proportion of the variation in wages of promoted workers than it does for workers who have moved between firms (89%). However, although under some more restrictive assumptions, the matching model explains more than 94% of the variation in wages of every type of job mobility. Results show that unobserved worker and firm heterogeneity are the main determinants of wage dispersion, observable time varying covariates are the third most important factor. Unobserved match quality makes a small contribution when compared to that made by the firm and worker effects, and is more important in explaining the dispersion of wages of workers who enter firms.

Despite finding little difference between automatic and merit promotions, we identify observed wage premiums to promotions generally and establish that promoted workers are high wage workers employed in high wage firms with which they match well. Differences appear for workers that have separated from firms. Although either type of separations (preceded by short or long gap of nonemployment) has a small negative observable associated return, the groups of workers experiencing each are different with respect to the behaviour of their unobserved effects. Workers that enter a new firm within one year from separation are improving their position by moving to higher paying firms with which they match better. Workers that enter a new firm more than one year from separation have the worst outcomes: they move to lower paying firms with which they match worse. These differences suggest that these separations are driven by two distinct processes. Workers that find a new job within one year are more likely to have been quits, whereas those that take more than 12 months to do so are more likely to have been laid off from firms.

Several issues in the context of search and job matching have not been treated here. For example, some theoretical models rely on the intensity with which workers search for alternative employment, which will determine the rate at which new job offers arrive (Jovanovic, 1979b). One question arising in this context is related to the empirical relevance of match quality in determining search intensity of workers and firms. Also, although we were able to characterize the situation of workers that have moved between firms, a natural question to ask is how do firms from which workers separate evolve? Jovanovic (1984) suggests a change in welfare after movements from job-to-job and in-and-out of employment, and that these movements reflect changes in the perceived value of market opportunities. While it may be easier to measure changes in nonmarket opportunities (through *e.g.*, family formation), can we understand the nature of changes in market opportunities, measure them and relate them to mobility decisions and compensation outcomes? These are questions that follow naturally from this work. Answers to some of these questions are possible using information currently available in matched employer-employee data sets. However, due to the way most of these data are collected (and to the costs involved), it is unlikely that the information necessary to answer some other questions will become available. But we may resort to the use of longitudinal data on workers or firms and explore possibilities of, *e.g.*, proxying match quality to make some progress in this topic.

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Tables

Table 1: Results of applying the grouping algorithm to the pooled dataset

	Largest group	%	2^{nd} largest group		All other groups	%	Total of all groups
Observations (i, t)	1,823,572	86.72	157	0.01	279,182	13.28	2,102,911
Persons (i)	377,866	80.79	22	0	89,797	19.20	467,685
Firms (j)	98,438	56.92	1	0	74,492	43.08	172,931
Groups (G)	1		1		60,770		60,772
Identified effects	476,304	82.14	22	0	103,519	17.85	579,844

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

Table 2: Distribution of types of job mobility

	Frequency	Percentage
Promotions:		
Automatic	139,450	7.65
Merit	53,475	2.93
Entry to firm after:		
Small gap	28,292	1.55
Big gap	56,845	3.12
No mobility	1,545,510	84.75
Total	1,823,572	100

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

Table 3: Distribution of wages, by type of job mobility

	Wage_t				Wage_{t-s}				$\%\Delta\text{Wage}_{(t-s,t)}$			
	P25	P50	P75	N	P25	P50	P75	N	P25	P50	P75	N
All	361.52	475.57	703.05	1,823,572	352.73	471.65	700.47	1,461,551	–2.44	2.38	11.35	1,410,525
Promotions:												
Automatic	374.46	521.87	867.97	139,450	345.81	488.34	806.19	130,180	0.24	6.33	16.11	126,662
Merit	382.28	523.53	863.54	53,475	328.62	460.32	764.19	53,475	1.40	9.24	22.96	51,607
Entry to firm after:												
Small gap	343.21	432.08	583.66	28,292	321.83	401.54	529.88	28,292	–7.99	6.65	31.44	28,246
Big gap	331.99	411.97	525.72	56,845	297.17	367.97	478.00	56,845	–10.87	10.94	43.80	56,622

Note: These are real wages in euro (base year 2000). P25, P50 and P75 mean percentile 25, 50 and 75 of the wage distribution. N is the number of observations for which we were able to compute these statistics. Small and big gap refers to the length of the non-employment in these job-to-job transitions. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 4: Descriptive statistics of variables

Variable	Mean	Variable	Mean
Log monthly real wage	6.3	Size of firm	
Seniority (years)	8.7	Micro	9.2
Experience (years)	22.2	Small	25.0
Hours of work (monthly)	170	Medium	29.2
Length of gap in years	0.15	Large	36.6
Gender		Legal structure of firm	
Men	61.7	Public (Private market law)	4.8
Women	38.4	Sole proprietor	5.3
Education		Anonymous partnership	29.0
ISCED 1	71.6	Limited liability company	55.2
ISCED 2	11.3	Instrument of collective regulation	
ISCED 3	12.6	Collective agreement	4.0
ISCED 5/6	4.6	Collective contract	82.7
Occupation		Regulating law	3.8
Directors	1.7	Firm agreement	8.7
Intellectual and scientific specialists	2.0		
Professional, technical (intermediate)	8.3	Percentage of foreign capital	9.1
Administrative and managerial workers	14.1	Industry	18 SIC codes
Clerical and sales workers	8.5	Region	20 Districts
Agriculture, silviculture and fishing	1.3	Years	1986-2000
Production and related workers	26.0		
Equipment operators and labourers	13.9		
Unqualified workers	18.0		
Skill Level			
High	18.4		
Medium	43.5		
Low	38.1		
Type of work			
Full time	91.5		
Part time	8.4		
Job mobility type			
Automatic promotion	7.7		
Merit promotion	2.9		
Separation, small gap	1.6		
Separation, big gap	3.1		

Note: These statistics are computed over the sample of 1,823,572 worker-year observations used in the analysis. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 5: Estimates of the effect of job mobility on wages - Standard techniques

	Firm level			Worker level		Firm-worker level	
	OLS	RE	WG	RE	WG	RE	WG
Promotion:							
Automatic	0.020	0.015	0.015	0.024	0.024	0.023	0.023
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Merit	0.018	0.011	0.011	0.021	0.025	0.022	0.029
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry to firm after:							
Small gap	0.041	0.024	0.017	0.033	0.032	0.017	–0.003
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Big gap	0.017	0.010	0.007	0.014	0.012	0.010	0.003†
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Gap length	–0.006	–0.004	–0.004	–0.005	–0.006	–0.003	–0.000†
	(0.0004)	(0.0003)	0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
No. of obs.		1,823,572		1,823,572		1,823,572	
No. of clusters		98,438		377,866		589,826	
R^2	0.714	0.550	0.552	0.462	0.472	0.410	0.430

Note: The base category for the mobility variable is "no mobility". Results from the OLS model are not reported for the specifications controlling for worker and match effects as we are only correcting standard errors for different levels of clustering. Standard errors in parentheses. Coefficients are generally significant at the 1% level of significance, except those marked with † which are not significant at any conventional level of significance.
Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 6: Person and firm effects model: estimated coefficients

$Y = ln$(real monthly wage)	Coefficient
Automatic promotion	0.011
Merit promotion	0.013
Entry, small gap	–0.004
Entry, big gap	–0.008
No mobility	–0.012
Gap (in years)	–0.003
Seniority	0.007
Seniority^2	–0.016
Experience	0.015
Experience^2	–0.033
Hours of work	0.011
Hours of work^2	–0.000
High skilled	0.055
Medium skilled	–0.007
Low skilled	–0.048
ISCED 1	–0.090
ISCED 2	–0.060
ISCED 3	–0.010
ISCED 5/6	0.160
Part-time work	–0.292
Micro firm	–0.050
Small firm	–0.012
Medium firm	0.017
Large firm	0.036
Constant	0.355

Note: All variables are in deviations from their grand means. Controls for occupation, legal structure of the firm, instrument of collective regulation, percentage of foreign capital, industry, region, and year are included. Standard errors are not estimated due to problems in inverting matrix (5). Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 7: Person and firm effects model: descriptive statistics for estimated components of log real wages

	All		Promotions				Entry after				Separation followed by			
	Observations		Automatic		Merit		Small gap		Big gap		Small gap		Big gap	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(real monthly wage)	0	0.526	0.109	0.562	0.125	0.550	–0.099	0.492	–0.175	0.442	–0.186	0.478	–0.293	0.450
Time varying cov. ($\widehat{x\beta}$)	–0.262	0.221	–0.211	0.210	–0.202	0.194	–0.264	0.213	–0.274	0.200	–0.304	0.225	–0.393	0.214
Worker fixed effect ($\widehat{\theta}$)	0	0.317	0.007	0.304	0.016	0.310	–0.061	0.283	–0.082	0.267	–0.061	0.283	–0.082	0.267
Time invariant cov. ($\widehat{\eta}$)	0	0.104	–0.004	0.105	0.004	0.103	0.003	0.103	0.004	0.103	0.003	0.103	0.004	0.103
Unobs. heterogeneity ($\widehat{\alpha}$)	0	0.300	0.011	0.287	0.011	0.295	–0.064	0.270	–0.086	0.253	–0.064	0.270	–0.086	0.253
Firm fixed effect ($\widehat{\psi}$)	–0.093	0.265	–0.042	0.275	–0.043	0.266	–0.129	0.286	–0.174	0.278	–0.167	0.255	–0.172	0.252
No. of observations	1,823,572		139,450		53,475		28,292		56,845		28,292		56,845	

Note: the variables are in deviations from their grand means. SD stands for standard deviations. Small and big gap stand for the length of non-employment when workers move between firms. t-tests on the equality of the mean firm-effects for entries into firms and separations from firms do not reject the hypothesis that these are statistically different from each other at conventional levels of significance. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 8: Person and firm effects model: proportional decomposition of variance in log real wages

	All	Promotions		Entry after	
	Observations	Automatic	Merit	Small gap	Big gap
Variance of ln(real monthly wage) [$Var(y)$]	0.276	0.316	0.303	0.242	0.196
Proportion of $Var(y)$ explained by:					
Time varying covariates $\left(\frac{Cov(y,\widehat{x\beta})}{Var(y)}\right)$	0.245	0.228	0.217	0.269	0.270
Worker fixed effect $\left(\frac{Cov(y,\widehat{\theta})}{Var(y)}\right)$	0.397	0.371	0.402	0.317	0.302
Time invariant covariates $\left(\frac{Cov(y,\widehat{\mu\eta})}{Var(y)}\right)$	0.051	0.050	0.047	0.043	0.054
Unobserved heterogeneity $\left(\frac{Cov(y,\widehat{\alpha})}{Var(y)}\right)$	0.346	0.321	0.354	0.274	0.248
Firm fixed effect $\left(\frac{Cov(y,\widehat{\psi})}{Var(y)}\right)$	0.280	0.323	0.315	0.323	0.314
Residual $\left(\frac{Cov(y,\epsilon)}{Var(y)}\right)$	0.078	0.069	0.067	0.091	0.114
Total	1	1	1	1	1
% Explained by the model:	92.2	93.1	93.3	90.9	88.6

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

Table 9: Person and firm effects model: correlation between log real wage components

	y	$\widehat{x\beta}$	$\widehat{\theta}$	$\widehat{\alpha}$	$\widehat{\mu\eta}$	$\widehat{\psi}$	ϵ
y	1						
$\widehat{x\beta}$	0.593	1					
$\widehat{\theta}$	0.657	0.146	1				
$\widehat{\alpha}$	0.607	0.144	0.945	1			
$\widehat{\mu\eta}$	0.255	0.031	0.329	0	1		
$\widehat{\psi}$	0.556	0.147	–0.016	–0.047	0.087	1	
ϵ	0.279	0	0	0	0	0	1

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

Table 10: Person and firm effects model: selected correlations between log real wage components, by type of job mobility

	Promotions:							
	Automatic				Merit			
	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$
y	1				1			
$x\widehat{\beta}$	0.610	1			0.616	1		
$\widehat{\alpha}$	0.629	0.175	1		0.662	0.241	1	
$\widehat{\psi}$	0.680	0.278	0.100	1	0.652	0.276	0.099	1
	Entry after:							
	Small gap				Big gap			
	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$
y	1				1			
$x\widehat{\beta}$	0.622	1			0.598	1		
$\widehat{\alpha}$	0.500	0.151	1		0.432	0.138	1	
$\widehat{\psi}$	0.557	0.170	–0.164	1	0.499	0.092	–0.286	1
	Separation followed by:							
	Small gap				Big gap			
	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	y	$x\widehat{\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$
y	1				1			
$x\widehat{\beta}$	0.643	1			0.624	1		
$\widehat{\alpha}$	0.514	0.149	1		0.472	0.149	1	
$\widehat{\psi}$	0.488	0.150	–0.187	1	0.474	0.108	–0.243	1

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

Table 11: Match effects model: descriptive statistics for estimated components of log real wages

	All Observations		Promotions				Entry after				Separation followed by			
			Automatic		Merit		Small gap		Big gap		Small gap		Big gap	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(real monthly wage)	0	0.526	0.109	0.562	0.125	0.550	–0.099	0.492	–0.175	0.442	–0.186	0.478	–0.293	0.045
Time varying cov. ($x\widehat{\beta}$)	–0.260	0.213	–0.213	0.200	–0.204	0.182	–0.255	0.206	–0.241	0.194	–0.291	0.217	–0.381	0.206
Worker fixed effect ($\widehat{\theta}$)	0	0.332	0.007	0.318	0.016	0.325	–0.064	0.297	–0.085	0.280	–0.064	0.297	–0.085	0.280
Time invariant cov. ($\mu_i\widehat{\eta}$)	0	0.109	–0.004	0.110	0.005	0.108	0.004	0.108	0.004	0.108	0.004	0.108	0.004	0.108
Unob. heterogeneity ($\widehat{\alpha}$)	0	0.314	0.011	0.301	0.012	0.309	–0.067	0.283	–0.090	0.265	–0.067	0.283	–0.090	0.265
Firm fixed effect ($\widehat{\psi}$)	–0.096	0.275	–0.043	0.286	–0.045	0.276	–0.133	0.297	–0.181	0.289	–0.173	0.264	–0.178	0.262
Match fixed effect ($\widehat{\gamma}$)	0	0.069	0.001	0.054	0.001	0.048	–0.003	0.118	–0.024	0.125	–0.015	0.124	–0.006	0.133

Note: t-tests on the equality of the mean firm- and match-effects for entries into firms and separations from firms do not reject the hypothesis that these are statistically different from each other at conventional levels of significance. See also notes for Table 7. Source: Own calculations based on Quadros de Pessoal (1986-2000).

Table 12: Match effects model: proportional decomposition of variance in log real wages

	All	Promotions		Entry after	
	Obs.	Automatic	Merit	Small gap	Big gap
Variance of ln (real monthly wage)[$Var(y)$]	0.276	0.316	0.303	0.242	0.196
Proportion of $Var(y)$ explained by:					
Time varying covariates $\left(\frac{Cov(y,\widehat{x\beta})}{Var(y)}\right)$	0.210	0.193	0.178	0.242	0.246
Worker fixed effect $\left(\frac{Cov(y,\widehat{\theta})}{Var(y)}\right)$	0.416	0.389	0.421	0.332	0.316
Time invariant covariates $\left(\frac{Cov(y,\widehat{\mu\eta})}{Var(y)}\right)$	0.053	0.052	0.050	0.045	0.057
Unobserved heterogeneity $\left(\frac{Cov(y,\widehat{\alpha})}{Var(y)}\right)$	0.363	0.336	0.371	0.287	0.259
Firm fixed effect $\left(\frac{Cov(y,\widehat{\psi})}{Var(y)}\right)$	0.291	0.346	0.327	0.336	0.326
Match fixed effect $\left(\frac{Cov(y,\widehat{\gamma})}{Var(y)}\right)$	0.020	0.012	0.012	0.060	0.075
Residual $\left(\frac{Cov(y,\xi)}{Var(y)}\right)$	0.063	0.061	0.062	0.030	0.037
Total	1	1	1	1	1
% Explained by the model:	93.7	93.9	93.8	97.0	96.3

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

Table 13: Match effects model: correlation between log real wage components

	y	$\widehat{x\beta}$	$\widehat{\theta}$	$\widehat{\alpha}$	$\widehat{\mu\eta}$	$\widehat{\psi}$	$\widehat{\gamma}$	ϵ
y	1							
$\widehat{x\beta}$	0.520	1						
$\widehat{\theta}$	0.657	0.081	1					
$\widehat{\alpha}$	0.607	0.081	0.945	1				
$\widehat{\mu\eta}$	0.255	0.015	0.329	0	1			
$\widehat{\psi}$	0.556	0.105	–0.016	–0.047	0.087	1		
$\widehat{\gamma}$	0.150	0.047	0	0.011	–0.033	0	1	
ϵ	0.251	0	0	0	0	0	0	1

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

Table 14: Match effects model: selected correlations between log real wage components, by type of job mobility

	Promotions:									
	Automatic					Merit				
	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$
y	1					1				
$\widehat{x\beta}$	0.542	1				0.538	1			
$\widehat{\alpha}$	0.629	0.103	1			0.662	0.159	1		
$\widehat{\psi}$	0.680	0.230	0.108	1		0.652	0.221	0.099	1	
$\widehat{\gamma}$	0.126	0.052	0.042	–0.004	1	0.142	0.067	0.062	0.018	1

	Entry after:									
	Small gap					Big gap				
	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$
y	1					1				
$\widehat{x\beta}$	0.579	1				0.561	1			
$\widehat{\alpha}$	0.500	0.108	1			0.432	0.104	1		
$\widehat{\psi}$	0.557	0.144	–0.164	1		0.499	0.073	–0.286	1	
$\widehat{\gamma}$	0.252	0.056	0.015	–0.023	1	0.264	0.049	–0.016	–0.041	1

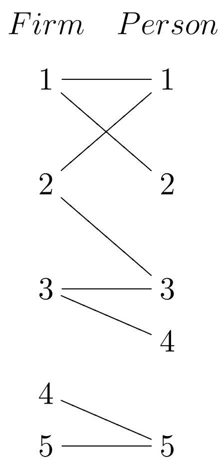
	Separation followed by:									
	Small gap					Big gap				
	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$	y	$\widehat{x\beta}$	$\widehat{\alpha}$	$\widehat{\psi}$	$\widehat{\gamma}$
y	1					1				
$\widehat{x\beta}$	0.602	1				0.590	1			
$\widehat{\alpha}$	0.514	0.103	1			0.472	0.112	1		
$\widehat{\psi}$	0.488	0.129	–0.187	1		0.474	0.092	–0.243	1	
$\widehat{\gamma}$	0.196	0.072	–0.064	–0.074	1	0.234	0.055	–0.054	–0.043	1

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

Figures

Figure 1: Visual perspective of connected groups of individuals and firms.

Firm	*Person*	*Group*
1	1	1
1	2	1
2	1	1
2	3	1
3	3	1
3	4	1
4	5	2
5	5	2



Note: Figure extracted from Abowd et al. (2002), p. 4