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Decomposing the structure of wages into firm and worker effects: some insights from a high unemployment economy

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JEL Classification: C24, C51, C55, D30, J30

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Abstract

This paper estimates an individual wage equation where firm and workers effects are considered and the estimation process controls for censored wages. This exercise is performed for the Spanish economy over the course of a whole business cycle (2000-2015). It is acknowledged that Spain is a country where firm wage setting policies are at least as important as they are in to other European countries with apparently less rigid labour market. Spanish firms explain around 27% of the individual wage heterogeneity but more importantly around 74% of inter-industry wage differentials and these numbers increased over the current Big Recession. It is found evidence of an important sorting process of individual and firms across industries. Finally, it is also demonstrated that, for some key topics in labour economics such as the effect job mobility on wages, it is important to explicitly consider firm fixed effects.

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1. Introduction

One of the most pervasive and difficult phenomena to explain in economics is the persistence of wage differences for measurably similar workers. One could argue that they are due to differential firm or industry compensation policies that do not follow the individual from job to job. While many theoretical models assign to firms an important role in the wage setting process (i.e., wage efficiency models, wage compensating differentials and search and matching models), in the empirical literature there is still lack of consensus regarding the extent to which different firms follow different wage policies what drives to large wage heterogeneity at the individual and sectorial level. Furthermore, identifying the contributions of firm heterogeneity to wage dispersion is an important step towards answering a number of economic questions, such as the return to seniority and its relationship with turnover, the sources of the scarring effects related to unemployment, the nature of sorting patterns between heterogeneous workers, firms and sectors, and the sources of wage inequality.

In this paper, we examine the role of firms in explaining individual and inter-industry wage dispersion using a longitudinal employer-employee dataset for Spain over the course of a whole business cycle (2000-2015). In particular, we want to uncover whether heterogeneity in firm´s wage policies is more important than the sorting process of workers across firms and industries in understanding individual wage dispersion. Moreover, the sample period allows us to study how the role of firm´s wage policies has evolved along the business cycle - including the Great Recession. In our empirical exercise we follow the literature on the statistical decomposition of wage rates into shares due to worker and firm heterogeneity introduced in Abowd, Kramarz and Margolis (1999, AKM decomposition). The estimation exercise is performed under optimal conditions for several reasons. First, we use individual monthly labour market status, instead of the yearly data, reducing the potential bias in fixed effects due to limited worker mobility. Second, we apply an estimator that enables to control for censoring in wages when estimating models with high-dimensional fixed effects.

Virtually all previous studies find a significant employer-specific wage component but its importance in explaining individual wage variance ranges from 10% -Denmark- or to 29% Portugal. This empirical literature has devoted less attention to the study of inter-industrial wage differentials and existing results are much less conclusive since the estimated role of firm effects varies between 25% -Denmark- and 75% -Portugal. Estimations about the process of matching between firms and workers are also characterized by large heterogeneity. In this regard, the correlation between individual and firm effects is estimated to be -40% in Norway, which contrasts with the results presented for Portugal, where this correlation is estimated to be approximately 29%.

In this paper we look at a country whose labour market performance differs markedly from other EU economics. Particularly, Spain is characterised by high rates of unemployment and temporary employment and rigid real wages. Institutional factors such as wage bargaining model, unemployment benefit system or employment protection legislation could explain this different performance making firm wage policies far less important in Spain than in other European countries. For instance, in this country, wage bargaining at the national and provincial levels is the main point of reference due to the large number of small and medium-sized firms that lack their own agreements (see Diez-Catalan and Villanueva, 2015). Its employment protection legislation for permanent workers may hamper job transitions into better matches (see Rebollo-Sanz, 2011) as well as limiting the bargaining power of firms in setting wages especially for high protected workers. A generous unemployment system like the Spanish one, might also lead to lower firm wage bargaining power and higher wage rigidity than in an alternative scenario. Indeed, during the year 2012 there has been two important labour market reforms whose aims were to reduce these labour market rigidities[1]. Though Spain represents an interesting case of analysis, to the best of our knowledge there is only one previous study that deals with some of the issues considered in this paper (Gonzalez de San Roman and Rebollo-Sanz, 2014). For instance, they show that similar to Portugal, Spanish firms explain around 22% of individual wage variability. In this paper we extend this previous empirical analysis in some important dimensions. For instance, we test whether wage changes related to job mobility patterns should be attributed to the wage policies of the hiring firm. Additionally, we also look at the role of firm wage policies at the industry level. Finally, we study the changing role of the employer in determining individual wage dispersion along the business cycle.

From our estimation we obtain some interesting results worth to highlight. Firstly, we acknowledge that Spain is a country where firm wage setting policies are at least as important as they are in to other European countries with apparently less rigid labour market since firms explain approximately 27% of individual wage heterogeneity. We also find evidence suggesting that good workers tend to be found in good firms as the matching and assignment literature predict whenever there are complementarities between workers and firms. Secondly,

[1] The reform of February 2012 meant a significant change in the Spanish collective bargaining structure to increase businesses' internal flexibility. In July 2012 there were other reform that reduced the generosity of the unemployment benefits (Rebollo-Sanz and Rodriguez-Planas, 2016).

we get that firms are much more important in determining the interindustry wage structure (74%) than wage differentials across individuals (27%). This is because the relative variance in a firm's contribution to the overall variance in wages is larger at the industry level (56%) than at the individual level (21%). This seems to indicate that there are more similarities between firms within industries than across industries and hence that high paying firms concentrate in particular industries. Additionally, the fact that the covariance between firm and worker effects within industries is positive and higher than that obtained for individual wages indicates that high-wage workers tend to sort into high-wage industries to a higher degree but sort into high-wage firms to lower degree.

Thirdly, our estimation reveals that there are sizeable biases effects that spread to some model parameters, thus emphasising the importance of careful model specification, both in terms of considering firm effects as well as controlling for censored. For instance, we show that wage changes traditionally related to job mobility should be partially attributed to the type of wage policies of the hiring firm, particularly when considering wage losses after involuntary job transitions. Similarly, we also obtain that wage growths traditionally related to human capital accumulation should be attributed to the sorting process of workers into firms with steeper tenure wage policies. Thus, the estimated returns to general labour market experience might be upward-biased in the traditional wage equations whereas the estimated returns to tenure might be downward-biased.

The remainder of the paper is organised as follows. The empirical framework is established in the next section. Section 3 describes the database and sample estimation. Section 4 displays the main results, followed by Section 5 where we present a series of robustness checks. The final section concludes with a summary of our main findings.

2. Decomposing Individual Wages:

We follow the AKM statistical decomposition of wage rates into shares due to worker and firm heterogeneity. The wage equation to be estimated has the following general form

$$y_{ijt} = \alpha_i + \beta_j + x_{ijt}'\gamma + \varepsilon_{ijt} \qquad (1)$$

N workers (i =1,.,N); J firms (j=1,.,J); T_i *observations for each individual*

where y_{ijt} is the log of the wage rate and the term x_{ijt}, is a vector of k observed time-varying characteristics specific for each individual-job spell[2]. The worker effect (α_i) captures differences

[2] Time-varying firm characteristics are not available in the dataset.

in pay due to constant individual heterogeneity. Similarly, the firm effect (β_i) captures differences in pay due to firm heterogeneity[3].

2.1 The role of firms in individual wage dispersion

To estimate equation (1), while simultaneously employing two high-dimensional fixed effects and adjusting for censoring, we proceed in two stages. In the first stage, we use the observed wage as our endogenous variable and obtain the coefficient estimates for the individual and firm effects using the partitioned iterative algorithm proposed by Carneiro et al. (2009) and Guimaraes and Portugal. (2009). Then, using these initial estimates, we correct the observed censored wage using an algorithm specially designed for that purpose and named Fill-in Least Squares (FILS).[4] These two steps are repeated iteratively until convergence of the parameters is reached. Once we get the parameters estimates of equation (1) we decompose the variance of log wages into a firm component, a worker component, a component due to time-varying characteristics (individual, job-individual and aggregate) and a transitory component[5]. In particular, to depict the role of firms in individual wage heterogeneity, $\{\upsilon_j\}$, we derive the following equation:

$$\upsilon_j \equiv \frac{Cov(\beta_j, y_{ijt})}{Var(y_{ijt})} = \frac{Var(\beta_j)}{Var(y_{ijt})} + \frac{Cov(\beta_j, x_{ijt}\gamma + \alpha_i)}{Var(y_{ijt})} \qquad (2)$$

Equation (2) shows that firms could play an important role in wage determination for two reasons[6]. The first term measures the variance in firm´s wage policies. The second term helps to study the characteristics of the job assignment process and a positive sign in this covariance

[3] The worker effect can be related to heterogeneity in worker productivity or bargaining ability, among other factors. The firm effect can be due to heterogeneity in rent sharing policies, productive heterogeneity, efficiency rents and compensating differentials, among other factors.

[4] The algorithm operates as follows. The simulated wage must be equal to the observed wage whenever the true wage is observed and it will be filled by random numbers from a truncated normal distribution whenever the observed wage is equal to the censor point. An OLS regression is run in which the simulated wage and the estimators are saved. This is performed iteratively as a sequence of least squares regressions until the estimators converge to the true parameter values. In each iteration, the estimated parameters change, as does the simulated wage distribution, which converges further towards the true wage distribution as the iterations proceed (see Gonzalez de San Roman and Rebollo-Sanz, 2014). The convergence criteria are defined in terms of some of the parameters of interest (i.e., correlation between the firm and person effects, age and tenure) and the sum of squared residuals (the change in the sum of squared residuals must be lower than 0.0000001).

[5] We acknowledge we are using a linear decomposition for a censored model. However, firstly note that the FILS algorithm is based on an estimation of a sequence of linear regression models. Secondly, even though one could argue that this linear decomposition for the wage equation could have some limitations, especially when giving a structural interpretation to some parameters estimates, still this is typically used in the empirical literature whose aim is to understand the role of firms in the explaining individual wage dispersion and wage inequality.

[6] The covariance of the firm´s and individual effects with the error term are zero by virtue of the conditions imposed on the estimates by least squares.

might be evidence of positive assortative matching. That is, workers with higher time-invariant characteristics (i.e ability or skills) will earn higher wages than their counterparts because they tend to be employed in better paying firms. If this is the case, wage inequality will be higher than the underlying inequality in worker time-invariant characteristics. Additionally, positive assortative matching may be evidence of complementarities in production between worker ability and firm productivity. This implies that if workers and firms are optimally matched, total output is higher than it would be under random matching, for example. As a consequence, job search frictions would have negative output effects, and policies to prevent search frictions would be welfare improving. For instance, Lise et al. (2016) presents a search-matching model to estimate the potential gains from optimal unemployment benefit policy when there is positive assortative matching between workers and firms.

Nevertheless, interpreting this empirical covariance as evidence of positive assortative matching must be made with caution for several reasons. For instance, the true covariance might be underestimated due to limited mobility bias and censored wage observations (Andrews et al., 2008; Andrews et al., 2012). Also, note that few structural models give rise to wage equations that are log-linear in the person and firm effects (see Bagger and Lentz, 2008, Eeckhout and Kircher, 2011). Consequently, the estimated covariance of person and firm effects using equation (1) must be better considered a first-order approximation of the true covariance effects. Interestingly, Abowd et al. (2004) demonstrate that sorting can be pervasive in economies in which there is negative or zero correlation between person and firm effects.

2.2 The role of firms in industry wage dispersion

The raw inter-industry wage differential, ($\overline{y}^s$) obtained in a cross-sectional regression of individual wages on the observable characteristics and a set of industry indicators consists of an industry-specific firm effect (β_j^s) and an industry-specific person effect (α_i^s). Hence, we can also decompose the importance of firm-industry wage determinants into two components (Abowd et al. 2004, Gruetter and Lalive, 2009):

$$\upsilon_j^s = \frac{Cov\left(\overline{y}^s, \hat{\beta}_j^s\right)}{\operatorname{var}\left(\overline{y}^s\right)} = \frac{Var\left(\hat{\beta}_j^s,\right)}{\operatorname{var}\left(\overline{y}^s\right)} + \frac{Cov\left(\hat{\beta}_j^s, \hat{\alpha}_i^s\right)}{\operatorname{var}\left(\overline{y}^s\right)} \qquad (3)$$

The first component refers to variance of the industry-specific firm effect. The second component measures the covariance between the industry-specific firm effect and the industry-specific person effect, and henceforth it test for the evidence of positive sorting of workers across industries. That is, if firms in each industry are not a random sample of the population of firms and there is positive sorting of individuals across firms and industries, wage differentials will be even larger at the industry level than at the individual level. Henceforth, we could expect that the contribution of firms to explain wage heterogeneity will be higher at the industry than at the individual level.

Combining the information provided by equations (2) and (3), we learn that the importance of firms in wage determination might differ at the individual versus at the industry level for two main reasons. First, the relative variance of the firm´s contribution at the individual level and at the industry level can differ. Second, differential sorting of individuals across firms and across firms and sectors can explain why firms contribute more strongly at the industry level than at the individual level even if relative variances are constant.

3. Data Description: The Longitudinal Working Lives Sample (LWLS)

We use a longitudinal employer-employee matched database drawn from the Spanish Social Security administrative register. This paper uses nine editions of the LWLS to obtain the complete labour market history of around the 4% of all individuals who appear in social security records at any time throughout the period 2005-2014. The final estimation sample is obtained through the following selection process. We restrict the analysis to full-time workers in regular employment aged 18-64 years over the period 2000-2014. We then we construct a monthly panel data where the unit of analysis is each worker-job-month combination.

Additional sample restrictions are imposed on this initial database. First, we restrict the analysis to firms with a minimum of five different observed employees to reduce the limited mobility bias. We are aware this sample restriction might have consequences for the results and in the robustness section we investigate this issue further. Second, we need to identify connected groups of workers and firms because firm fixed effects are only identified for each connected group (see Abowd et al., 2004). Once all of the connected groups are identified, we retain only the largest group which accounts for 98.7% of observations. After theses sample restrictions, our final database comprises 18,499,616 observations with 418,947 individuals and 32,845 firms (in a given year, we tend to have between 105,000 and 150,000 workers and 9,000 and 10,000 firms with at least 5 full-time employees). Table 1 below provides evidence of the considerable labour mobility present in our database: workers are observed on average 22 months, job movers represent 39% of the individuals, and their average number of firm movements is 2.7. Finally, we observe that the average number of different workers per firm is 14 and the average number of job movers per firm is 7.8.

[Insert Table 1]

The dataset contains information on monthly earnings, which are censored at the upper and lower social security contribution limits fixed by the government each year[7]. The monthly wage is deflated using the consumer price index for each period. We use in the analysis the following time-varying covariates: i) individual characteristics such as age (four dummy variables) and labour market experience; ii) individual-job specific characteristics that measure the returns to characteristics of the worker-firm match component such as tenure, type of contract (temporary versus permanent) and job qualifications (three skill levels); iii) job transition types; iv) year and quarterly dummy variables; v) a binary variable which takes value one after an important labour market reform was implemented (February, 2012).

We define previous work experience as the number of accumulated years actually worked since the employee's first employment experience. Tenure reflects the number of consecutive years the worker remained with the same firm despite possible short-spells of unemployment[8]. Labour market experience, tenure and previous unemployment duration are modelled as three-degree polynomials. We consider the following job transition types: job-to-job, job-unemployment-job to a different firm and job-unemployment-job to the same firm[8]. We also include as a covariate the duration of the unemployment spells –months-, and the type of contract - fixed-term contracts versus open-ended contracts-, held in each job spell.

In our analysis, we also want to disentangle the role of observed versus unobserved individual and firm time-invariant determinants on individual wages. For that purpose, we estimate the influence of some observed individual and firm time-invariant characteristics on the estimated individual and firm fixed effects (See Appendix A). Among the individual time-invariant characteristics, we consider gender, nationality and educational dummies. On the firm side, we consider industry dummies, firm size, firm ownership (public versus private) and region of firm´s location.

Table 2 presents the main characteristics of the full sample and the estimation sample. This final sample is largely representative of the full sample of observations (Column 1). The

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[7] The wage information provided by the dataset is based on the employer's social security contributions and it can be top- or bottom-coded.

[8] We measured experience and tenure in years since we observed that monthly wages hardly vary with monthly variation on tenure and experience. Moreover, at the beginning of the project we checked whether the results changed when using monthly experience and tenure and we did not find relevant differences. [8] The intermediate period of unemployment lasts at least four weeks.

sample statistics show that the main differences, as expected, concern firm size since small firms are underrepresented, though they constitute a meaningful share[9]. The proportion of censored observations is approximately 18% (right-censored) and 0.8% (left-censored).

[Insert Table 2]

Table 3 offers the raw inter-industry wage differential defined as the difference between the within-industry average log wage and the overall average of log wages. The data suggests the existence of important inter-industry wage differentials, with some industries paying wages that are 0.2-0.5 log points below the economy-wide average (Agriculture, Restaurant and Hotels and Social Services), while others pay wages that are 0.2-0.4 log points above the average wage (Finance and Communication).

[Insert Table 3]

4. Main Results: The contribution of firm wage policies to wage dispersion

Table 4 displays the results for three alternative models[10]: Model 1 contains person effects and observable characteristics. Model 2 adds to Model 1 firm effects -OLS estimation. Model 3 is the same as Model 2 but estimation amends for censored wages using the FILS estimator.

[Insert Table 4]

As expected, the discrepancy in parameters estimates between these three models is considerable in several dimensions. For instance, the standard deviations of both estimated fixed effects inform that there is considerable wage heterogeneity not only at the individual level but also at the firm level. Note that controlling for firm heterogeneity not only increases the proportion of wage variation explained by the model but it also reduces the portion attributed to workers heterogeneity.

All estimated coefficients are of the expected sign and statistically significant at the 1% level. The three sets of estimates show that both human capital accumulation –general and specific-, and mobility patterns are important determinants of individual´s wage growth. A careful inspection of the parameter estimates reveals that there are sizeable biases that spread to some

[9] We cannot properly use weights to correct for this sample bias given the algorithms used in the estimation process.
[10] We lack the sufficient information required to estimate a model with job matching effects together with individual and firm effects. Card et al. (2013) show that a model that includes separate fixed effects for each job (worker-establishment match) provides only a small improvement in explanatory power relative to the AKM specification

parameters, thus emphasising the importance of careful model specification. For instance, the typical "scarring effect" associated with the effect of unemployment duration on post unemployment wages is overestimated in the traditional OLS model (Model 2). Thus, we get that monthly wages for workers who suffered an unemployment spell of 12 months are 0.02 lower than those who did not change jobs, when using the FILS estimator (Figure 1). Whereas in Model 1, this scarring effect is estimated to be approximately 0.03 log points. Furthermore, wage gains from job-to-job movements are overestimated in Model 1 (0.008 log points in Model 1 versus 0.002 log points in Model 2), which might suggests that part of the wage gains traditionally related to voluntary job movements should be attributed to movements to better-paying firms. Similarly, part of the wage losses typically related to involuntary job movements should be attributed to worse-paying firms.

Studying the returns to general and specific human capital skills is a key topic in labour economics and our estimation reveals that biases for these two covariates are even more important than the one previously shown for the scarring effect. The estimated experience and tenure profiles are represented in Figure 2. The experience profiles are steeper in the Model 1 than in the other two models. The return to 10 years of experience is approximately 0.06 log points in Model 1 and 0.04 log points for Models 2 and 3. However, the estimated tenure profiles are steeper for Model 3 than for the other two models. The return to 10 years of tenure is 0.06 log points in the FILS model and 0.04 and 0.02 log points for Models 2 and 1, respectively. This suggests that part of the individual wage growth traditionally attributed to general labour market experience should be explained by the tendency of workers to sort into firms with steeper tenure wage policies. Thus, the estimated returns to general labour market experience might be upward-biased in the traditional wage equations whereas the estimated returns to tenure might be downward-biased. Additionally, the wage returns for high-skill jobs are underestimated. For instance, while our FILS estimator finds that high-skill jobs command approximately 0.15 log points higher monthly wages than low skill jobs, this return declines to 0.12 log points when wages are not corrected for censoring and to 0.108 log points when firm effects are not accounted.

We report the estimated correlations among the different components of monthly wages –time-varying characteristics, worker and firm fixed effects in the final rows of Table 4. The highest correlation is observed between individual and time-varying effects (20%-21% for Models 3 and 2, respectively), whereas, the lowest correlation is found between firm effects and time varying characteristics though again, this correlation is positive (11%). The correlation between firm effect and individual effects is low but positive, indicating positive sorting between firms and workers (between 12%-14% depending on the model). Note that it is possible that these firm and worker time-invariant effects are not entirely due to unobserved heterogeneity but could also result from observed time-invariant heterogeneity. We attempt to investigate this issue in greater depth by estimating an equation for individual and firm time-invariant effects in relation to some observed time-invariant characteristics. For the sake of concreteness, detailed results of these estimations are displayed in Appendix B (Tables B.1 and B.2 for the individual and firm fixed effects models, respectively). These estimations indicate that nearly 75-80% of these time-invariant fixed effects are related to unobserved individual and firm factors. We then consider again the estimated correlation coefficient between individual and firm effects (see Table 5), but separating the observed from the unobserved component. The estimated correlation between time-invariant firm and worker characteristics is 24% informing that there is some degree of positive sorting between workers and firms. However, this positive correlation is due primarily to time invariant observed characteristics.

[Insert Table 5]

Hence, combining both results we find evidence of positive selection of workers into better paying firms and this is due to time-varying and time-invariant characteristics. Thus, in term of observables, high wage workers due to time invariant characteristics –i.e high educated workers-, tend to have better labour patters –i.e higher labour market experience-, and these workers with better labour patters stay in high wage firms.[11] The matching and assignment literature includes models that predict complementarity between worker and firm productivity levels, suggesting that good workers tend to be found in good firms. Our results are consistent with this literature. By the same token, we do not find evidence of assortative matching in terms of the unobservables. We find that the unobserved components are negatively correlated (-4.8% in Model 3 and -9.1% in Model 2).

4.1 The importance of firms in individual wage determination

In this section, we use equation (2) and Models 2 and 3 to assess the role of firms in generating individual wage heterogeneity. For instance, we have shown that there is positive sorting between workers and firms and now we can measure how important this process is to explain individual wage dispersion.

[11] Andrews et al. (2012) report a correlation of −0.066 (Germany, 1993-1997); Sorensen and Vejlin (2013), obtain a correlation that varies in the range of -0.06%-11% (Danish data, 1980-2006), and similarly Woodcock (2008) find it might vary between 0%-18%, in both cases, depending on the model estimation and time horizon. Torres et al. (2012), find for Portugal that the correlation between observed firm and worker fixed effects is 27%, whereas the correlation between the unobserved firm and worker effects is -4%.

[Insert Table 6]

The first column of Table 6 displays the contribution of each element of the model towards explaining individual wage heterogeneity. Firstly, interestingly we obtain that failing to adjust for censoring could mislead research on the respective role of firms and workers in explaining wage dispersion. This error results primarily from the overestimation of firm time-invariant effects. The OLS model states that firm and worker time-invariant characteristics explain approximately 32% and 49%, of the observed wage dispersion, whereas in the FILS approach, these figures are 27% and 55%, respectively. Interestingly, the contribution of the variance in firm wage policies represents 21% whereas the contribution of the covariance between firm effects and the rest of components is not very large (approximately 1.2% with time-varying characteristics and 4.5% with worker effects). We then use the estimated firm fixed effects to test whether this contribution (27%) must be mostly related to unobserved time-invariant firm characteristics versus observed ones (Table B.1, Appendix B). We obtain that the unobserved component explains 16% of the variance in wages, whereas the observed component explains 11%, which is essentially attributable to firm´s sector (see Table B.3).

Note that if employers were simple wage-takers, the employer variation in wages would be entirely determined by the larger individual effects. Henceforth, the results just presented confirm that employers have a role in the wage setting process as it is emphasizes for some theoretical models such as the efficiency wage view (Shapiro and Stiglitz, 1984), the equilibrium search theory (Postel-Vinay and Robin, 2002) or the matching models (Mortensen and Pissarides,1994). More importantly they suggest that firms are as important to wage setting in Spain as in other countries that might have different institutional wage settings. For instance, Torres et al. (2012), for Portugal, and Gruetter and Lalive (2009), for Austria, report that firms account for approximately 29% and 26%, respectively, of the total variance in individual wage rates.

The total contribution of individual time-invariant effects amounts to 56%, whereas time-varying observable characteristics explain only 10% (mainly related to job characteristics). As expected, the unobserved component of the individual effects contributes the most to the variance of individual wages (41%), whereas the observed component represents just 14% (educational attainment levels primarily and gender in second place). Hence, as echoing existing empirical we find that while firms are important in explaining individual wage variance, individual characteristics are more relevant.

Job Movers versus Job Stayers

We test whether the nature of the inter-firm mobility present in the data might affect the contribution of firms to the variance in wage rates. For that purpose, we present in Table 7 the wage variance decomposition for stayers, job-to-job movers and job-to-unemployment movers. As it was found in Gruetter and Lalive (2009), our analysis reveals that firm effects are more important in setting wages for involuntary job movers. They argue that the firm´s contribution in the case of involuntary job movers should be higher than for others because the range of acceptable job offers – job offers that are defined by the firm – is much larger for unemployed than for employed individuals. This result supports the empirical evidence that wage adjustment in period of crisis should be more related to involuntary job movers than to stayers. Interestingly, in Spain, wages for job entrants drop significantly more than their counterparts during the recent Big Recession (see Font, Izquierdo, Puente 2015).

[Insert Table 7]

4.2 The importance of firms in inter-industry wage differentials

First column of Table 8 shows the raw inter-industry wage differential which corresponds to the difference between the within-industry average log wage and the overall average of log wages. The following Columns 2 and 3 report the inter-industry differences in the average worker and firm effects, respectively. Note that there are sectors where the low pay level seems to be related to the combination of low-wage workers and low-wage firms (i.e., Agriculture, Restaurants, Business Services, Public Administration, or Health). Conversely, there are sectors where the high pay levels are related to a combination of high-wage workers and high-wage firms such as Industry, Financial Services, Communications and Transport.

[Insert Table 8]

Turning to the importance of firms at the industry level, Table 9 presents a decomposition of industry wage heterogeneity into firm versus worker effects for Model 3. Results demonstrate that firm heterogeneity is far more important in explaining inter-industry wage differentials than worker heterogeneity (74% relative to 26%). First, firm wage policies account for approximately 56% of the overall inter-industry variance whereas the variance in the remuneration of the average worker across industries is approximately 9% of the total wage variance. Second, the correlation between the typical compensation wage policies in the industry for the typical worker is positive but only amounts to 17% of the total variance.

[Insert Table 9]

We plot in Figure 3 the raw industry wage against the industry-specific firm effect and the industry-specific person effect. This figure reveals that industry wage differentials from a cross sectional perspective are very closely related to the typical wage policy of firms in an industry.

[Insert Figure 3]

Our results suggest that, on the one hand, there are strong systematic differences in firm wage policies across industries and that, on the other hand, worker sorting across industries is much less important in explaining inter-industry wage differentials. Interestingly, previous empirical evidence offers different results when studying the role of firms in inter-industry wage differentials. For instance, Gruetter and Lalive (2004) and Woodcock (2008), find that firm differences explain the bulk of the variation in industry average wages (75% and 72%, respectively). Conversely, Sorensen and Vejlin (2013), find that worker differences explain roughly 74% of the raw inter-industry wage differentials. Card et al. (2013) report that both components, firm and individual effects, are important, although worker effects are slightly more important than firm effects (i.e., 35% versus 20%). Abowd et al. (2004) and Card et al. (2013) also find that the correlation between worker and firm effects across sectors is strong and positive (echoing our results), which is predicted by positive assortative matching, meaning that workers sort themselves into industries that vary systematically in the average productivity of firms within the industry. Note however, that none of these paper found positive wage sorting in terms of workers across firms.

To sum up, contrasting the importance of firms setting wages across individuals and across industries provides a striking result. Firms are much more important in determining the interindustry wage structure (74%) than wage differentials across individuals (27%). This is because the relative variance in a firm's contribution to the overall variance in wages is larger at the industry level (56%) than at the individual level (21%). This seems to indicate that there are more similarities between firms within industries than across industries and hence that high paying firms concentrate in particular industries. Additionally, the fact that the covariance between firm and worker effects within industries is positive and higher than that obtained for individual wages indicates that high-wage workers tend to sort into high-wage industries to a higher degree but sort into high-wage firms to lower degree. Hence we find evidence of the existence of a sorting process of individual and firms across industries.

5. Some Robustness Exercises: Model Specification and Sample Selection Issues

We begin this section by testing whether there is evidence of bias due to endogenous mobility in our data. One assumption typically made in this framework is that job mobility is exogenous, but this assumption is violated when workers systematically sort into firms based on firm´s job characteristics. Substantial sorting based on matching effects changes the interpretation of the firm effects, as the impact of transitioning between firms depends on the comparative advantage of the individuals making the transition. Gruetter and Lalive (2009) note that firm effects might be underestimated or overestimated depending on the type of job mobility that predominates in the dataset. Following Card et al. (2013), we search for neglected interactions[12] between worker and firm characteristics. For that purpose, we divide the estimated person and firm effects into deciles and compute the mean residual in each of the 100 crossed person-firm decile cells. We get that mean residuals are very small and uniformly no higher than 0.5% in magnitude (Figure 4). Hence, it appears that the assumption of orthogonality between firm and individual effects does not seem to be an important issue in our estimation exercise. [13]

[Insert Figure 4]

The wage equation is also estimated for alternative sample schemes related to firm characteristics to assess the generalizability of the results. We test for firm´s sizes and firm´s ownership. Detailed estimation results are presented in Table B.4 (Appendix B). Columns (1) and (2) of Table 10 report the wage variance decomposition when only firms with a minimum of 10 and 20 employees in a particular year are considered, respectively. Column (3) displays results for private firms. In these three cases, we find that the role of the firm in explaining individual wage variance hardly changes since we get that explains between 24% and 26% of the individual wage variability.

[Insert Table 10]

[12] First-order conditions for the OLS estimator ensure that the mean residuals for each worker and for each firm are zero. However, there is no such mechanical restriction on interactions between different groups of workers and firms, providing the basis for a basic test of the additively assumptions in the AKM model.

[13] Abowd et al. (2010) and Card et al. (2013) find that correcting for endogeneity does not overturn the qualitative findings from previous analysis that assumed mobility to be exogenous.

5.1 The contribution of firms in wage heterogeneity along the business cycle

To date, there is little evidence on whether the employer role in determining individual wages has increased or decreased over time. Card et al. (2013) and Sorensen and Vejlin (2012) find that the employer component increased during the 1990s and the early part of the current century. Card et al. (2013) cover the period 1985-2009 and argue that this result should be related to an increasing presence of new establishments that are outside traditional sectoral agreements and pay relatively low wages. On the contrary, Sorensen and Vejlin (2013) argue that this process is mainly driven by changes in the covariance between individuals and firm effects.

We test whether the crisis could have also implied a changing role of firm wage policies that might affect individual wage dispersion. For that purpose we divide our 15-year sample into two overlapping intervals: a period of economic growth (2000-2007), and a period that covers the Great Recession, (2007-2014). In each interval, we fit linear wage models that include additive person and firm fixed effects.

Columns (4) and (5) of Table 10 display the corresponding variance decomposition and Table 11 shows the detailed wage variance decomposition for each time interval. The results indicate that the role of firm effects in explaining inter-individual wage variance increased by two percentage points whereas the role of individual effects decreased by three percentage points from the upturn to the downturn. The increasing role of firm effects during the crisis could well be due to the change in the composition of employers or due to a change in the sorting process, or both.

[Insert Table 11]

Results of Table 11 provide evidence that the importance of firm wage policies in explaining individual wage variability increased in Spain during the crisis due to an increasing role of dispersion in firm´s wage policies (from 20% to 26%) whereas the importance of the positive sorting process has declined (4.8% to 0.4%). Hence, our results are opposite to the one presented in Sorensen and Vejlin (2013) and are in line with those presented in Card et al. (2013). Nevertheless, to investigate the hypothesis raised by Card et al. (2013), we compare the standard deviation of estimated firm effects for firms born during the period 2007-2014 versus the standard deviation of firm effects that were present in the 2000-2007 sample and we did not find relevant differences. An alternative explanation is that the institutional reforms that took place in Spain since the beginning of the crisis[14] could induce the rise of firm-specific policies such as pay-for-performance schemes in the wage bargaining process leading to an increase in plant-level variation in wage outcomes. In favour of this idea is the finding that the role of sectorial effects became more important in explaining firm wage heterogeneity during the recession period (the sector effect explains 7.5% of the variance in firm effects in 2000-2007 and 15% in 2007-2014).

6. Summary and Main Conclusions

This paper estimates a wage equation that includes worker and firm fixed effects, using a longitudinal matched employer-employee dataset covering Spanish employees for just less than two decades (2000-2015). This exercise is performed for a high-unemployment economy like the Spanish one, under optimal conditions which refer to the type of data used and the econometric methodology applied. The analysis has focused on three main ideas. Firstly, we examine the role of firm´s wage policies in generating individual wage heterogeneity. Second, we explore whether there is evidence of positive sorting of workers across firms and/or across industries. Thirdly, try to find out whether firm´s wage policy have become more or less important since the current Big Recession. Importantly, while trying to answer to these empirical issues we take into account misreporting issues in some parameters estimates such as returns to tenure and job mobility whenever the wage equation is estimated without considering firm effects and/or censoring in wages. We have examined the robustness of these results in a variety of subsample and estimation sensitivity tests.

Summarising broadly, we confirm the evidence of misreporting issues when the model estimator does not control for firm fixed effects and for wage censoring. The time-invariant person-specific is the most seriously misreported, but the problem also affects other person-specific parameters and job characteristics, such as tenure, job mobility and the scarring effect.

More importantly, we find evidence that firms actively *set wages* in Spain. Firms account for approximately 74% of wage differentials across industries and approximately 27% of the variance in individual wages. In both cases heterogeneity in individual firm wage policies is the most important component. Whereas the sorting process of workers into firms plays a minor

[14] Since 2010, far-reaching reforms, billed as making the labour market more flexible and efficient, have been implemented. For instance, the reform that took place in February 2012 consisted of two main elements. First, it gave priority to collective bargaining agreements at the firm level and made it easier for firms to implement internal flexibility measures as an alternative to job destruction. Second, the provisions of Spain’s Employment Protection Legislation were modified (i.e reshaping the definition of fair economic dismissal, reducing monetary compensations for unfair dismissal; see OCDE report, 2014).

role in explaining industry- or individual-level wage variability (17% and 4.5%, respectively). Interestingly, compared with previous empirical evidence, and abstracting from differences in time horizon and other potential methodological issues, it appears that firm wage policies are as important in setting wages in Spain as in other countries such as Portugal or Austria. Moreover, this role has increased during the current Big Recession and it seems to be related to changing patterns in existing firm wage policies. This finding that wages differ systematically across employers implies that when considering labour market questions such as returns to job mobility and labour policy issues such as wage rigidity, the employer side must also be considered in Spain.

References

Abowd, J. & Kramarz, F. & Margolis, F. D. (1999):"High wage workers and high wage firms". *Econometrica*, Vol.67 No.2. pp. 251-333.

Abowd, J. & Kramarz, F. & Lengermann, P. & Perez-Duarte, S. (2004):"Are Good Workers Employed by Good Firms? A test of a simple assortative mating model for France and the United States". *Mimeo*

Abowd, J. & McKinney, K. & Schmutte, I. (2010):"How important is endogenous mobility for measuring employer and employee heterogeneity"· *Mimeo*.

Andrews, M. J. & Gill, L. & Schank, T. & Upward R., (2008):"High wage workers and low wage firms: negative assortative matching or limited mobility bias?" *Journal of the Royal Statistical Society Series A*, vol. 171(3), pages 673-697.

Andrews, M. J. & Gill, L. & Schank, T. & Upward R., (2012):"High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias" *Economics Letters*, vol.117(3), pages 824-827.

Bagger, J., Lentz, R., (2008): "An empirical model of wage dispersion with sorting". Mimeo

Carneiro, A., P. Guimaraes, & P. Portugal. (2009):"Real Wages and the Business Cycle: Accounting for Worker and Firm Heterogeneity" IZA DP 4174 .

Card, D. & Heining, J., & Kline, P., (2013):"Workplace Heterogeneity and the Rise of West German Wage Inequality" *The Quarterly Journal of Economics*, vol.128(3), pages 967-1015.

De la Rica, S. & Rebollo-Sanz, Y.F. (2015):"Gender Differentials in Unemployment Ins and Outs during the Great Recession in Spain" IZA DP 9135.

Diéz-Catalán, L. & Villanueva, E. (2015):"Contract staggering and unemployment during the great recession: evidence from Spain" Banco de España WP 1431.

Eeckhout J. & Kircher, P. (2011):"Identifying Sorting-In Theory," *Review of Economic Studies*, vol. 78(3), pages 872-906.

Font, P. & Izquierdo, M. & Puente, S. (2015): "Real Wage Responsiveness To Unemployment In Spain: Asymmetries Along The Business Cycle," Working Papers 1504, Banco de España;Working Papers Homepage.

González de San Román, A. & Rebollo-Sanz, Y.F., (2017):"An estimation of worker and firm effects with censored data" *Bulletin of Economic Research*, DOI: 10.1111/boer.12112**.**

Gruetter, M. & Lalive, R. (2009):"The Importance of Firms in Wage Determination". *Labour Economics* 16 (2), pages 149-160.

Guimaraes, P. & Portugal, P., (2009):"A Simple Feasible Alternative Procedure to Estimate Models with High-Dimensional Fixed Effects" IZA DP 3935.

Lise, J. & Meghir, C. & Robin, J.M. (2016): "Matching, Sorting and Wages," *Review of Economic Dynamics*, Elsevier for the Society for Economic Dynamics, vol. 19, pages 63-87, January.

Mortensen, D.T. & Pissarides, C.A (1994):"Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, vol. 61(3), pages 397-415.

OCDE (2014):"The 2012 Labour Market Reform in Spain: A Preliminary Assessment", OECD Publishing

Postel-Vinay, F. & Robin, J.M. (2002):“Equilibrium Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, vol. 70(6), pages 2295-2350, November.

Rebollo-Sanz, Y.F., (2011): "Landing A Permanent Contract In Spain: Do Job Interruptions And Employer Diversification Matter?," *Manchester School*, University of Manchester, vol. 79(6), pages 1197-1236, December.

Rebollo-Sanz, Y.F. & Rodríguez-Planas, N. (2016):“When the Going Gets Tough... Financial Incentives, Duration of Unemployment and Job-Match Quality,” IZA DP 10044.

Shapiro, C. & Stiglitz, J.E. (1984): “Equilibrium Unemployment as a Worker Discipline Device”, *The American Economic Review* Vol. 74, No. 3, pages. 433-444

Sørensen, K.L. & Vejlin, R. (2013):“Return to Experience and Initial Wage Level: Do Low Wage Workers Catch Up?” *Journal of Applied Econometrics*, Vol 29, Iss 6 pages 984-1006.

Torres, S. & Portugal, P. & Addison, J.T. & Guimaraes, P. (2012):“The Sources of Wage variation: A three way high dimensional fixed effects model” IZA DP Nº 7276.

Woodcock, S.D. (2008):“Wage differentials in the presence of unobserved worker, firm, and match heterogeneity” *Labour Economics*, vol. 15(4), pp. 771-793, August.

Figures and Tables

Table 1. Main Sample Characteristics (2000-2014)

	Total Sample	**Estimation Sample**
Total Nº of Observations	28,524,892	18,499,616
Sample of Workers Nº		
of Individuals	560,080	418,947
Nº of Time Periods per Worker (months)	25 (26)	22 (25)
Average Number of Firms Per (Movers)	3.1 (1.4)	2.7 (1.2)
% of workers who are Movers	48%	39%
Sample of Firms Nº		
of Firms	71,138	32,845
Nº of Different Workers per Firm (yearly)	5 (11)	14 (20)
Nº of Movers per firm (yearly)	2.1 (7)	7.8 (12)

*Standard Deviation Between brackets

Table 2: Main descriptive statistics of the sample for different censoring levels

	Full Sample	Estimation Sample	Estimation sample for: Uncensored	Left-Censored	Right-Censored
Real Wage (Euros)	1128 (437)	1177 (443)	1055 (357)	410 (44)	1831 (29)
Age (years)	39 (10)	39 (10)	38 (10)	34 (12)	43 (8.8)
Labor Market Experience (Years)	6 (6)	6 (6)	9 (8)	6 (8)	12 (9)
Men	65%	64%	61%	49%	77%
Education					
Less than Primary	15%	14%	15%	26%	5%
Primary	34%	33%	37%	42%	13%
Secondary	29%	29%	38%	18%	36%
University	20%	22%	18%	11%	45%
Tenure (Months)	64 (92)	64 (92)	61 (60)	21 (38)	99 (92)
Job Transition Type					
Non-employment Duration (months)	8.1 (15)	9.7 (15)	9.2 (14)	13 (17)	1.4 (11)
Job-to-Job	40%	39%	38%	20%	47%
Job-U-Job	21%	20%	22%	35%	11%
U. Benefits	10%	10%	11%	11%	5%
Permanent Contract	73%	72%	68%	28%	91%
Job Skills					
High	21%	23%	16%	11%	65%
Medium	32%	33%	35%	15%	25%
Firm Size (employees)					
< 5	25%	18%	18%	23%	16%
10-20	11%	5%	5%	12%	2%
20-50	13%	9%	10%	19%	5%
50-150	16%	19%	19%	21%	15%
150-500	15%	21%	21%	14%	23%
>500	18%	25%	22%	7%	36%
Sector of Activity					
Agriculture	0.5%	0.5%	0.5%	5%	0%
Industry	25%	24%	24%	7%	26%
Construction	11%	9%	10%	2%	5%
Services	44%	44%	43%	40%	54%
Non-commercial services	18%	20%	21%	44%	13%
N %	100%	100%	83%	0.8%	18%

Table 3: Inter-Industry Wage (log) differentials $\left(\overline{W}_s - \overline{W}\right)$

Sector	Observations (%)	Industry Wage Differential
Agriculture	0.5%	-0.492
Extractive Industry	0.2%	0.152
Industry (Manufacturing and Energy)	24.8%	0.087
Construction	9.5%	-0.131
Wholesale & retail Trade	12.6%	-0.193
Restaurant and Hotels	4.8%	-0.232
Transport	5.5%	0.089
Communications	4.8%	0.226
Financial Services	6.4%	0.343
Business Services	10%	-0.181
Publ. Admon	7.6%	-0.057
Education	3.0%	0.064
Health	7.9%	0.012
Culture, Sports	0.7%	-0.127
Other Social Services	0.7%	-0.202

Table 4. Results for the Wage Equation, 2000-2014

	Model 1: One F.E		Model 2: Two-F.E (OLS)		Model 3: Two-F.E (FILS)	
	Coeff.	S.e	Coeff.	S.e	Coeff.	S.e
Individual Characteristics						
Age <30	-0.007**	0.000	-0.008**	0.000	-0.003**	0.000
Age 30-40	0.042**	0.000	0.037**	0.000	0.041**	0.010
Age 40-50	0.030**	0.000	0.027**	0.000	0.032**	0.000
Labour Experience (log)	0.078**	0.000	0.059**	0.000	0.063**	0.000
Labour Experience ^2	-0.017**	0.000	-0.017**	0.000	-0.015**	0.000
Labour Experience ^3	-0.002**	0.000	-0.001**	0.000	-0.002**	0.004
Non-employment Duration (log)	0.015**	0.000	0.011**	0.002	0.015**	0.000
Non-employment Duration^2	-0.018**	0.000	-0.012**	0.008	-0.015**	0.001
Non-employment Duration^3	0.003**	0.000	0.002**	0.004	0.003**	0.000
Individual Transition Type						
Job-to-Job	0.008**	0.000	0.002**	0.000	0.004**	0.000
Unemployment-Job (new firm)	-0.024**	0.000	-0.015**	0.000	-0.014**	0.000
Unemployment-Job (same firm)	-0.008**	0.000	-0.011**	0.000	-0.011**	0.000
U. benefits	-0.009**	0.000	-0.006**	0.000	-0.009**	0.000
Individual-Job Characteristics						
Tenure (log)	0.022**	0.000	0.021**	0.000	0.022**	0.001
(Tenure)^2	0.005**	0.000	0.004**	0.000	0.007**	0.012
(Tenure)^3	-0.003**	0.000	-0.003**	0.000	-0.003**	0.027
Permanent Contract	0.055**	0.000	0.054**	0.000	0.050**	0.000
High Skill Job	0.108**	0.000	0.123**	0.000	0.159**	0.000
Medium Skill Job	0.016**	0.000	0.035**	0.000	0.030**	0.000
Aggregate-Covariates						
Reform-2012	-0.009**	0.000	-0.009**	0.000	-0.009**	0.000
Year Dummies	Yes		Yes		Yes	
Quarterly Dummies	Yes		Yes		Yes	
Constant	6.788**	0.000	6.812**	0.044	6.817**	0.000
$\left(\bar{\hat{\alpha}}_i, s.e_{\hat{\alpha}_i}\right)$[15]	-0.114	0.319	-0.101	0.257	-0.113	0.329
$\left(\bar{\hat{\beta}}_j, s.e_{\hat{\beta}_j}\right)$	-	-	-0.099	0.243	-0.104	0.261
$Corr\left(\hat{\alpha}_i, \hat{\beta}_j\right)$	-	-	12%	-	14%	-
$Corr\left(x_{ijt}\hat{\gamma}, \hat{\beta}_j\right)$	-	-	11%	-	11%	-
$Corr\left(\hat{\alpha}_i, x_{ijt}\hat{\gamma}\right)$	16%	-	21%	-	20%	-
R^2	90%	-	92%		94%	

Model 1: F.E=Fixed Effect. One-way model contains observable characteristics and person effects. Model 2: We add firm effects to model 1 but wages are not corrected for censoring; Model 3: Is the same as model 2 but wages are corrected by censoring using the FILS estimator.
Constant Term: Old, low skill workers holding a temporary contract
* 95% statistical significance; ** 99% statistical significance

[15] The mean of the person effects shown are computed across the person observations in the dataset. Similarly, the firm mean of the effects are estimated across the firm observations in the dataset.

Figure 1: The Estimated Scarring Effect of unemployment

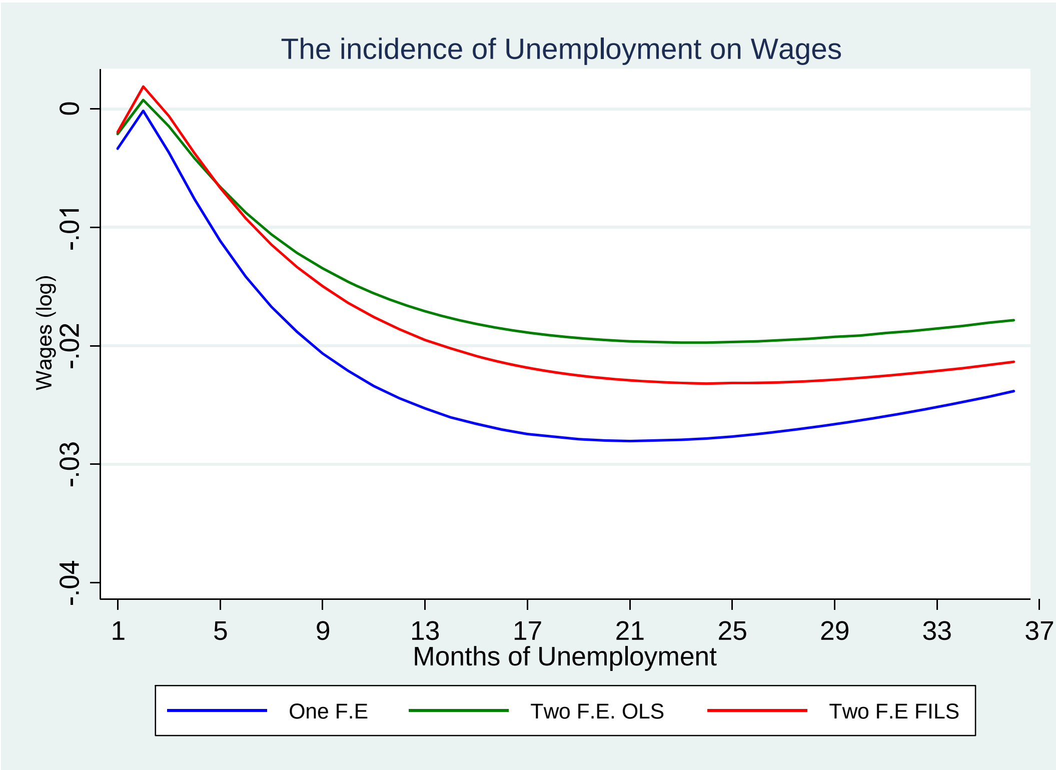

Figure 2: The Estimated Returns to Specific and General Human Capital

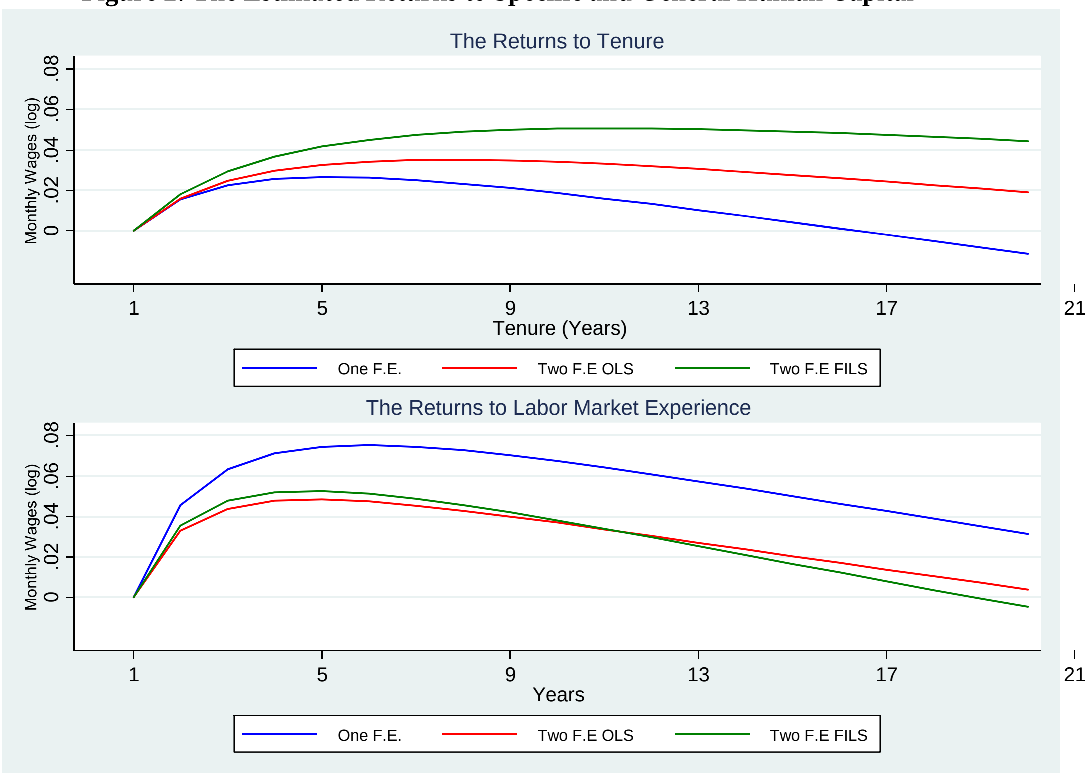

Table 5: Estimated Correlation Structure of Wage Components

Model 2: Two-Way FE (OLS)		X_{ijt}	*Firms* β_j		*Workers* α_i	
			η_j	θ_j	η_i	θ_i
Time-varying characteristics	(X_{ijt})	-	10%	6.4%	28%	10%
Firms (β_j)	Observed η_j	10%	-	-7.2%	27%	15%
	Unobserved θ_j	6.4%	-7.2%	-	14%	-9.1%
Workers (α_i)	Observed η_i	28%	27%	14%	-	4.5%
	Unobserved θ_i	10%	15%	-9.1%	4.5%	-
Model 3: Two-Way FE (FILS)						
Time-varying characteristics	(X_{ijt})	-	6.1%	8.4%	29%	9.4%
Firms (β_j)	Observed η_j	6.1%	-	-14%	24%	14%
	Unobserved θ_j	8.4%	-14%	-	13%	-4.2%
Workers (α_i)	Observed η_i	29%	24%	13%	-	4.5%
	Unobserved θ_i	9.4%	14%	-4.2%	4.5%	-

Table 6: Wage Variance Decomposition

		Covariance With		
	Total	X_{ijt}	β_j	α_i
Model 2: Two-Way FE (OLS)	**(1=2+3+4)**	(2)	(3)	(4)
Time-varying characteristics (X_{ijt})	11%	5.8%	1.4%	3.3%
Firms (β_j)	32%	1.4%	26%	4.4%%
Workers (α_i)	49%	3.3%	4.4%	42%
Error Term (ε_{ijt})	7.7%	0%	0%	0%
Model 3: Two-Way FE (FILS)				
Time-varying characteristics (X_{ijt})	10%	5.8%	1.2%	3.4%
Firms (β_j)	27%	1.2%	21%	4.5%
Workers (α_i)	56%	3.4%	4.5%	48%
Error Term (ε_{ijt})	6.3%	0%	0%	0%

Table 7: Wage Variance Decomposition by Job Mobility Patterns (Model 3, FILS)

	Stayers	*Job-to-Job*	*Job-Unemp-Job*
	(1)	(2)	(3)
Time-varying characteristics (X_{it})	9%	*10%*	12%
Firms (β_j)	27%	26%	30%
Workers (α_i)	56%	57%	51%
Error Term	7%	6%	7%

Table 8: Wage Variance Decomposition: Inter-Industry Wage Differentials (Model 3: FILS)

Sector	**Raw Industry Wage Differential**	**Average Fixed Effect Within Industry: Person Effect (α_i)**	**Firm Effect (β_i)**
	(1)	(2)	(3)
Agriculture	-0.551	-0.177	-0.325
Extractive Industry	0.171	0.074	0.114
Industry (Manufacturing and Energy)	0.091	0.016	0.094
Construction	-0.147	-0.068	-0.016
Wholesale & retail Trade	-0.210	-0.076	-0.131
Restaurant and Hotels	-0.272	-0.177	-0.058
Transport	0.078	0.009	0.073
Communications	0.289	0.178	0.042
Financial Services	0.444	0.229	0.177
Business Services	-0.199	-0.060	-0.142
Public Administration	-0.089	-0.059	-0.024
Education	0.037	0.021	-0.044
Health	-0.000	-0.006	-0.024
Culture/Sports	-0.139	-0.014	-0.101
Other Social Services	-0.221	-0.067	-0.149
Between Industry Correlation *(α_i, β_j)*	75%	-	-
% of Wage Variance explained	-	26%	74%

Note: Inter-industry raw differential are adjusted for observables {Xijt}. The inter-industry wage differentials adjusted for observables include time-varying and time-invariant observed characteristics.

Table 9: Decomposition of Inter-industry Wage Differentials: Person and Firm Effects

	Total	**Covariance with:** Firm {β_i}	Worker {α_i}
Model 3: Two-Way FE (FILS)	**(1=2+3)**	**(2)**	**(3)**
Firm	74%	56%	17%
Worker	26%	17%	9%
Total	100%	74%	26%

Figure 3 : Inter-industry wage differentials

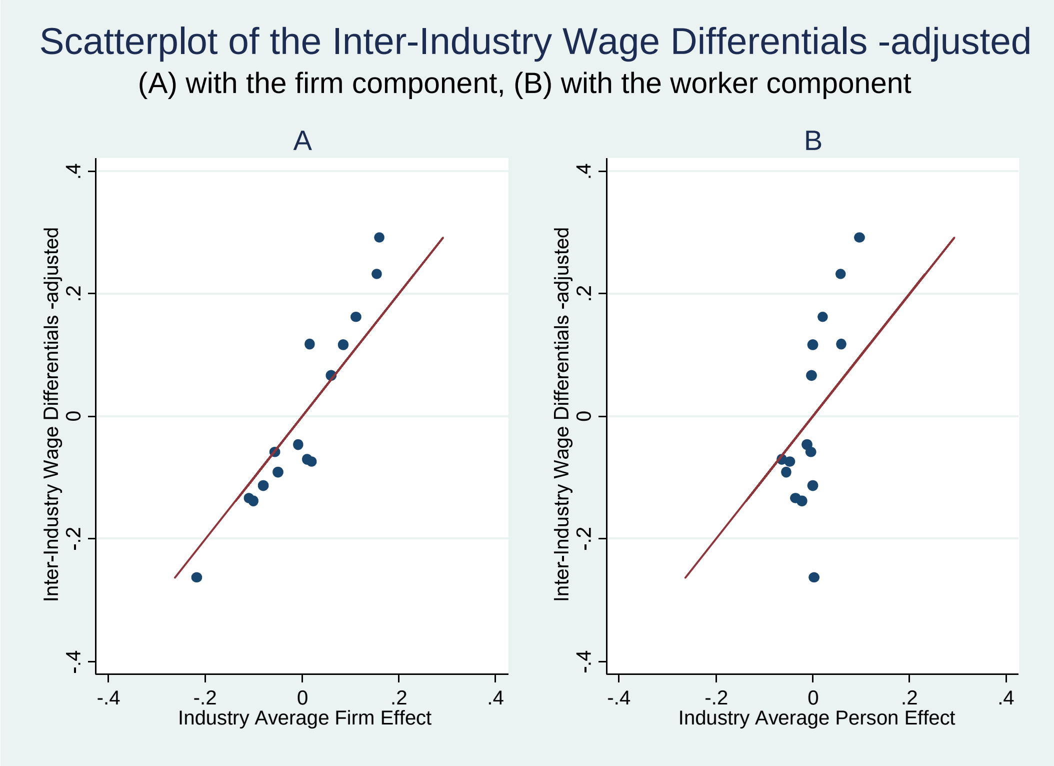

Figure 4: Exogenous Mobility Analysis

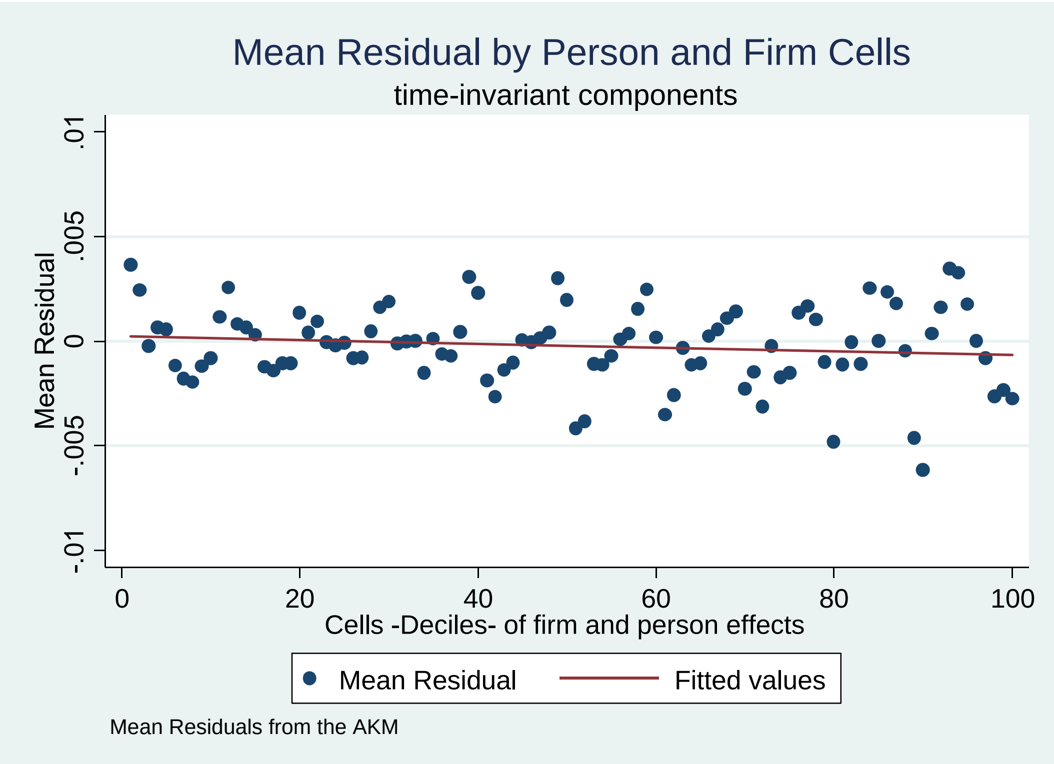

Table 10: Robustness Analysis

	Number of Employees		Firm Ownership	Time Period	
	10	20	Only Private Firms	2000-2008	2007-2014
Wage Variance Decomposition	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Time-varying characteristics (X_{ijt})	10%	10%	11%	6.8%	7.6%
Firms (β_j)	26%	24%	26%	25%	27%
Workers (α_i)	57%	58%	55%	62%	59%
Error Term (ε_{ijt})	6.8%	6.5%	7%	5.8%	5.5%
Total	100%	100%	100%	100%	100%

Table 11: Detailed Results for 2000-2007 and 2007-2014 estimation samples

	Variance of wages	Wage Variance Decomposition			
			Covariance With		
	(1)	**Total (2=3+4+5)**	X_{ijt} (2)	$\boldsymbol{\beta_j}$ (3)	$\boldsymbol{\alpha_i}$ (4)
2000-2007					
Wages (logs)[16]	0.487	-	-	-	-
Time-varying characteristics (X_{ijt})	0.114	6.8%	5.7%	0.0%	1.9%
Firms (β_j)	0.255	25%	0.0%	20%	4.8%
Workers (α_i)	0.364	62%	1.9%	4.8%	56%
2007-2014					
Wages (logs)	0.420	-	-	-	-
Time-varying characteristics (X_{it})	0.073	7.6%	3.0%	0.7%	3.9%
Firms (β_j)	0.268	27%	0.7%	26%	0.4%
Workers (α_i)	0.321	59%	3.9%	0.4%	55%

[16] This log wages are corrected by censoring.

APPENDIX A: Estimation of the Worker and Firm Time-Invariant Effects

We decompose the pure person effect as,

$$\alpha_i^p = \theta_i^p + \pi_i^p \eta^p \qquad \text{(A.1)}$$

where θ_i^p is the unobservable personal heterogeneity, π_i^p is a vector of time-invariant personal characteristics and η^p is a vector of the effects associated with time-invariant personal characteristics. Similarly, for the pure firm effects, we have

$$\beta_i^f = \theta_i^f + \pi_i^f \eta^f \qquad \text{(A.2)}$$

where θ_i^f is the unobservable firm heterogeneity, π_i^f is a vector of time-invariant firm characteristics (sector, size and so on) and η^f is a vector of the effects associated with time-invariant firm characteristics. The estimated individual fixed effects are regressed on gender, nationality and education (five groups), and we allow for heterogeneous effects of education by gender and nationality. Results are display in Table B.1. Similar to Woodcock (2008) and Sørensen and Vejlin (2012) we find that observable differences are able to explain only a small part of wage variation. Interestingly, Model 1 –compared to Models 2 an 3-, overestimates the importance of gender and education to explain individual wage heterogeneity. That is, empirical studies concerned with gender differences in wages should take into account the role that firms wage policies and the process of sorting of workers into firms might play. These differences reflect the biases incurred when omitting firm fixed effects in the analysis and point that high educated male workers tend to locate in high wage firms.

Similarly, the estimated firm fixed effects are regressed on sector of activity (15 dummy variables), firm size (8 dummy variables) and type of ownership (6 dummy variables). We see that firm´size (as measured by the number of employees), and the industry affiliation play some role in explaining differences in firm fixed effects. Specifically, the firm fixed effects are on average larger among bigger firms. There is also strong evidence of differences in firm fixed effects across industry.

Table 1.A. Regression of individual Fixed Effects: $\{\hat{\alpha}_i\}$

	Model 1: One-Way		**Model 2: Two-Way F.E (OLS)**		**Molde 3: Two-way F.E (FILS)**	
	Coeff.	S.e	Coeff.	S.e	Coeff.	S.e
Male	0.230**	0.002	0.144**	0.001	0.161**	0.002
Educational Attainment Levels						
Elementary	0.032**	0.002	0.001**	0.001	0.001**	0.001
Secondary	0.208**	0.002	0.103**	0.001	0.115**	0.001
High School Degree	0.314**	0.002	0.169**	0.002	0.168**	0.002
University Degree	0.405**	0.003	0.246**	0.002	0.271**	0.002
Male* Education						
Elementary	-0.022**	0.001	-0.001**	0.002	-0.003	0.002
Secondary	-0.048**	0.001	0.012**	0.004	0.009**	0.002
High School Degree	-0.130**	0.002	-0.060**	0.003	-0.027**	0.004
University Degree	-0.129**	0.002	-0.065**	0.002	-0.022**	0.003
Immigrant	-0.151**	0.001	-0.057**	0.001	-0.059**	0.003
Male*Immigrant	-0.041**	0.001	-0.036**	0.001	-0.055**	0.002
Immigrant* Education						
Elementary	-0.011**	0.003	-0.003**	0.002	-0.003	0.002
Secondary	-0.105**	0.004	-0.081**	0.002	-0.102**	0.004
High School Degree	-0.162**	0.006	-0.112**	0.004	-0.126**	0.003
University Degree	-0.064**	0.006	-0.076**	0.003	-0.088**	0.002
Constant	-0.477**	0.002	-0.251**	0.001	-0.292**	0.002
R^2	25%		17%		16%	

Note: Model 1: One-way model contains observable characteristics and person effects. Model 2: We add firm effects to model 1 but wages are not corrected for censoring; Model 3: Is the same as model 2 but wages are corrected by censoring.
* 95% statistical significance; ** 99% statistical significance

Table 2.A. Regression of Firm Fixed Effects $\{\hat{\beta}_j\}$

	Model 2: Two-Way FE (OLS)		*Model 3: Two-Way FE (FILS)*	
	Coefficient	S.e.	Coefficient	S.e.
Sectoral Dummys Added (15 groups)	Yes		Yes	
Firm Size				
5-20 Employees	-0.034**	0.002	-0.036**	0.002
20-50	-0.034**	0.002	-0.038**	0.002
50-100	-0.016**	0.002	0.022**	0.002
100-150	0.025**	0.003	0.022**	0.003
151-500	0.051**	0.004	0.048**	0.004
500-1000	0.061**	0.005	0.059**	0.006
1001-5000	0.060**	0.007	0.060**	0.007
>5000	0.102**	0.020	0.103**	0.021
Public Firm	0.094**	0.007	0.089**	0.007
Private Firms:				
Limited Partnership	-0.079**	0.002	-0.084**	0.003
Individual Employer	-0.178**	0.012	-0.189**	0.013
Business partnership	0.032	0.036	0.030	0.038
Common joint ownership	-0.042**	0.006	-0.045**	0.006
Social Associations	-0.145**	0.039	-0.164**	0.039
Civil partnership	0.032	0.021	0.039	0.024
Foreign Firms	0.047**	0.013	0.047**	0.014
Constant	-0.421**	0.009	-0.424**	0.004
R^2	24%		22%	

Note: In the constant term we have a small firm <5 employees

* 95% statistical significance; ** 99% statistical significance

APPENDIX A: Estimation of the Worker and Firm Time-Invariant Effects

We decompose the pure person effect as,

$$\alpha_i^p = \theta_i^p + \pi_i^p \eta^p \qquad \text{(A.1)}$$

where θ_i^p is the unobservable personal heterogeneity, π_i^p is a vector of time-invariant personal characteristics and η^p is a vector of the effects associated with time-invariant personal characteristics. Similarly, for the pure firm effects, we have

$$\beta_i^f = \theta_i^f + \pi_i^f \eta^f \qquad \text{(A.2)}$$

where θ_i^f is the unobservable firm heterogeneity, π_i^f is a vector of time-invariant firm characteristics (sector, size and so on) and η^f is a vector of the effects associated with time-invariant firm characteristics. The estimated individual fixed effects are regressed on gender, nationality and education (five groups), and we allow for heterogeneous effects of education by gender and nationality. Results are display in Table B.1. Similar to Woodcock (2008) and Sørensen and Vejlin (2012) we find that observable differences are able to explain only a small part of wage variation. Interestingly, Model 1 –compared to Models 2 an 3-, overestimates the importance of gender and education to explain individual wage heterogeneity. That is, empirical studies concerned with gender differences in wages should take into account the role that firms wage policies and the process of sorting of workers into firms might play. These differences reflect the biases incurred when omitting firm fixed effects in the analysis and point that high educated male workers tend to locate in high wage firms.

Similarly, the estimated firm fixed effects are regressed on sector of activity, firm size and type of ownership. We see that firm´size (as measured by the number of employees), and the industry affiliation play some role in explaining differences in firm fixed effects. Specifically, the firm fixed effects are on average larger among bigger firms. There is also strong evidence of differences in firm fixed effects across industry.

APPENDIX B: MORE ESTIMATION RESULTS

Table 1.B: Individual Wage Variance Decomposition: observed and unobserved components

		Covariance With				
	Total	X_{it}	η_j	θ_j	η_i	θ_i
Model 2: Two-Way FE (OLS)	**(1=2+3+ 4+5+6)**	(2)	(3)	(4)	(5)	(6)
Time-varying characteristics (X_{it})	11%	*5.8%*	0.7%	0.6%	1.8%	1.4%
Firms (β_j)						
Observed η_j	14%	0.7%	*9.3%*	-0.9%	2.3%	2.6%
Unobserved θ_j	19%	0.6%	-0.9%	*19%*	1.6%	-2.2%
Workers (α_i)						
Observed η_i	14%	1.8%	2.3%	1.6%	*7.1%*	0.7%
Unobserved θ_i	36%	1.4%	2.6%	-2.2%	0.7%	*33%*
Model 3: Two-Way FE (FILS)	(1=2+3+ 4+5+6)	(2)	(3)	(4)	(5)	(6)
Time-varying characteristics	11%	*5.8%*	0.4%	0.8%	2.0%	1.4%
Firms (β_j)						
Observed θ_j	11%	0.4%	*7.7%*	-1.5%	1.8%	2.2%
Unobserved η_j	16%	0.8%	-1.5%	*17%*	1.6%	-1.0%
Workers (α_i)						
Observed θ_i	14%	2.0%	1.8%	1.6%	*7.6%*	0.7%
Unobserved η_i	41%	1.4%	2.2%	-1.0%	0.7%	*38%*

Table 2.B: Detailed Variance Decomposition of the Worker and Firm Effects: time-invariant observed individual and firm characteristics

	Model 2: Two-Way FE (OLS)	*Model 3: Two-Way FE (FILS)*
Time-varying observed characteristics (X_{ijt})		
Tenure	1.0%	1.4%
Job-Type	8.1%	9.1%
Age	1.6%	0.4%
Experience	-0.3%	-0.9%
Job-Transition Type	0.3%	0.3%
Agg. Vbles.	0.1%	0.1%
Worker Effects (α_i)		
Gender	5.1%	4.3%
Education	9.6%	7.9%
Gender*Education	-1.7%	-0.2%
Inmigrant	1.4%	1.0%
Gender*Inmigrant	0.4%	0.5%
Inmigrant*Education	0.4%	0.5%
Firm Effects (β_j)		
Sector	14%	16%
Firm Size	1.7%	1.1%
Region	5.4%	5.4%
Firm Ownership	3.8%	3.4%

Table 3.B. Robustness Analysis: Main Sample Characteristics

	Number of Employees		Firm Ownership	Sample Period	
Total Sample	10	20	Private Firms	2000-2007	2007-2014
Total Nº of Observations	13,820,664	8,685,661	15,007,887	9,593,711	9,794,887
Sample of Workers					
Nº of Individuals	262,462	162,052	354,748	319,722	286,703
Nº of Time Periods per Worker (months)	26 (31)	26 (31)	21 (24)	25 (19)	21 (16)
Average Number of Firms Per Worker (All)	1.5 (0.8)	1.4 (0.7)	1.6 (0.7)	1.5 (0.9)	1.3 (0.7)
Average Number of Firms Per (Movers)	2.5 (0.8)	2.4 (0.7)	2.7 (0.7)	2.6 (1.0)	2.4 (0.8)
% of workers who are Movers	32%	27%	37%	32%	27%
Sample of Firms					
Nº of Firms	63,841	58,105	29,487	25,056	20,047
Nº of Different Workers per Firm (mean)	41 (62)	82 (106)	13 (19)	13 (20)	15 (22)
Nº of Movers per firm (mean)	13 (25)	22 (38)	7 (11)	6 (9)	5 (10)

*Standard Deviation Between brackets

Table 4.B Model Estimation Results of the Wage Equation

	Number of Employees		Firm Ownership	Time Period	
	10	20	Private Firms	2000-2007	2007-2014
Individual Characteristics					
Age <30	-0.004**	-0.003**	-0.003**	0.003**	-0.010**
Age 30-40	0.043**	0.046**	0.049**	0.033**	0.024**
Age 40-50	0.031**	0.033**	0.036**	0.024**	0.018**
Labour Experience (log)	0.065**	0.068**	0.048**	0.044**	0.061**
Labour Experience ^2	-0.017**	-0.021**	-0.002**	-0.014**	-0.021**
Labour Experience ^3	-0.001**	-0.009**	-0.004**	-0.003**	-0.001**
Non-employment Duration (log)	0.016**	0.015**	0.016**	0.016**	0.016**
Non-employment Duration^2	-0.015**	-0.013**	-0.016**	-0.015**	-0.015**
Non-employment Duration^3	0.002**	0.002**	0.003**	0.002**	0.003**
Individual Transition Type					
Job-to-Job	0.002**	0.001**	0.008**	0.003**	-0.002**
Unemployment-Job (new firm)	-0.016**	-0.017**	-0.013**	-0.013**	-0.017**
Unemployment-Job (same firm)	-0.014**	-0.016**	-0.010**	-0.010**	-0.013**
U. benefits	-0.009**	-0.011**	-0.009**	-0.007**	-0.007**
Individual-Job Characteristics					
Tenure (log)	0.023**	0.022**	0.019**	0.009**	0.013**
(Tenure)^2	0.007**	0.021**	0.016**	0.018**	0.009**
(Tenure)^3	-0.003**	-0.004**	-0.005**	-0.010**	-0.004**
Permanent Contract	0.050**	0.052**	0.050**	0.044**	0.043**
High Skill Job	0.152**	0.144**	0.152**	0.164**	0.119**
Medium Skill Job	0.028**	0.025**	0.030**	0.028**	0.028**
Aggregate-Covariates					
Reform-2012	-0.009**	-0.011**	-0.005**	-0.009**	-0.009**
Year Dummies	Yes	Yes	Yes	Yes	Yes
Quarterly Dummies	Yes	Yes	Yes	Yes	Yes
Constant	6.827**	6.873**	6.799**	6.898**	6.981**
$\left(\bar{\hat{\alpha}}_i, s.e_{\hat{\alpha}_i}\right)$[17]	-0.115 (0.317)	-0.116 (0.332)	-0.123 (0.313)	-0.149 (0.364)	-0.106 (0.321)
$\left(\bar{\hat{\beta}}_j, s.e_{\hat{\beta}_j}\right)$	-0.058 (0.251)	-0.053 (0.233)	-0.099 (0.248)	-0.098 (0.255)	-0.084 (0.268)
$Corr\left(\hat{\alpha}_i, \hat{\beta}_j\right)$	15%	13%	14%	12%	1.2%
$Corr\left(x_{ijt}\hat{\gamma}, \hat{\beta}_j\right)$	9%	8%	10%	0.2%	8.1%
$Corr\left(\hat{\alpha}_i, x_{ijt}\hat{\gamma}\right)$	20%	19%	18%	5%	30%
R^2	93%	93%	93%	94%	94%

[17] The mean of the person effects shown are computed across the person observations in the dataset. Similarly, the firm mean of the effects are estimated across the firm observations in the dataset.