Estimating Labor Market Monopsony Power from a Forward-looking Perspective

Online Appendices

Qingyang Han*

May 30, 2024

Appendix A. Sample Construction and Variable Definition

This appendix describes the sample construction and variable definition. The original SIEED data covers job spells that are reported by employers to the Social Security Administration (SSA). Each spell can last between one day and one year.

Constructing Yearly Panel

In case an employment spell continues after one year, the SSA updates the spell at June.30 every year, so the dataset records a new entry representing the job spell at the current year. If the spell terminates within an one year, the SSA either records a new spell associated with the worker's new job, or leaves blank for this worker if they do not keep working. A worker, therefore, can have multiple job spells within a given year.

In case a worker has multiple job spells in a given year, I take the weighted average of their daily wage rates across all job spells, weighted by the duration of each job spell. The occupation and associated employer representing the longest job spell within a year will apply to the whole year. After this step, the cleaned data have a unique identifier: person id, year.[1]

Determining Non-full-time Employment

A worker in a given year is coded as "non-full-time" employment if any of the following is true.

1. There is no recorded data entry for the worker in this year.

2. The duration of all job spells in this year is shorter than 180 days.

*Johns Hopkins University, 3400 N Charles Street, Baltimore, Maryland 21211, USA. Email: hanqecon@outlook.com.

[1]In the sample, the original variable names are persnr and jahr.

3. The average daily wage rate in this year is less than 17 euros while the worker is not undergoing vocational training.[2]

Education Status

The original school-leaving qualifications variable (schule) identifies the following categories:

1 No school leaving certificate

4 Lower secondary school certificate/ grade school certificate

6 Intermediate school leaving certificate

8 Completion of education at a specialised upper secondary school/completion of higher education at a specialised college or upper secondary school leaving certificate, A-level equivalent, qualification for university; 13 years of schooling

I recoded categories 1, 4, and 6 into "no high school" and category 8 into "high school".

Appendix B. Definition of Occupations

The task operationalization dataset is compiled by IAB based on an expert database BERUFENET. (Dengler et al. (2014)) The dataset measures the composition of tasks for different occupational classifications.

BERUFENET is an "online information portal provided by the German Federal Employment Agency for all occupations known in Germany which are mainly used in career guidance and job placement." The database contains a rich set of information regarding the required tasks in an occupational activity, required qualifications and legal regulations. From there a requirements-matrix is obtained for all occupations.

Then, the exact requirements are converted to five task types, i.e. (1) Analytical non-routine tasks, (2) interactive non-routine tasks, (3) Cognitive routine tasks, (4) manual routine tasks, and (5) manual non-routine tasks. Table 2 shows the descriptions corresponding to each of the five task dimensions. The data give a fractional weight for each of these five requirements measuring their relative intensity. For each occupation m, the task composition $s^m = (s_1^m, s_2^m, s_3^m, s_4^m, s_5^m)$ is therefore defined as the relative intensity of requirements in these five task types. For each occupation m, $\sum_{k=1}^{5} s_k^m = 1$.

Table 1 provides several examples of the task composition.

The 5-digit occupation code in the SIEED data has a hierarchical structure. The first digit identifies 9 occupation categories, while the first two digits can identify 36 occupations. I use the 2-digit code as the base classification for occupations, and then use the k-means algorithm to categorize these 36 occupations into 5 occupation-clusters based on similarity in terms of task composition. Dodini et al. (2020) uses similar approaches to cluster occupations based on task composition. Occupations that belong to the same occupation-cluster are similar in terms of their task composition. Compared to the 2-digit occupation codes, the definitions for occupations-clusters reduce the state space and accelerates the computation.

[2]A worker is undergoing vocational training if erwstat is either 102, 105, or 106.

Table 1: Task compositions of some example occupations

Occupation	Major Task Type	s1	s2	s3	s4	s5
Professions in law and administration	1: Analytical Non-routine	**0.56**	0.10	0.34	0.00	0.00
Performing, entertaining professions	1: Analytical Non-routine	**0.41**	0.16	0.26	0.01	0.16
Advertising, marketing, commercial, editorial media jobs	2: Interactive Non-routine	0.37	**0.47**	0.15	0.00	0.00
Mechanical and automotive engineering jobs	3: Cognitive Routine	0.13	0.01	**0.35**	0.30	0.20
Plastic and wood manufacturing and processing	4: Manual Routine	0.06	0.01	0.07	**0.65**	0.21
Cleaning professions	5: Manual Non-routine	0.04	0.00	0.09	0.13	**0.73**
Tourism, hotel and catering professions	5: Manual Non-routine	0.13	0.29	0.18	0.01	**0.38**

Notes. This table shows the task decomposition of several 2-digit occupations. Each occupation is associated with 5 task dimensions, namely, analytical non-routine (s_1), interactive non-routine (s_2), cognitive routine (s_3), manual routine (s_4), and manual non-routine (s_5). The five dimensions add up to one.

Figure 1 shows the clustering results. Each bar shows the average task compositions of an occupation cluster which includes several two-digit occupations. Occupation cluster 1 demands multiple task components relatively equally, whereas cluster 2 through 5 mainly require only one major tasks.

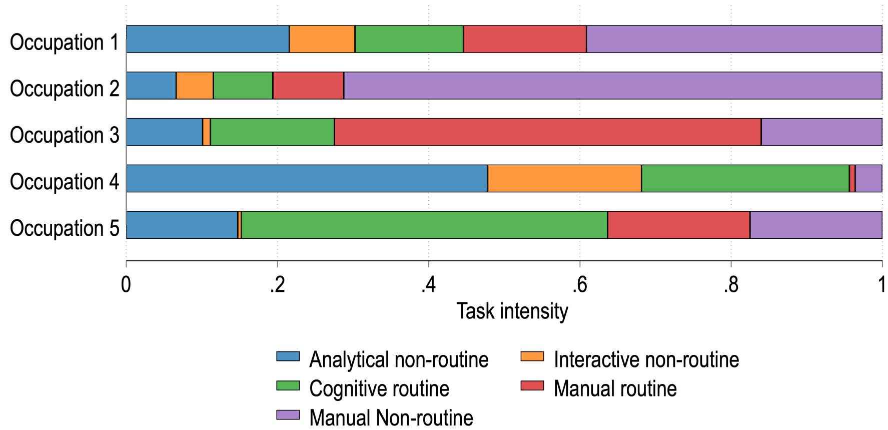
While occupations belonging to the same 1-digit occupation category may differ largely in terms of task composition, the occupation-clusters defined in this paper is obtained in a data-driven approach that better approximates the task requirements of each occupation. Throughout the paper I use “occupation” to refer to an occupation-cluster, where the notation $m \in \{1, \cdots, 5\}$ refers to an occupation cluster.

Table 2: Description of the five task dimensions

Task Dimensions	**Contents**
Analytical non-routine	Research, analyse, evaluate, plan, construct, design, create, work out rules/regulations, apply and interpret rules
Interactive non-routine	Negotiate, represent interests, coordinate, organise, teach or train, sell, purchase, acquire customers, advertise, entertain, present, employ or manage staff
Cognitive routine	Calculate, accounting, correct texts/data, measure length/height/temperature
Manual routine	Operate or control machines, equip machines
Manual non-routine	Repair or refurbish houses/flats/machines/vehicles, renovate paintings/monuments, serve or accommodate guests

Source. Dengler et al. (2014)

Figure 1: Task decomposition of the five occupation clusters



Notes. This figure shows the decomposition of the five task components of the five occupation clusters. The occupation clusters are constructed from the 36 two-digit occupations, such that the two-digit occupations that fall in the same cluster share similar task decomposition.

Appendix C. Firm Type Assignment

This paper uses a recursive Lloyd's approach to estimate the type assignment of firms. Similar to the typical k-means algorithm, in each round of iteration, the g-type and h-type of each firm is updated by picking the cluster that minimizes the within-firm likelihood function.

1. **Initialization** Estimate the following equation with firm fixed effects and firm specific slopes.

$$\log w_{ijt} = \varphi_0^j + \varphi_1^j \ln(t) + \alpha_i + \epsilon_{it} \tag{1}$$

   Obtain the distributions of the estimated coefficients: $F^{\varphi_0}(\cdot)$ and $F^{\varphi_1}(\cdot)$ of $\widehat{\varphi}_0^f$ and $\widehat{\varphi}_1^f$, respectively. Cluster the estimated $\widehat{\varphi}_0^f$ into $\mathcal{I}$ quantiles and $\widehat{\varphi}_1^f$ into $\mathcal{S}$ quantiles. These quantiles are the initial type assignment of the (φ_0, φ_1) parameters.

2. **Iterations** At step $k \geq 1$, execute the following steps until the convergence criterion is reached.

   (a) Using the estimated group assignment $\{\widehat{g}^{(k-1)}(j), \widehat{h}^{(k-1)}(j)\}_{j\in\mathcal{J}}$, change the wage equation 1 by replacing the firm specific coefficients with (g,h) specific coefficients, and obtain the parameter $(\widehat{\varphi}_{0g}, \widehat{\varphi}_{1h})^{(k)}$ by estimating 2:

$$\ln w_{ight} = \varphi_0^{g^{(k-1)}} + \varphi_1^{h^{(k-1)}} \ln(t) + \varphi_i + \epsilon_{it} \tag{2}$$

   (b) For each firm $j = 1, \cdots, \mathcal{J}$, update the g-type membership by picking the group g that maximizes the likelihood function $\widehat{L}_j$, without changing the previously assigned h-type:

$$g^{(k)}(j) = arg \max_{g \in \{1,\cdots,\mathcal{G}\}} \widehat{L}_j(\widehat{\varphi}, g, h(j)^{(k-1)})$$

(c) Re-estimate the parameter φ in:

$$\ln w_{wght} = \varphi_0^{g^{(k)}} + \varphi_1^{h^{(k-1)}} \ln(t) + \varphi_i + \epsilon_{it}$$

(d) For each firm $j = 1, \cdots, \mathcal{J}$, update the h-type membership by picking the group h that maximizes the likelihood function $\hat{L}_i$, without changing the previously assigned g-type:

$$h^{(k)}(j) = arg \max_{h \in \{1,\cdots,\mathcal{H}\}} \widehat{L}_j(\widehat{\varphi}, g(j)^{(k)}, h)$$

(e) Assess the convergence criterion and finish the iteration if

$$\left|\widehat{L}^{(k)} - \widehat{L}^{(k-1)}\right| \leq \epsilon.$$

Appendix D. Full Wage Equation Estimates

Table 3 shows the full estimation results of the wage equation.

Appendix E. Reduced Form Evidence

As a baseline analysis, I estimate the firm-specific separation elasticity in reduced-form. I compare two specifications: the first is to put only firm fixed effect on the right hand side of the equation, and the second approach is to put the projected sum of lifetime earnings should the worker keeps working at the incumbent employer. In both specifications, I estimate a Probit equation 3 where the left-hand-side is the probability of job staying from period $t-1$ to period t, denoted by $\Pr(s_{ijt} = 1)$, and the key right-hand-side regressor is W_j the firm-specific wage components at the incumbent firm. Time-varying worker characteristics are also included in the right-hand-side variable X_{it}, including age, age squared, and occupation.

$$\Pr(s_{ijt} = 1) = \Phi(\theta W_j + X_{it}'\beta) \tag{3}$$

In the first specification, a simplified version of the wage equation is estimated, with the omission of the slope term $\varphi_1^j \ln(t)$. This wage equation recovers the firm fixed effect $\widehat{\varphi}_0^j$ of each firm.[3] Then, the Probit equation 3 is estimated to fit the relationship between job staying s_{ijt} and the firm wage component $W_j = \widehat{\varphi}_0^j + \varphi_1^j \ln(t)$, controlling for individual characteristics (age, experience, education, gender).

[3]In practice, the firm fixed effect in this step is clustered into 25 groups, consistent with the number of total latent types used in the two-dimensional heterogeneity approach.

Table 3: Wage Equation Results

	(1) Occupation 1 log(wage)	(2) Occupation 2 log(wage)	(3) Occupation 3 log(wage)	(4) Occupation 4 log(wage)	(5) Occupation 5 log(wage)
Male×NoHS×experience	-0.005	0.001	0.003	-0.021	0.021
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male×HS×experience	0.017	0.010	0.022	0.004	0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female×NoHS×experience	-0.005	0.013	-0.004	-0.011	-0.010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female×HS×experience	0.010	0.038	0.033	0.009	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male×NoHS×experience^2	0.000	-0.000	-0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male×HS×experience^2	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female×NoHS×experience^2	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female×HS×experience^2	-0.001	-0.001	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept Type					
Type 1	Base	Base	Base	Base	Base
Type 2	0.311	0.308	0.334	0.291	0.325
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Type 3	0.522	0.533	0.510	0.479	0.521
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Type 4	0.735	0.702	0.679	0.663	0.706
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Type 5	0.997	0.962	0.877	0.867	0.895
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Slope Type					
Type 1× log(experience)	0.004	-0.056	-0.014	0.079	-0.006
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Type 2× log(experience)	0.099	0.017	0.063	0.198	0.090
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Type 3× log(experience)	0.182	0.084	0.133	0.288	0.182
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Type 4× log(experience)	0.277	0.159	0.200	0.371	0.257
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Type 5× log(experience)	0.372	0.250	0.284	0.455	0.342
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Individual FE	Yes	Yes	Yes	Yes	Yes
R squared	0.826	0.886	0.866	0.834	0.861
Observations	8612358	5350991	3529150	19437929	4907314

Notes. This table shows the wage coefficients estimated from the wage equation with two-dimensional firm heterogeneity. Each firm is assigned an intercept-type and a slope-type. Individual fixed effects are always included, and the table includes a summary of individual FEs by gender and education.

In the second specification, based on the estimation of the wage equation and two-dimensional firm wage heterogeneity, I impute the projected lifetime earnings associated with the incumbent employer type (g, h):

$$\widehat{W}_{igh}^{PDV} = \sum_{\tau=t}^{T} \beta^{\tau-1} \widehat{w}_{gh\tau} \tag{4}$$

The present discounted value (PDV) of lifetime earnings do not represent the entire earnings a worker can accumulate. Rather, it only accounts for the PDV of firm-specific wage components. This restriction is in line with Bassier et al. (2022) which states that job separation should not respond to worker wage components. Setting $W_j = \widehat{W}_{igh}^{PDV}$ and then taking it into the right hand side of the equation, I subsequently estimate how sensitive job separation rate responds to the projected PDV of the firm wage components.

Table 4 shows the estimation results for the reduced form relationship between job staying and firm wage components. The estimated coefficients in front of firm wage components can then recover the job separation (staying) elasticities. All specifications are Probit with the binary indicator of "job staying" being the outcome variable. Therefore, a positive coefficient in front of firm wage component suggests that a worker is more likely to stay in their incumbent employer, and a greater magnitude of this coefficient suggests a larger labor supply elasticity specific to the employer.

Columns (1), (3), (5), and (7) use the imputed projected lifetime earnings from Equation 4 as the right-hand-side regressor. In contrast, columns (2), (4), (6), and (8) use the firm fixed effect on the right hand side. These firm FEs are recovered from the wage equation without the term $\varphi_1^j \ln(t)$, i.e. a FE-only wage equation. The estimated coefficients in Table 4 are presented in their marginal effects, which can be interpreted as elasticity after being divided by the average staying probability.

It is seen that for all demographic groups, using the imputed PDV of lifetime earnings yield a larger R squared, suggesting that my measure of firm-specific wage components fit the data better than the fixed effect term used in the literature. Except for males without high school, in the other three demographic groups, the separation elasticity would be greater if $\ln(\widehat{W}^{PDV})$ is used, suggesting that most workers' mobility decisions do respond to future expected earnings.

References

Bassier, I., Dube, A., and Naidu, S. (2022). Monopsony in movers: The elasticity of labor supply to firm wage policies. *Journal of Human Resources*, 57(S):S50–s86.

Dengler, K., Matthes, B., and Paulus, W. (2014). Occupational tasks in the german labour market. *FDZ Methodenreport*, 12.

Dodini, S., Lovenheim, M., Salvanes, K. G., and Willén, A. (2020). Monopsony, skills, and labor market concentration.

Table 4: Reduced-form Elasticity Estimation

	(1) Male no HS	(2) Male no HS	(3) Male HS	(4) Male HS	(5) Female no HS	(6) Female no HS	(7) Female HS	(8) Female HS
log(PDV)	0.0537		0.0350		0.0313		0.0224	
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
firm FE		0.0607		0.0157		0.0011		-0.0153
		(0.0004)		(0.0006)		(0.0004)		(0.0005)
prob. Stay	0.7300	0.7300	0.7281	0.7281	0.7345	0.7345	0.7038	0.7038
sep. Elas	0.0736	0.0831	0.0481	0.0216	0.0426	0.0015	0.0318	-0.0217
R squared	0.0299	0.0227	0.0203	0.0166	0.0238	0.0209	0.0222	0.0209
Obs	12055697	12055697	5778731	5778731	9091956	9091956	5307133	5307133

Notes. This table shows the reduced-form relationship between **job staying** and firm wage components by gender and education. Columns (1), (3), (5), and (7) use the firm fixed effect as the main regressor, which is recovered from a FE-only wage equation. Columns (2), (4), (6), and (8) use the imputed PDV of earnings from Equation 4 as the main regressor. All models are Probit. Marginal effects are reported instead of the raw coefficients. For each subsample and each specification, age, age squared, and occupation are controlled.