Job Mobility and Industry Wage Differentials Evidence from Matched Employer Employee Data

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Abstract

The 1990s have witnessed enormous advances in the methods for decomposing wages into the person and the firm component. Typically, the main source of identification is due to individuals moving from one employer to another employer – job mobility. The aim of this paper is to investigate the sensitivity of these methods to two fundamentally distinct types of job mobility, job-to-job transitions (JTJ) and job-unemployment-job transitions (JUJ). In a matched employer-employee dataset covering a 25 % sample of all males employed in the private sector in the period from 1990 to 1997 in Austria, we find that the firms' wage policy is more strongly correlated with the wage rate in the JUJ sample than in the JTJ sample. Moreover, in contrast to the previous literature, we find that industry wage differentials reflect differences in wage policies rather than unobserved skills. This finding holds strongest for the effects identified using JUJ transitions.

JEL-Classification: C23, J31

Keywords: Job mobility, Industry wage differentials, Matched employer employee data

1 Introduction

The aim of this paper is to investigate the sensitivity of the recently developed methods of decomposing wages into a person and a firm component to job mobility.[1] Intuitively, the change of a worker from one employer to a different employer is the main source of variation which one needs to separate person and firm effects. The main identifying assumption is that job mobility is exogenous. It is useful to distinguish between at least two fundamentally distinct types of job mobility in order to study the degree to which endogenous mobility affects the wage decomposition: job-to-job (JTJ) transitions on the one hand and job-unemployment-job (JUJ) transitions on the other hand. Workers changing directly from one employer to another employer are likely to do so because the new employer offers a superior remuneration package. This means that the employment contract of the job held with the firm prior to the job change is likely to affect the new employment contract. In contrast, workers who enter unemployment between jobs are more likely to have been laid off by the previous employer. Thus, pre-displacement job attributes are likely to be less important for job-unemployment-job transitions than for job-to-job transitions.

In order to illustrate the consequences of endogenous mobility for the decomposition of wages we provide results that allow assessing to what extent industry wage differences reflect differences in wage policies as opposed to differences in worker characteristics across firms. A long literature has documented persistent, large wage differences across industries (Murphy and Topel (1987), Krueger and Summers (1987), Krueger and Summers (1988) or Gibbons and Katz (1992)). Various studies have shown that these are stable over time and countries.[2] The existing literature has offered numerous competing lines of explanations for persistent differences in wages across industries. It is useful to classify the literature with respect to the side of the labor market at which industry differences are thought to originate. On the one hand, standard human capital theory combined with informational asymmetries rationalize industry wage differences originating from non-random sorting of workers with different skills or abilities across in-

[1] See Abowd et al. (1999b) and Abowd et al. (2002a) for a discussion of statistical methods to decompose wages into person and firm components. Abowd and Kramarz (1999) give a review of the literature using matched employer employee data.

[2] see for example Carruth et al. (1999) for the UK, Goux and Maurin (1999) for France, Vainiomki and Laaksonen (1995) for Finnland or Winter-Ebmer (1994) for Austria. Zweimueller and Barth (1994) compare six countries with and without strong influences of unions and conclude that unionism has an impact on the size of the differential. Kahn (1998) compares the standard deviations of log industry wage effects while controlling for collective bargaining and finds that industry wage differentials are smaller in continental Europe than in the United States. Furthermore he concluded that "if the ongoing decentralization of wage setting institutions in European countries continues, my results imply an increase in industry wage differentials" (p. 527).

dustries.[3] On the other hand, a basket of theories explain why industry wage differentials might exist even if workers were identical. These firm based stories comprise efficiency wage theories (Krueger and Summers (1987)), bargaining and union hypotheses (Booth (1995)), but also the theory of equalizing differences (Rosen (1986)). Abowd et al. (1999) pioneered a graphical method to assess to what extent observed differences in wages across industries might be due to the worker's or the firm's side of the market. The findings in that paper and Abowd et al. (2002a) suggest that both sides of the labor market contribute to persistent differences in wages.

In this paper, we use matched employer employee (MEE) data provided by "Hauptverband der Österreichischen Sozialversicherungsträger"[4] and from "Arbeitsmarktservice Österreich"[5] for the period between 1990 and 1997 to investigate the extent to which job mobility affects worker and firm components of the wage rate. Besides our main sample which includes 2'179'485 observations for 399'804 persons, we construct two sub-samples. The JTJ sub-sample comprises all persons who ever changed directly from one employer to another employer. The JUJ sub-sample contains all person who ever lost their job and experienced at least one day of unemployment before they found a new employer.[6] The JTJ sample contains 442'183 observations of 68'766 persons while the JUJ sample covers 299'372 observations of 55'023 persons.

We then apply an iterative quasi-gradient algorithm in order to find the full least squares solution to the model that decomposes wages into a person and a firm effect. Findings indicate that, at the micro level, the firm wage component is more strongly correlated with the wage rate in the JUJ sample than in the JTJ sample. Second, results suggest that industry wage differentials reflect differences in firms' wage policies more strongly than differences in unobserved skills of individuals. This result holds strongest in the JUJ sample that is, arguably, the least affected by endogenous mobility.

In the following section we describe the data, discuss the main variables, and present a statistical analysis of the determinants of job mobility. Section 3 presents the statistical model, the estimation algorithm, and the definition of aggregate statistics based on firm and worker components. Section 4 presents the main results, and section 5 concludes.

[3] See Gibbons and Katz (1992) for a discussion of how information asymmetries, worker heterogeneity combined with endogenous mobility can generate persistent industry wage differentials.

[4] Association of the Austrian Social Insurance Carrier

[5] Austrian Unemployment Register

[6] Workers who come back to their former employer after some days of unemployment, so called recalls, are not treated as job changers.

2 Data

The data used in the empirical analysis stems from two sources. The first and main source are the Austrian Social Security Records, a very complete administrative database of matched employer-employee information collected by the "Hauptverband der Österreichischen Sozialversicherungsträger". This dataset contains detailed information on the workers' employment and earnings history between 1972 and 1998. For each individual, information on the number of days worked at a particular firm is available. Additionally sex and date of birth of each individual, as well as location, industry and size of the firms are known. The annual earnings are reported with an upper bound of the determination base for the social security system. Top-coding affects approximately 15% of all observations. The second source of information is the Austrian Unemployment Register which provides additional information such as education and nationality of all persons unemployed at least once between 1986 and 1998.

2.1 Data selection

The particular data set used in this work contains a 25% sample of all males employed in the private sector who worked on any October 10^{th} between 1990 and 1997.[7] We restrict the analysis to employees between 25 years and 55 years due to two reasons. First, the data set does not provide information on working hours. At 25 years of age, most individuals have completed their education and are able to work full-time.[8] Second, early retirement starts at age 60 (for males) and 55 (for females). In order to rule out early retirement effects we focus on an age group that is well below the early retirement age. Due to the administrative character of the data we also know if a person is unemployed, ill, and we know if a person has more than one job at the time. We focus only on those employees who were working and evaluate the job with the highest earnings in the case of multiple jobs.[9] Using this selection criteria our data-set includes 2'179'485 observation of 399'804 different persons and 124'906 firms.

The focus of our analysis is on two subsamples which we use to analyze the effect of endogenous mobility on wage decompositions. These two sub-samples are constructed as follows:

The JTJ sample contains all individuals who changed their job at least once but never through unemployment. A job change occurs if the employer in one year is different from the employer in the preceding year.[10] Our assumption

[7]This is not a 25% sample of all observations but a 25% sample of all individuals ever worked on October 10^{th} between 1990 and 1997.

[8]Referring to the data of Statistik Austria only 2.36 % of all male employees with an age between 25 and 54 but 25.0 % of all employed women worked as part-time worker in 1994.

[9]Multiple job holders make up less than 1 % of the dataset.

[10]This classification means that if an employee changed within a year away from his old

is that those who changed directly, did this because of an better remuneration package in the new job. Thus the selection of the new employer would be an endogenous decision. Comparing the wage in the new job with the wage in the old job will not reveal the firm wage differential that applies to an exogenous move. The JTJ sample is mainly drawn for reasons of comparison. It contains 442'183 observations of 68'766 different individuals and 54'674 firms.

Table 1: Groups and Identifiable Effects

	not connected	Largest Group	2^{nd} Largest Group	Average of all other Groups	Total of all Groups
main sample					
Observations	89'002	1'956'062	191	11.70	2'090'483
Persons	21'560	352'716	30	2.22	378'244
Firms	21'560	83'535	4	1.73	103'346
Groups		1	1	11'475	11'477
Identifiable Effects		436'250	33		470'113
JTJ sample					
Observations	283	365'706	248	8.61	441'900
Persons	88	56'251	33	1.40	68'678
Firms	88	33'441	7	2.40	54'586
Groups		1	1	8'822	8'824
Identifiable Effects		89'691	39		114'440
JUJ sample					
Observations	62	271'527	66	6.01	299'310
Persons	32	49'538	9	1.18	54'991
Firms	32	40'886	2	2.33	51'630
Groups		1	1	4'613	4'615
Identifiable Effects		90'423	10		102'006

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: In this table all 1 Person - 1 Firm Groups are eliminated, because there no effect is identifiable. Thus the numbers of observation, persons and firms are different from the results in table (2).

The JUJ sample contains all individuals who changed jobs at least once and always experienced at least one day of unemployment between successive jobs.[11] Relative to the JTJ sample, job mobility in the JUJ sample is less likely to be endogenous in the sense that the choice of the new employer is not driven by a

employer and than back again, this would not count as a job change. Also so called recalls do not count as job changes.

[11]Individuals who changed directly at least once and indirectly at least once again are excluded and do not show up in any sub-sample.

better wage compared to the former job. Thus comparing the new wage with the old one should reveal the true firm wage differential. The JUJ sample contains 299'372 observations of 55'023 different individuals and 51'662 different firms.

While by construction no individual shows up in both samples, 21'381 firms are in the JTJ sample as well as in the JUJ sample.

In order to identify one person and two firm effects (see section 4.2 for the definition of these effects) we need connected groups of firms and workers with at least two different persons or firms. Thus for the econometric analysis we drop those persons and those firms which are not connected with any other person or firm. This reduces the number of observations used in the wage decomposition in all samples slightly, for instance from 2'179'485 to 2'090'483 in the main sample. Table 1 shows the number of connected groups as well as the size of these groups by sample. In order to establish connected groups we rely on the algorithm discussed in Abowd et al. (2002a). In every sample the vas majority of observations, persons, and firms is connected within one big group.

2.2 Construction of Main Variables

This sub-section describes the main variables used in the following empirical analysis. We concentrate on those variables which needed to be constructed.

The wage information is measured as annual earnings including a possible 13^{th} or 14^{th} wage for each employee-employer combination. Because of the known daily employment history we can construct a income per day worked, the 'daily wage'. For a proper use of this variable we deflate the wage and calculate the natural logarithm. For those observations where the wage is reported at the upper bound of the determination base we need to apply an approximation. In order to address the top-coding problem, we construct a cluster of 1'440 cells[12] based on age, experience, working place, blue collar or white collar and year and estimate a tobit regression for each cell with log wage as the dependent variable and a constant as the only regressor. This estimation yields the moments of the censored normal variable that fits the wage distribution best within each cell. With this information in hand, it is possible to replace the censored wage informations with their expectation in the absence of censoring. Because the fixed effects method is a regression on the mean, this approximation is an appropriate method to impute these wages.

Because of the known working history we can calculate labor force experience and job tenure as the years actually worked instead of using potential labor force experience. For persons who started their career before 1972 (29.41% of all persons in the sample already worked before 1972) these variables are left censored. We address this problem by recoding work experience into eight different cate-

[12]See figure 4 in Appendix B for an illustration of the clustering.

gories (0, 1, 2-3, 4-5, 6-8, 9-12, 13-17, 18+ years of experience). Only the last class includes persons whose work experience is affected by left censoring.

To control for the different labor markets in Vienna and in big cities we include a geographic dummy variable for big cities if a city has more than 100.000 residents and another one for Vienna. The variable education captures the number of years necessary for a certain education level. It is only recorded if a person has at least once been unemployed and registered at the Austrian Unemployment Register which is available after 1986. This information is available for roughly half of the sample. We construct a dummy variable taking the value 1 if the education information is available, and 0 otherwise. Thereafter we replace missing information in the education variable with 0. This procedure is useful because we do not have to restrict the sample to those individuals with non-missing information. At the same time, it is important to keep in mind that the education effect is identified using variation due to the sub-sample of individuals who ever contacted the regional employment service office in the period between 1986 until 1998. Some descriptive statistics are provided in table 2.

Comparing the JTJ sample and the JUJ sample in table 2, we note that the average worker in the JTJ sample earns a higher wage than the average worker in the JUJ sample, which supports our assumption that a job-to-job change might be driven by a higher wage offer. Further a person in the JTJ sample has a higher education, more experience and tenure that individuals in the JUJ sample. Because of the lacking information on education for those who have never been unemployed between 1990 and 1997 the number of observations is much lower for this variable.[13] Additionally the JTJ worker is less likely to hold a blue collar position, works with a higher probability in Vienna and his firm has more workers. Because the tenure is job specific the average tenure must be lower than in the main sample, where fewer job changes occur. These descriptive statistics show that those who were never unemployed have better observable characteristics on average and therefore they earn higher wages.

2.3 Determinants of Job Mobility

In this section we assess the determinants of JTJ transitions compared to JUJ transitions. For this reason we present a multinomial logit analysis of the determinants of job mobility.

Table 3 reports the results from a multinomial logit analysis. The dependent variable equals 0 if there is no job change (base category), 1 if the individual moves from one employer to the next employer without entering unemployment (column JTJ), and 2 if a person changes employers with at least one day in

[13]Note that also in the JUJ sample there is a tiny subset of workers with missing education information. These workers are classified as unemployed in the main data source but never showed up at the employment service.

Table 2: Descriptive Statistics of Selected Variables

Industry	Main Sample Nobs	Main Sample Mean SD	JTJ Sample Nobs	JTJ Sample Mean SD	JUJ Sample Nobs	JUJ Sample Mean SD
Log(Wage)	2'179'485	6.774	442'183	6.821	299'372	6.562
		0.481		0.524		0.375
Education	1'012'228	9.956	148'021	10.237	296'238	9.874
		1.718		1.972		1.573
Experience	2'179'485	13.468	442'183	13.172	299'372	11.661
		5.332		5.415		5.587
Age	2'179'485	37.869	442'183	36.976	299'372	35.958
		8.666		8.126		7.730
Tenure	2'179'485	6.212	442'183	4.195	299'372	2.196
		6.815		5.401		3.526
Working in Vienna	2'179'485	0.223	442'183	0.259	299'372	0.222
		0.416		0.438		0.416
Blue Collar	2'179'485	0.560	442'183	0.466	299'372	0.762
		0.496		0.499		0.426
Firmsize	2'179'485	974.238	442'183	790.336	299'372	493.680
		3'219.259		3'026.124		2'385.812
Number of person	399'804		68'766		55'023	
Number of firms	124'906		54'674		51'662	

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: All samples include male employed between 1990 and 1997; JTJ sample includes all male employed between 1990 and 1997, except those who at least once experienced unemployment between two jobs: JUJ sample includes all male employed between 1990 and 1997, except those who at least once changed their job directly.

unemployment (column JUJ). The focus of this analysis is to assess whether job mobility patterns differ across industries. The estimated industry effects (reference category is "Retail Trade") suggest that, at the qualitative level, job mobility patterns do not differ strongly across industries. In 4 out of 39 cases the estimated coefficients are significantly different with opposite sign. For instance, individuals in the "Food, Drink, & Tobacco" industry are more likely to change directly from the previous employer to the new employer than in "Retail Trade".

The opposite is true for JUJ transitions. The same pattern emerges for the industries "Cloth", "Leather", and "Road Traffic". The estimated coefficients in the remaining 35 industries are either of the same sign or of opposite sign but not significantly different from zero. Focusing on the magnitude of the estimated coefficient, a set of about 7 industries can be distinguished with a difference between the effect in the JTJ and the JUJ transition equation exceeding .2 which is a rather substantial difference. For instance, in "Education & Research" JUJ transitions are much less likely than in "Retail Trade", whereas JUJ transitions are only slightly less likely than in "Retail Trade".

Table 3: Probability of a Job Change

	JTJ		*JUJ*	
Variable	Coef.	SE	Coef.	SE
Education	0.041**	0.003	0.016**	0.003
No Educ.	0.214**	0.030		
Age	-0.011**	0.001	-0.009**	0.001
Experience	-0.023**	0.001	-0.038**	0.001
Tenure (0-3 Years)	0.841**	0.012	0.477**	0.017
Tenure (3-10 Years)	0.332**	0.011	-0.308**	0.018
Unemployed before	-0.187**	0.009	-0.240**	0.010
Log Wage(t-1)	-0.163**	0.009	-0.248**	0.011
Big City	0.120**	0.010	0.137**	0.011
Vienna	0.336**	0.011	0.159**	0.012
Blue Collar	-0.228**	0.009	0.259**	0.011
Industry				
Unknown	0.159**	0.017	-0.003	0.020
Agricult. & Fishing	-0.239**	0.038	-0.465**	0.038
Forest	-0.636**	0.054	-0.402**	0.046
Energy	-1.205**	0.053	-1.368**	0.106
Water	-0.946**	0.265	-0.518	0.337
Mining	-0.301**	0.045	-0.217**	0.044
Food, Drink; & Tobacco	0.068**	0.022	-0.086**	0.025
Cloth	-0.089*	0.039	0.124**	0.039
Clothes	0.053	0.057	0.087	0.060
Leather	-0.282**	0.075	0.108*	0.071
Wood	-0.224**	0.022	-0.238**	0.023
Music Instr. & Toys	0.137**	0.060	0.128**	0.063
Paper	-0.103**	0.039	-0.207**	0.052
Print	-0.043	0.030	0.021	0.034
Rubber & Chem.	-0.209**	0.024	-0.070*	0.028
Building Materials	-0.274**	0.029	-0.214**	0.029
Metal	-0.008	0.019	-0.052**	0.021
Machine	-0.125**	0.023	-0.016	0.025
Electro-Technics	-0.082**	0.023	-0.076*	0.029
Vehicles	-0.085**	0.024	-0.083*	0.029
Fine-Mechanics	-0.300**	0.047	-0.075	0.052
Constructions	-0.079**	0.016	0.029	0.016
Wholesale Trade	0.084**	0.016	0.031	0.018
Accommodation	0.038	0.021	0.041	0.021
Road Traffic & Railway	0.195**	0.019	-0.145**	0.021
Inland Navigation	0.874**	0.084	-0.029	0.111
Air Traffic	-0.318**	0.066	-0.482**	0.107
Shipping	0.204**	0.030	0.109**	0.033
Telecommunication	-0.486**	0.067	-0.149*	0.071
Banking & Credit	-0.478**	0.028	-0.514**	0.051

Table 3: (continued)

	JTJ		*JUJ*	
Variable	Coef.	SE	Coef.	SE
Insurance	-0.339**	0.032	-0.128**	0.045
Real Estate	0.163**	0.018	0.163**	0.022
Cleaning	0.132**	0.031	0.011	0.034
Art & Entertainment	-0.143**	0.035	-0.230**	0.045
Health	-0.298**	0.028	-0.434**	0.037
Education & Research	-0.137**	0.030	-0.457**	0.045
Regional Corporation	-0.392**	0.019	-0.622**	0.026
Building Maintenance	0.294**	0.103	-0.179	0.137
Retail Trade				
Firm Size Dummies	yes		yes	
Time Dummies	yes		yes	
Constant	-1.458**	0.063	0.082**	0.077
Nobs		1'779'681		
chi^2		108'098.80		
LogL		-727'303.21		
Pseudo R^2		0.164		

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: This table presents the results of a multinomial logit. The dependent variable equals 0 if the person does not change her job. JTJ represents those who changed directly, while JUJ represents those who changed through unemployment. The sample include male employed between 1990 and 1997.
** Significant at 1% level, * Significant on 5% level

With respect to other individual level characteristics, we find that education increases the probability of a job change without unemployment. The dummy variable "No Education Info" refers to individuals with no education information. Since we have education information for almost all individuals with at least one JUJ transition, this dummy variable is not identified in the JUJ equation. In the JTJ equation, we note that "No Education Info" tends to be associated with a higher probability of a job change compared to the baseline outcome of staying with the employer. Furthermore increasing experience and age are associated with reduced likelihood of a job change. Individuals with at most 3 years of tenure are very likely to change jobs directly. Even if the tenure is between 3 and 10 years there is a positive likelihood of a direct job change compared to those with more than 10 years of tenure. With respect to JUJ transitions, we can see that persons, who recently started a new job, are more likely to change through unemployment while this probability decreases with higher tenure. Persons who were unemployed at least once before the current period are less likely to change the job at all. Individuals with higher wages change jobs less frequently than those with lower wages. High wages reduce the probability of a JUJ transition more strongly than that of JTJ transition. Persons working in Vienna or in a big city have a high probability of a job change compared to those living in smaller municipalities, even if the likelihood of a change through unemployment is smaller. The reason might be a bigger labor market which provides more jobs. Blue collar worker change their job less likely directly than their white collar colleagues but change with a higher probability through unemployment.

3 Statistical Model and Methods

This section discusses the statistical model that we use to decompose wages into person and firm components, the iterative quasi-gradient algorithm used to estimate these effects, and the aggregation of person and firm effects to the industry level.

3.1 The Statistical Model

Let y_{it} be the log of the wage rate of worker i at time t, let x_{it} denote the time-varying characteristics (labor market experience), let s_{it} denote years of seniority of worker i at time t, and let $J(i,t)$ be the employer identification number of worker i at time t. The number of workers in the dataset is N, the number of firms is J, and the number of observations is N^*. We assume that

$$y_{it} = x_{it}\beta + \theta_i + \phi_{J(i,t)} + \gamma_{J(i,t)}s_{it} + \epsilon_{it} \tag{1}$$

and

$$E[\epsilon_{it}|i,t,J(i,t),x_{it}] = 0 \tag{2}$$

The wage policy of the firm is captured with two parameters. The entry wage, ϕ_j, captures the wage differential earned in the present firm compared to the average firm in the dataset ($j = 1,...,J$). The tenure effect, γ_j, captures differences across firms in the wage increases due to changes in seniority ($j = 1,...,J$). The worker's wage component, θ_i, reflects differences in pay due to unobserved or observed time-constant characteristics of each worker ($i = 1,...,N$).

The main statistical assumption is that of exogenous mobility in equation (2). This assumption rules out any correlation between unmeasured time-varying effects on the wage rate captured by ϵ_{it} with person or firm effects. The aim of this paper is to assess the sensitivity of the estimated effects to the assumption of exogenous mobility. Arguably, the assumption of exogenous job mobility is valid to a different extent in the JTJ sample compared to the JUJ sample. While the

JUJ sample comprises primarily individuals who were laid off by their previous employer or who did not have enough time to search for a new employer while still on the job, the JTJ sample contains individuals who moved directly from the previous employer to the new employer. Thus, in the JTJ sample, there are more grounds to believe that the exogenous mobility assumption is violated than in the JUJ sample.

In matrix notation equation (1) is written as follows:

$$y = X\beta + D\theta + F\phi + S\gamma + \epsilon \tag{3}$$

with D as a $N^* \times N$ matrix of indicator variables for the persons, F as a $N^* \times J$ matrix of indicator variables for the firm effects, and S as $N^* \times J$ the matrix containing years of seniority.

3.2 Estimation Method

The least squares estimator of β, θ, ϕ, and γ solves the following normal equations

$$\begin{bmatrix} X'X & X'D & X'F & X'S \\ D'X & D'D & D'F & D'S \\ F'X & F'D & F'F & F'S \\ S'X & S'D & S'F & S'S \end{bmatrix} \begin{bmatrix} \beta \\ \theta \\ \phi \\ \gamma \end{bmatrix} = \begin{bmatrix} X'y \\ D'y \\ F'y \\ S'y \end{bmatrix} \tag{4}$$

It is not possible to invert the cross-product matrix due to the large number of person and firm effects and due to computer memory constraints. In this paper we apply an iterative quasi-gradient method to find the solution to the normal equations. Rearranging the system of linear equations in (4) yields

$$\begin{bmatrix} X'X\beta \\ D'D\theta \\ F'F\phi \\ S'S\gamma \end{bmatrix} = \begin{bmatrix} X'(y - D\theta - F\phi - S\gamma) \\ D'(y - X\beta - F\phi - S\gamma) \\ F'(y - X\beta - D\theta - S\gamma) \\ S'(y - X\beta - D\theta - F\phi) \end{bmatrix} \tag{5}$$

These are four blocks of normal equations that yield the required least squares solution given the least squares solution of the remaining three sets of parameters.

It is possible to construct an iteration protocol based on (5). Choose starting values $\beta_0, \theta_0, \phi_0$, and γ_0. Let l index iterations. Solve for $\beta_l, \theta_l, \phi_l$, and γ_l using (5) based on the estimate of the other parameters in iteration $l-1$. This gives the following updating rule

$$\begin{bmatrix} \beta_l \\ \theta_l \\ \phi_l \\ \gamma_l \end{bmatrix} = \begin{bmatrix} [X'X]^{-1} X'(y - D\theta_{l-1} - F\phi_{l-1} - S\gamma_{l-1}) \\ [D'D]^{-1} D'(y - X\beta_l - F\phi_{l-1} - S\gamma_{l-1}) \\ [F'F]^{-1} F'(y - X\beta_l - D\theta_l - S\gamma_{l-1}) \\ [S'S]^{-1} S'(y - X\beta_l - D\theta_l - F\phi_l) \end{bmatrix} \tag{6}$$

Intuitively, the current estimate of β, for instance, is found by regressing the residuals $y - D\theta_{l-1} - F\phi_{l-1} - S\gamma_{l-1}$ on the matrix X.

The algorithm is partially recursive in using the fact that the current value of β, β_l, can already be used in estimating θ_l. In estimating ϕ_l, the current values of β_l and θ_l are used to form the residuals, etc. The algorithm converges to the true least squares solution because parameter updates are chosen to fulfill the normal equations given the values of the other parameters. We determine convergence to be achieved when the absolute change in the sum of squared errors between iteration l and $l-1$ falls below $1 \cdot 10^{-11}$.

After the least squares solution $\widehat{\beta}, \widehat{\theta}, \widehat{\phi}$, and $\widehat{\gamma}$ is obtained, we apply the grouping algorithm discussed in Abowd et al. (2002a) in order to establish the number of identified effects. We normalize the person constant, the firm constant, and firm tenure parameter to be relative to the mean value of this parameter within each group. Table 1 provides a summary of the results of the grouping procedure.

The person effect θ_i can be decomposed in a component due to the observable personal characteristics (u_i; education, age in 1990) and a person-specific intercept (α_i):

$$\theta_i = \alpha_i + u_i\eta \tag{7}$$

We apply this procedure separately, to the main dataset, to the JTJ dataset, and to the JUJ dataset. Thus, we end up with three sets of parameters which we index by the dataset in which they were obtained. For instance, $\widehat{\beta}_M, \widehat{\theta}_M, \widehat{\phi}_M$, and $\widehat{\gamma}_M$ are the estimates from the main (M) sample.

3.3 Endogenous Mobility and Industry Effects

Much of the literature has focused on the question whether the raw industry effects κ^{**} (obtained in a cross section regression of y on X and a set of industry indicators) reflect differences in the average wage policy of firms across industries or whether they reflect differences in unobserved skills across industries. The raw industry effects are defined in the following regression

$$y = X\beta + FA\kappa + \nu \tag{8}$$

with

$$\nu = F\phi + S\gamma + D\theta + \epsilon$$

where the matrix A, $J \times K$, sorts each firm J into one of the K industries.

Standard regression algebra shows that the raw industry effect consists of three components

$$\kappa^{**} = \underbrace{(A'F'M_XFA)^{-1}A'F'M_X(F\phi_M + S\gamma)}_{\kappa^f} + \underbrace{(A'F'M_XFA)^{-1}A'F'M_XD\theta}_{\kappa^p} + \\ + \underbrace{(A'F'M_XFA)^{-1}A'F'M_X\epsilon}_{\kappa^{EM}} \tag{9}$$

Equation (9) shows that κ^{**} consists of an industry specific firm effect (κ^f), an industry specific person effect (κ^p) and an industry specific endogenous mobility (EM) component. Intuitively, the industry specific firm effect κ^f captures cross industry differences in firms' wage policies in a hypothetical world without differences in observable characteristics X.

The existing literature has postulated that the industry specific endogenous mobility component κ^{EM} is zero. Then, in order to assess the relative importance of firm wage policies vs. differences in worker characteristics in explaining industry wage differentials, it suffices to plot $\widehat{\kappa}^{**}$ against the estimates of the industry specific firm wage component $\widehat{\kappa}^f$ and to plot $\widehat{\kappa}^{**}$ against the estimated industry specific person component $\widehat{\kappa}^p$.[14]

This paper departs from the literature in postulating differences in the degree to which the assumption of exogenous mobility is valid in the three datasets we study. Specifically, we expect that endogenous mobility is more relevant in the JTJ sample than in the JUJ sample.

Before analyzing this question we have to prove how comparable are firms and workers in the main sample to the firms and workers in the JUJ sample and the JTJ sample respectively. There are two reasons why the effects in the different samples may vary. While we are interested in the endogenous mobility effect, a selectivity effect may disturb our results. This selectivity effect may arise if the persons and the firms in all three samples are not randomly drawn, as it is the case in this study. To test how far selectivity of firms and workers in the to sub-samples is critical for our results we calculate the industry average effects of both sub-samples identified in the main sample, $\widehat{\kappa}^r_{m(q)}$, with $r = f, p$ and $q = JUJ, JTJ$. These additional sub-samples enclose the same persons and firms as the JUJ sample and the JTJ sample respectively, but different industry average effects. Thus differences in the correlation of the industry specific effects and the raw industry effects in the main sample on the one hand and the same correlation in the sub-sample based on the main effects reflect the error due to selectivity. In other words, without selectivity:

[14] It is also true that estimated industry specific firm and worker effects should add up to the estimated raw industry differential. We find that this condition is satisfied in all three datasets. Specifically, the correlation coefficient between the sum of the industry specific firm and worker component with the raw industry differential exceeds 0.99 in all three datasets.

$$\rho(\widehat{\kappa}^{**}_m, \widehat{\kappa}^r_m) - \rho(\widehat{\kappa}^{**}_{m(q)}, \widehat{\kappa}^r_{m(q)}) = 0 \tag{10}$$

To show how endogenous mobility affects the correlation of the raw industry effect and the industry specific effects we compare the sub-sample effects based on the main sample with the effects obtained in the sub-samples. Due to the construction of the JUJ sample the endogenous mobility is minimized. Thus we can use estimates of this sample as a baseline. If endogenous mobility leads to an overestimation of an industry specific effect, then

$$\Delta\rho^r_{m(JUJ);JUJ} = \rho(\widehat{\kappa}^{**}_{m(JUJ)}, \widehat{\kappa}^r_{m(JUJ)}) - \rho(\widehat{\kappa}^{**}_{JUJ}, \widehat{\kappa}^r_{JUJ}) > 0 \tag{11}$$

On the other hand by construction of the JTJ sample we impose relative high endogenous mobility. Thus we should observe the opposite effect comparing the results of this sample with the effects of the JTJ sample based on the main effects.

4 Results

This section first discusses whether industry effects in Austria are relevant and how these differentials compare to those found for the U.S. The section then provides the results of the fixed effects regression described before and elaborate on the correlation coefficients for components of the log real wage. The section closes with the results regarding the role of endogenous mobility in decomposing wages into a worker and a firm component.

4.1 Inter-Industry Wage Differentials in Austria

Based on the main sample we estimate the regression (8). The results are shown in the first column of table 4. All estimated differentials are highly significant. For example wages in the mining, metal, printing, building materials, or air traffic industry are higher than the average wage while they are lower in most service sector industries. As control variables we include experience, age, tenure (and the squared of these), education, year dummies and dummies for Vienna, big cities and blue collar. The adjusted[15] standard deviation of the industry wage differential shows the overall variability of the industry effect. It is very similar to the one reported in Krueger and Summers (1988).

In the second column we present the results of the 1979 estimation of Krueger and Summers (1988). Because of the different industry classifications[16] it is not

[15]Following Krueger and Summers (1988) we compute the adjusted standard deviation by using the formula $SD(\kappa) \approx \sqrt{var(\hat{\kappa}) - \sum_{i=1}^{K} \frac{\hat{\sigma}_i^2}{K}}$.

[16]Krueger and Summers (1988) use May CPS while in Austria ÖNACE (The Austrian version of the European industry classification) is used.

possible to provide an exact comparison. Thus, we concentrate on the sub-set of Krueger-Summer industries which we could match with the corresponding industry in Austria (column 2 of table 4). The correlation between industry differentials in Austria with those in the U.S. is remarkably strong (.532). This suggests that not only are industry wage differentials as relevant in Austria as in the U.S. in terms of wage dispersion but it is also true that, on average, high wage industries in the U.S. are also high wage industries in Austria.

Table 4: Estimation of the Inter-Industry Differentials

Main Sample			Krueger & Summers 1979		
Variable	Coef.	(SE)	Variable	Coef.	(SE)
Energy	0.168	(0.005)	Public Utilities	0.068	(0.028)
Water	-0.012	(0.014)			
Mining	0.216	(0.005)	Mining	0.263	(0.031)
Food, Drink, & Tobacco	0.064	(0.004)	Food	0.019	(0.026)
			Tobacco	-0.040	(0.156)
Cloth	-0.019	(0.005)	Textiles	-0.034	(0.156)
Clothes	-0.163	(0.006)	Apparel	-0.132	(0.030)
Leather	-0.143	(0.007)	Leather	-0.233	(0.051)
Wood	-0.031	(0.004)	Lumber	-0.35	(0.035)
			Furniture	-0.120	(0.036)
Music Instr. & Toys	-0.002	(0.006)	Instruments	0.137	(0.040)
Paper	0.176	(0.005)	Paper	0.088	(0.033)
Printing	0.179	(0.005)	Printing	0.039	(0.028)
Rubber & Chem.	0.136	(0.004)	Rubber	0.023	(0.036)
			Chemical	0.148	(0.029)
Building Materials	0.165	(0.004)	Stone, Clay & Glass	0.052	(0.034)
Metals	0.148	(0.004)	Primary Metals	0.114	(0.026)
			Fabricated Metals	0.039	(0.026)
Machine	0.149	(0.004)	Machinery, excl. Elec.	0.092	(0.022)
			Electrical Machinery	0.045	(0.021)
Electrotechnics	0.188	(0.004)			
Vehicles	0.037	(0.004)	Transport Equipment	0.156	(0.021)
Constructions	0.113	(0.004)	Constructions	0.137	(0.016)
Wholesale Trade	-0.007	(0.004)	Wholesale Trade	-0.015	(0.020)
Retail Trade	-0.087	(0.004)	Eating & Drinking	-0.125	(0.020)
			Other Retail	-0.093	(0.050)
Road Traffic, Railway	-0.028	(0.004)	Railroad	0.120	(0.037)
Inland Navigation	0.097	(0.011)			
Air Traffic	0.208	(0.006)			
Shipping	0.028	(0.005)	Other Transport	0.120	(0.022)
Telecommunication	-0.399	(0.006)	Communications	0.064	(0.027)
Banking & Credit	0.109	(0.004)	Banking	-0.063	(0.031)
Insurance	-0.012	(0.005)	Insurance	0.022	(0.027)
Art & Entertainment	0.001	(0.005)	Entertainment	-0.078	(0.019)
Health	-0.073	(0.005)	Hospitals	0.063	(0.018)
			Medical Services	-0.039	(0.022)
			Welfare Services	-0.190	(0.032)
Education & Research	-0.372	(0.005)	Education Services	-0.185	(0.019)
Accommodation	-0.185	(0.004)			
Agriculture & Fishing	-0.224	(0.005)			
Forest	-0.030	(0.005)			
Regional Corporation	-0.180	(0.004)			
Building Maintenance	-0.144	(0.012)			
Real Estate	0.025	(0.004)			
Cleaning	-0.163	(0.005)			
Fine-Mechanics	0.017	(0.005)			
Unknown	0.051	(0.004)			
Nobs	2'068'150			8'978	
SD	0.122			0.108	

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger. Estimation for 1979 by Krueger and Summers (1988) (Table II)
note: The pooled regressions is based on the main sample. Other explanatory variables are education, no education dummy, experience, age, tenure, tenure^2, year dummies, Vienna dummy, big city dummy, and blue collar dummy. Only those Industries (May CPS classification) are shown in the latter row which are more or less comparable to the industry classification in Austria. The standard deviation is the same as shown in Krueger and Summers (1988).

4.2 Full Least Squares Results

Table 5 shows the results of the fixed effects regression on log wages using the iterative procedure discussed in section 3.[17]

Table 5: Fixed Effects Regression on Wages

	Main Sample		JTJ Sample		JUJ Sample	
Variable	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Experience						
1 Year	-0.006**	(0.002)	-0.021**	(0.005)	0.005	(0.004)
2-3 Years	0.030**	(0.002)	0.017**	(0.005)	0.034**	(0.004)
4-5 Years	0.067**	(0.002)	0.059**	(0.005)	0.054**	(0.005)
6-8 Years	0.098**	(0.002)	0.090**	(0.006)	0.059**	(0.006)
9-12 Years	0.130**	(0.002)	0.120**	(0.007)	0.066**	(0.007)
13-17 Years	0.124**	(0.003)	0.097**	(0.008)	0.066**	(0.008)
18 and more Years	0.128**	(0.003)	0.096**	(0.009)	0.060**	(0.009)
1991	0.040**	(0.000)	0.048**	(0.001)	0.031**	(0.002)
1992	0.058**	(0.000)	0.074**	(0.001)	0.044**	(0.002)
1993	0.072**	(0.001)	0.096**	(0.002)	0.052**	(0.002)
1994	0.080**	(0.001)	0.110**	(0.002)	0.056**	(0.002)
1995	0.098**	(0.001)	0.136**	(0.002)	0.066**	(0.002)
1996	0.100**	(0.001)	0.142**	(0.002)	0.067**	(0.002)
1997	0.107**	(0.001)	0.152**	(0.002)	0.070**	(0.003)
Vienna	-0.003**	(0.001)	-0.005	(0.003)	-0.001	(0.003)
Big city	-0.018**	(0.001)	-0.007*	(0.002)	-0.008**	(0.002)
Blue Collar	-0.084**	(0.001)	-0.048**	(0.002)	-0.065**	(0.002)
Nobs		2'090'483		441'900		299'310
R^2		0.937		0.937		0.924

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: For a description of the samples see note of table (1).
Standard Errors are calculated by the person first method.
All results are deviations from the sample mean.
** Significant at 1% level, * Significant on 5% level

We regress the log wage on experience as a level variable, seven time dummies, dummies for Vienna, big cities and blue collar workers and a constant. Results for the main sample show that there is a strong increase of the wage rate with experience, the maximum of the experience profile occurring after 9-12 years. This profile is estimated quite similarly in the JTJ sample. While the experience profile in the JUJ sample reaches the maximum also after 9-12 years, the increase in wages due to labor market experience is only about half as strong (0.066 log

[17] Because it is not possible to invert the cross-product matrix as described in section 3, the standard errors are calculated with the "Person First" method. (see Abowd et al. (1999b))

points) compared to the JTJ (0.120 log points) or the main sample (0.130 log points). The maximum of the experience profile occurs rather early. This may have to do with the fact that we use the actual number of days worked since 1972.[18] Second, wages increase very strongly over the time period. The time effect on wages is strongest in the JTJ sample and weakest in the JUJ sample. Working in a city with more than 100'000 inhabitants in 1991[19] is associated with slightly lower wages compared to working in cities or communities with less than 100'000 inhabitants. Blue collar workers earn less than white collar workers in all three samples.

Table 6: Descriptives of the Components of the Log Real Wage

	Main Sample		JTJ Sample		JUJ Sample	
Variable	Mean	SD	Mean	SD	Mean	SD
Log(wage)	6.787	0.444	6.829	0.503	6.568	0.356
Indiv. char. ($x'\beta$)	0.000	0.062	-0.000	0.060	0.000	0.037
Person effect (θ)	0.000	0.392	0.000	0.442	-0.000	0.347
Unobs. PE (α)	-0.010	0.377	-0.009	0.438	-0.014	0.346
Obs. PE ($u'\eta$)	0.010	0.079	0.009	0.056	0.014	0.006
Firm effect (ψ)	-0.002	0.287	-0.009	0.360	-0.005	0.335
Unobs.FE (ϕ)	-0.000	0.278	0.000	0.373	0.000	0.343
Tenure ($\gamma' s$)	-0.002	0.154	-0.009	0.202	-0.005	0.176

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: For a description of the samples see note of table (1).

Table 6 shows the descriptive statistics of components of the log real wage. As described in section 3, we decompose these components into observable time varying personal characteristics ($x'\beta$), into non-time varying personal heterogeneity (θ) and into unobserved heterogeneity of firms' wage policy. Differences in firm wage policies are measured as the sample average of $\psi_{J(i,t),it} = \phi_{J(i,t)} + \gamma_{J(i,t)} s_{it}$, that is, the predicted wage premium in firm j after s_{it} years of seniority. The non time-varying personal heterogeneity we decompose again into an unobservable part (α_i) and an observable part ($u'_{it}\eta$; education and age in 1990). In all samples, the person effect and the firm effect vary much more strongly than the components of wages that are related to time-varying personal characteristics. In the main sample and in the JTJ sample, person effects (SD=0.392 (main); SD=0.442 (JTJ)) vary stronger than firm effects (SD=0.287, (main); SD=0.360 (JTJ)). In the JUJ sample, however, the firm effect (SD=0.335) seems to be

[18]For instance, for workers who are seasonally employed, the difference between actual and potential experience can be large.
[19]We use the information of the 1991 census in Austria.

about as important as the person effect (SD=0.347) in generating differences in wage rates.

Table 7: Correlation between Components of the Log Real Wage

Variable	lnwage	$(x'\beta)$	(θ)	(α)	$(u'\eta)$	(ψ)	(ϕ)	$(\gamma's)$
main sample								
Log(wage)	1							
Indiv. char. $(x'\beta)$	0.412	1						
Person effect (θ)	0.724	0.305	1					
Unobs. PE (α)	0.688	0.271	0.977	1				
Obs. PE $(u'\eta)$	0.245	0.192	0.217	0.003	1			
Firm effect (ψ)	0.389	0.010	-0.293	-0.306	0.028	1		
Unobs.FE (ϕ)	0.344	-0.025	-0.232	-0.243	0.026	0.852	1	
Tenure $(\gamma's)$	0.102	0.063	-0.126	-0.130	0.004	0.323	-0.221	1
JTJ sample								
Log(wage)	1							
Indiv. char. $(x'\beta)$	0.271	1						
Person effect (θ)	0.618	0.145	1					
Unobs. PE (α)	0.603	0.141	0.992	1				
Obs. PE $(u'\eta)$	0.157	0.037	0.131	0.001	1			
Firm effect (ψ)	0.355	0.034	-0.388	0.122	0.008	1		
Unobs.FE (ϕ)	0.305	0.023	-0.348	-0.006	0.018	0.849	1	
Tenure $(\gamma's)$	0.069	0.019	-0.050	0.059	-0.019	0.217	-0.333	1
JUJ sample								
Log(wage)	1							
Indiv. char. $(x'\beta)$	0.297	1						
Person effect (θ)	0.488	0.234	1					
Unobs. PE (α)	0.487	0.232	1	1				
Obs. PE $(u'\eta)$	0.111	0.112	0.114	0.097	1			
Firm effect (ψ)	0.397	-0.039	-0.543	-0.543	-0.023	1		
Unobs.FE (ϕ)	0.349	-0.063	-0.469	-0.470	-0.027	0.863	1	
Tenure $(\gamma's)$	0.074	0.050	-0.116	-0.117	0.010	0.217	-0.306	1

source: Authors' calculation based on data from Hauptverband der Österreichischen Sozialversicherungsträger.
note: For a description of the samples see note of table (1).

Table 7 shows the correlation matrix of the components of the log real wage. The correlation structure appears to be rather similar to findings in Abowd et al. (2002a). We compare to their results because, to our knowledge, this is the only paper that is based on the full least squares solution. The correlation between the log real wage and $x'\beta$ (0.412) in the main sample is slightly higher than the corresponding correlation in the Washington State sample (0.304) and much higher than in France (0.141). The person effect is very strongly correlated with the log real wage (0.724). This finding is also present in France (0.704) but to a weaker degree for Washington State (0.511). We find a correlation between the firm effect and the log real wage (0.389) that lies between the results for France (0.201) and for Washington State (0.518). The correlation between the person effect and the firm effect in Austria (-0.293) is very similar to that in France (-0.283) but more negative than the corresponding correlation in Washington State (-0.025). Thus, results for the main sample appear to be in line with findings in the literature.

With respect to the details of the wage policy of the firm, we note that the starting wage (ϕ) is negatively correlated (-0.221) with the seniority component of the wage rate ($\gamma' s$).

There are some interesting differences in the correlation structure in the JTJ sample when compared to the JUJ sample. While there is a strong correlation between person effects and the log real wage in the JTJ sample (0.618), the corresponding correlation is much weaker in the JUJ sample (0.488). Interestingly, the firms' wage policy is somewhat more strongly correlated with the wage rate in the JUJ sample (0.397) than in the JTJ sample (0.355). The correlation between the person effect and the firm effect is more negative in the JUJ sample (-0.543) than in the JTJ sample (-0.388). Thus, in the JUJ sample, firms are more important in wage determination than in the JTJ sample. Also, individuals with good unobserved skills tend to be observed in firms with worse than average wage policies.[20] Comparing results with the main sample, we note that the correlation structure in the JTJ sample is more in line with findings for the main sample than the JUJ sample.

Another way to compare the effects of the three samples is to correlate them across the samples (results are not shown). This exercise yields a very similar correlation of the firm effect of the JTJ and the JUJ sample with the firm effect of the main sample (0.639 (JTJ), 0.654 (JUJ)), while both effects are less strongly correlated with each other (0.403).[21] The correlation of the person effect in the JTJ sample with the person effect in the main sample is very strong (0.799). The corresponding correlation between the person effect in the JUJ sample and the main sample is weaker (0.686).

4.3 Endogenous Mobility and the Meaning of Industry Wage Differentials

In order to address the 'meaning' of industry wage differentials, we investigate the correlation between the raw industry effect $\widehat{\kappa}^{**}$ with the industry specific person effect $\widehat{\kappa}^{p}$ and with the industry specific firm effect $\widehat{\kappa}^{f}$, respectively. We

[20]The issue of why high wage workers sort into low wage firms is discussed in Abowd et al. (2002b).

[21]This correlation is based on 21'381 firms which are included in each of the samples.

first present two plots based on the main sample. In a second step, we assess the relevance of endogenous mobility by providing two additional sets of plots, the first referring to the JTJ sample, the second referring to the JUJ sample. The section closes with a discussion of which component of wages is more strongly affected by endogenous mobility.

Figure 1(a) plots the raw industry effect $\widehat{\kappa}_k^{**}$ against the industry average person effect $\widehat{\kappa}_k^p$ and (b) plots the raw industry effect $\widehat{\kappa}_k^{**}$ against the industry average firm effect $\widehat{\kappa}_k^f$ (the sub-script k indexes industries and runs from 1 to 39). Figure 1 reveals a striking result. The industry wage differentials from a cross section are very closely related to the industry average wage policy of firms ($\rho = 0.906$; plot b). Upon closer inspection, we find that all industries, except "Agriculture", "Air Traffic", and "Telecommunication" appear to lie on the 45^o line. In comparison, the correlation between the raw industry wage differentials and the industry average quality of workers is much less strong (plot a). The slope is steeper than in plot b and the correlation weaker ($\rho = 0.675$). Also, industries such as "education" are clear outliers. Individuals in education have average unobserved job skills but the education sector is estimated to have a very low raw industry differential.

The finding that raw industry differentials reflect primarily unobserved differences in firms' wage policies rather than the differences in unobserved skills of workers across industries stands in contrast to the literature. However, note that existing studies that investigated the correlation between raw industry differentials with industry specific person and firm effects have relied either on conditional estimation methods (Abowd et al. (1999b); Abowd et al. (1999a)) or did not apply the full statistical model discussed in section 3 (Goux and Maurin (1999)). Abowd et al. (2002a) find that conditional estimation methods may not work very well if the set of conditioning variables Z is limited.

Figure 2 reports the corresponding analysis based on the JUJ sample. Interestingly, we find a very strong association between the raw industry effect[22] and the average person effect ($\rho = 0.812$; plot a). Moreover, raw differentials appear to reflect even more tightly differences in firm wage policy across industries than in the main sample ($\rho = 0.931$; plot b). Thus, using a sample that is less affected by endogenous mobility than the main sample, one might conclude that industry wage differentials reflect primarily differences in firm wage policies

Figure 3 reports the corresponding analysis based on the JTJ sample. The association between raw industry effects and industry average person effects (plot a) is tighter than in the main sample ($\rho = 0.735$), but looser than in the JUJ sample. Using the JTJ sample yields much weaker correlation of the raw industry

[22]These raw differentials are estimated within the JUJ sample and thus not comparable to the one obtained from the main sample. The correlation between these raw industry effect and the estimated raw industry effect is $\rho = 0.981$

differential with the industry specific firm effect ($\rho = 0.807$). Thus, using a sample that is affected by endogenous mobility more strongly than the main sample, one tends to conclude that industry wage differentials are due to differences in the skills of workers and due to unobserved differences in firms' wage policies to the same extent. Note that in the JTJ sample there are outlier industries like "Agriculture", "Accommodation", "Air Traffic", and "Inland Navigation" which are identified to be very close to the 45^o line in the JUJ sample. Thus, the result that industry wage differentials reflect primarily differences in firm wage policies appears to be a robust finding. Moreover, this finding holds strongest when we focus on a sub-sample where endogenous mobility appears to be less of a concern than in the main or JTJ sample.

The second column of table (8) resumes the correlations from figure (2) & (3), while the correlations of the main sample are displayed at the bottom of the first column. The additional shown correlation between the firm specific and the person specific industry effect differs strongly between the JUJ sample on the one hand and the main and the JTJ ample on the other hand. In the absence of endogenous mobility it is shown that on the aggregate level the firm specific effect and the person specific effect are highly correlated ($\rho_{JUJ}(\kappa^f, \kappa^p) = 0.610$), i.e. high productive workers work in high paying firms. This result is not observed in the two other samples.($\rho_{main}(\kappa^f, \kappa^p) = 0.311$; ($\rho_{JTJ}(\kappa^f, \kappa^p) = 0.200$))

Table 8: Selectivity & Endogenous Mobility: Correlation of the raw industry effect and the industry specific effects

	based on main sample	based on sub-sample	Selectivity	endogenous mobility
JUJ				
$\rho(\kappa, \kappa^f)$	0.902	0.931	0.004	-0.029
$\rho(\kappa, \kappa^p)$	0.837	0.812	-0.162	0.024
$\rho(\kappa^f, \kappa^p)$	0.518	0.610	-0.207	-0.092
JTJ				
$\rho(\kappa, \kappa^f)$	0.833	0.807	0.073	0.025
$\rho(\kappa, \kappa^p)$	0.744	0.735	-0.069	0.009
$\rho(\kappa^f, \kappa^p)$	0.249	0.200	0.062	0.049
Main				
$\rho(\kappa, \kappa^f)$	0.906			
$\rho(\kappa, \kappa^p)$	0.675			
$\rho(\kappa^f, \kappa^p)$	0.311			

source: Authors' calculation based on data from Hauptverband der österreichischen Sozialversicherungsträger.
note: For a description of the samples see note of table (1).

The third column shows the effect due to selectivity as described in section 3.3. We compare the correlations within the sub-samples with the correlations within the main sample. Unfortunately all differences except for the correlation of the firm specific industry effect and the raw industry effect in the JUJ sample are far away from zero. Thus we cannot neglect the importance of selectivity.

Nevertheless we can show how the results are influenced by endogenous mobility. Therefore we compare the correlations within the sub-samples with the correlations within the sub-samples based on the main sample. Both samples include the same observations, thus selectivity does not play a role. Comparing the correlation of the raw industry differential with the firm specific effect shows that firm wage policy is relevant in the JUJ sample ($\Delta\rho^{f}_{m(JUJ);JUJ} = -0.029$). The opposite is true for the JTJ sample. Here the firm effect is more relevant in the main sample than in the JTJ sample ($\Delta\rho^{f}_{m(JTJ);JTJ} = 0.025$). Because the JTJ sample is strongly affected by endogenous mobility and the JUJ sample is hardly affected by endogenous mobility we can conclude that disregarding the effect of endogenous mobility will underestimate the importance of the firm wage policy.

The inverse relation is revealed if one compares the correlation of the raw industry differential with the person specific effect. While there is a positive difference in the JUJ sample ($\Delta\rho^{p}_{m(JUJ);JUJ} = 0.024$), the difference in the JTJ sample is close to zero ($\Delta\rho^{f}_{m(JTJ);JTJ} = 0.009$). Thus neglecting endogenous mobility leads to overestimate the impact of the unobservable person characteristics on the industry wage differential.

Even if we cannot exclude the selectivity effect we point out that endogenous mobility will lead to an underestimation of the importance of the firm wage policy on the one hand and an overestimation the unobservable person characteristics in favor to the latter.

5 Conclusions

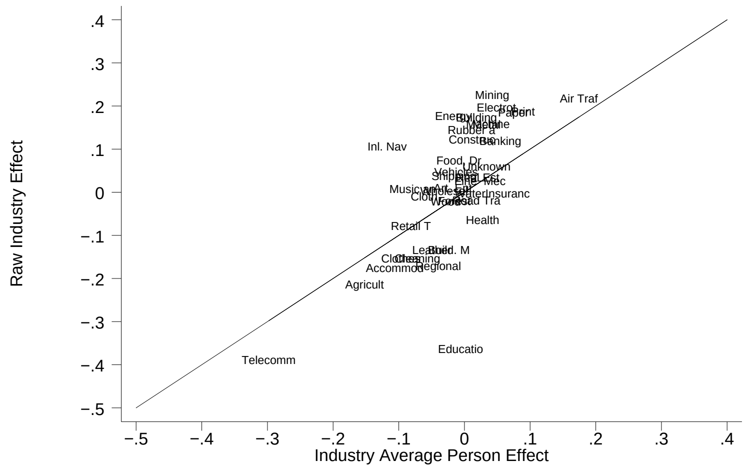
The existence and persistence of inter-industry wage differentials is well documented. However, there is a considerable and ongoing debate regarding the nature of these wage differentials. The two main lines of explanation focus on unobservable heterogeneity of workers on one hand or on differences across firms on the other hand (rent sharing or compensating wage differentials). Recent advances in statistical modelling as well as availability of MEE data allow investigating the question whether industry wage differentials reflect differences in firm wage policies or worker skills across industries. Studies that perform such detailed wage decompositions reach the conclusion that industry wage differentials reflect both, differences in unobserved skills as well as different wage policies.

This paper investigates the sensitivity of the new statistical modelling techniques to job mobility. Job mobility is the main requirement in separating person effects from firm effects. Arguably, transitions that occur directly from one employer to the next employer (job-to-job; JTJ) are fundamentally different from transitions that involve a spell of unemployment between the previous and the next employer (job-unemployment-job; JUJ).

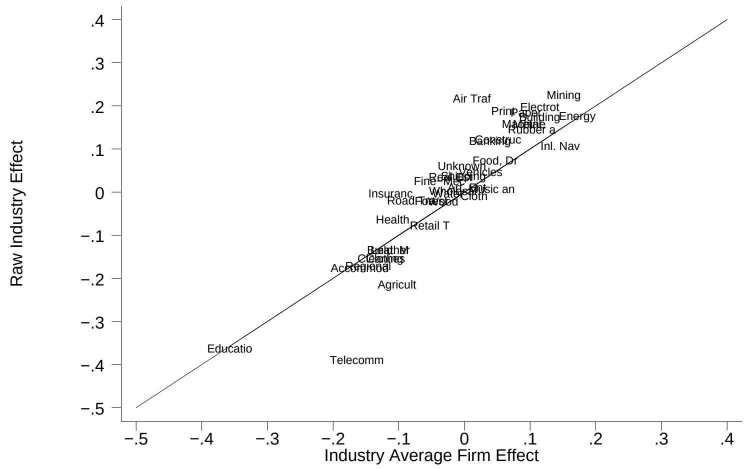
Based on a MEE dataset for Austria, we obtain the full least squares solution to the statistical model that decomposes wages into a person and a firm component. Findings suggest that the firms wage policy is more strongly correlated with the wage rate when identified in the JUJ sample than in the JTJ sample. Second, industry wage differentials reflect differences in firm wage policies more strongly than differences in person characteristics. Third, it is shown that endogenous mobility tends to lead to overrating the importance of person differences in explaining industry wage differences.

Future work should address the determinants of the relative importance of firm and worker effects in explaining industry effects in a cross country comparison on one hand. On the other hand, the relevance of differences in the amenities or disseminates provided by jobs (such as safety hazards or unemployment risk) in explaining the differences in firms' wage policies could be assessed.

A Appendix

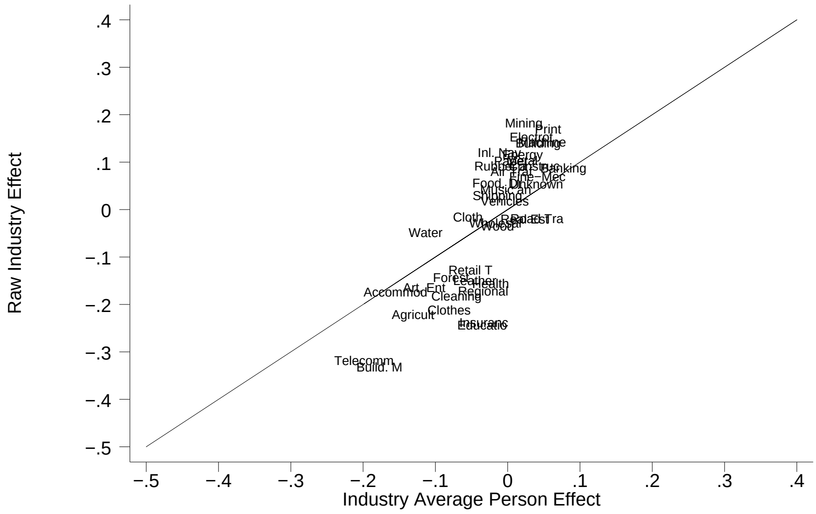


(a)

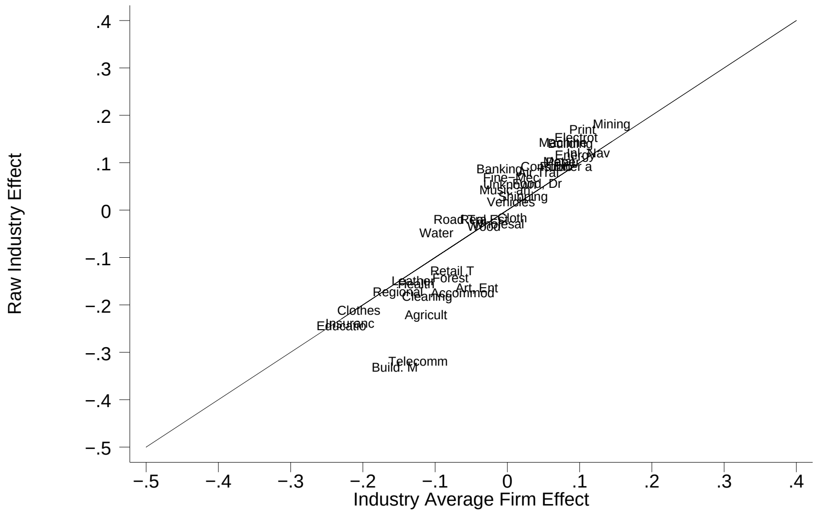


(b)

Figure 1: Correlation of the Raw Industry Differential with (a) Industry Average Person (based on α) ($\rho = 0.711$) and (b) Firm Effect (based on ψ) ($\rho = 0.907$); main sample.

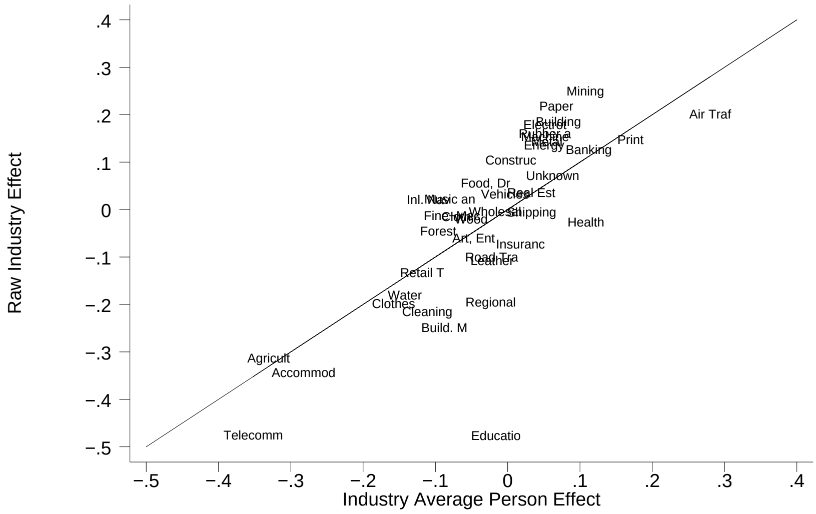


(a)

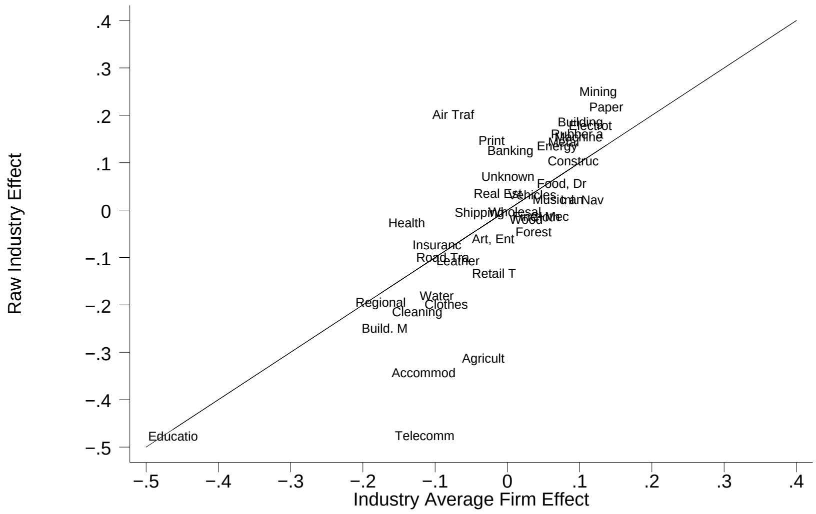


(b)

Figure 2: Correlation of the Raw Industry Differential with (a) Industry Average Person (based on α) ($\rho = 0.778$) and (b)Firm Effect (based on ψ) ($\rho = 0.784$); JUJ sample.



(a)



(b)

Figure 3: Correlation of the Raw Industry Differential with (a) Industry Average Person (based on α) ($\rho = 0.821$) and (b) Firm Effect (based on ψ) ($\rho = 0.926$); JTJ sample.

B Appendix

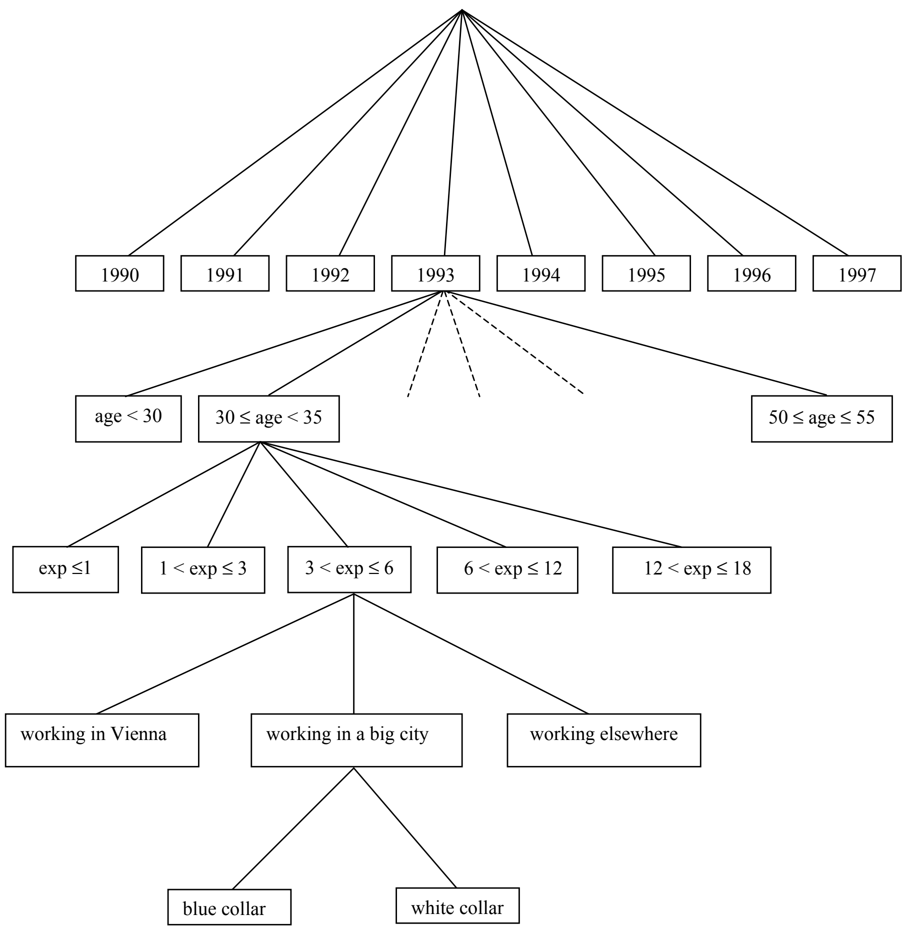


Figure 4: Clustering Scheme for the Construction of Censored Wages

References

Abowd, J. M., Creecy, R., and Kramarz, F. (2002a). Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data. Working paper, Cornell University.

Abowd, J. M., Finer, H., and Kramarz, F. (1999a). Individual and Firm Heterogeneity in Compensation: An Analysis of Matched Longitudinal Employer and Employee Data for the State of Washington. In Haltiwanger, J., Lane, J., Spletzer, J., and Troske, K., editors, *The Creation and Analysis of Employer-Employee Matched Data*, pages 3–24. North-Holland.

Abowd, J. M., Kramarz, F., Lengermann, P., and Perez-Duarte, S. (2002b). Sorting Within and Between Industries. Working paper, CREST.

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999b). High-Wage Workers and High-Wage Firms. *Econometrica*, 67(2):251–333.

Abowd, J. M. and Kramarz, F. (1999). The Analysis of Labor Markets Using Matched Employer-Employee Data. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 3B, chapter 26, pages 2629–2710. North-Holland.

Booth, A. (1995). *The Economics of Trade Unions*. Cambridge.

Carruth, A., Collier, B., and Dickerson, A. (1999). Inter-Industry Wage Differences and Individual Heterogeneity: How Competitive is Wage Setting in the UK? Discussion Paper 99/14, University of Kent, Department of Economics.

Gibbons, R. and Katz, L. (1992). Does Unmeasured Ability Explain Inter-Industry Wage Differences? *Review of Economic Studies*, 59(3):515–535.

Goux, D. and Maurin, E. (1999). The Persistence of Inter-Industry Wages Differentials: a Reexamination on Matched Worker-firm Panel Data. *Journal of Labor Economics*, 17(3):492–533.

Kahn, L. M. (1998). Collective bargaining and the interindustry wage structure: International evidence. *Economica*, 65(2):507–534.

Krueger, A. B. and Summers, L. H. (1987). Reflections on the inter-industry wage structure. In Lang, K. and Leonard, J., editors, *Unemployment and the Structure of Labor Markets*, chapter 2, pages 17–47. Basil Blackwell Inc.

Krueger, A. B. and Summers, L. H. (1988). Efficiency Wages and the Inter-Industry Wage Structure. *Econometrica*, 56(2):259–293.

Murphy, K. M. and Topel, R. H. (1987). Unemployment, risk, and earnings: Testing for equalizing wage differences in the labor market. In Lang, K. and Leonard, J., editors, *Unemployment and the Structure of Labor Markets*, chapter 5, pages 103–140. Basil Blackwell Inc.

Rosen, S. (1986). The Theory of Equalizing Differences. In Ashenfelter, O. C. and Layard, R., editors, *Handbook of Labor Economics*, volume 1, chapter 12, pages 641–692. North Holland.

Vainiomki, J. and Laaksonen, S. (1995). Inter-Industry Wage Differentials in Finland: Evidence from longitudinal census data for 1975-85. *Labour Economics*, 2(2):161–173.

Winter-Ebmer, R. (1994). Endogenous Growth, Human Capital, and Industry Wages. *Bulletin of Economic Research*, 46(4):289–314.

Zweimueller, J. and Barth, E. (1994). Bargaining Structure, Wage Determination, and Wage Dispersion in 6 OECD Countries. *Kyklos*, 47(1):81–93.