Estimating Labor Market Monopsony Power from a Forward-looking Perspective

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Abstract

This paper proposes a new approach to estimate the monopsony power of the labor market based on a forward-looking model of firm wage posting and worker job separation. Contrast to the literature, workers make job switch decisions based on firm-specific wage growth trajectories associated with different employers. The model is estimated using a matched employer employee panel data from Germany. The separation elasticity estimated from this model is greater than that from the conventional approach, suggesting that ignoring worker responses to heterogeneous wage growth rates lead to a potential overestimation of the actual monopsony power.

Keywords: Monopsony Power, Firm-specific Labor Supply Elasticity, Wage Heterogeneity

JEL Codes: C51, J23, J24, J31, J42, J62

Highlights:

- I estimate employer monopsony power in a forward-looking model of worker job separation and firm wage posting.
- Workers may stay at a low-paying job expecting higher future rewards, a phenomenon which should not be interpreted as high monopsony power.
- Estimates show that job mobility is more responsive to lifetime earnings as compared to static wage rates, suggesting that monopsony power may be lower from a lifecycle perspective.
- Employers exert larger monopsony power over female workers than male workers.

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1 Introduction

“Monopsony” was initially introduced by Joan Robinson in her 1933 book, *The Economics of Imperfect Competition*. (Robinson (1933)) This term finds significant application in the labor market, where employers possess wage-setting powers and pay workers less than their marginal product of labor (MPL). The wage markdown is inversely proportional to workers’ employer-specific labor supply elasticity (henceforth, elasticity). The empirical objective to estimate the monopsony power of a specific labor market boils down to estimate this elasticity. Manning (2003) suggests an approach based on Burdett and Mortensen (1998) to estimate the job separation elasticity with respect to wage rates. More papers follow this direction, as summarized in Sokolova and Sorensen (2021).

This literature, however, generally focuses on the static relationship between wages and job separations. Noting that workers may stay at a low-paying job in exchange for higher future wages (Agarwal (2015)), this paper extends the static approach by building a forward-looking model in which firms set wage schedules for workers with different experiences. In each period, worker decides job switching considering the entire future wage trajectories at different employers. The equilibrium wage markdown over the entire employment duration is solved directly from the firms’ optimality conditions.

The forward-looking model is estimated using a matched employer-employee panel in Germany. The overall wage markdown is around 37%, with female workers suffering from a much greater degree of markdown than male workers. My estimates for the wage markdown in Germany is lower than Bachmann et al. (2022), whose analyses are based on a static approach.

2 A Forward-looking Model of Monopsony

The baseline static monopsony model establishes a first order condition to the firm’s wage posting problem, where q is the MPL of workers, w is the posted wage rate, and $l(w)$ is the labor supply function.

$$\frac{q-w}{w} = \frac{l(w)}{wl'(w)} = \frac{1}{\varepsilon_w} \tag{1}$$

This paper allows the labor supply function to depend on future wages, too. Let subscript t denote the number of periods a worker is employed at the firm; this also equals the unit of job-specific experiences the worker possesses. Let q_t, $(t = 1, \cdots, T)$ denotes the evolution of MPL as long as the employment relationship persists.

Let n_t be the **cumulative** probability that a worker keeps working at the firm from Period 1 to Period t. It is a function of the entire wage schedule $w_1, \cdots, w_t, \cdots, w_T$. Knowing the cumulative staying probability $\{n_t\}_{t=1}^T$, the firm’s problem is to post a wage schedule $\{w_t\}_{t=1}^T$ to maximize the profit function 2 extracted from hiring the worker. β is the time discount factor.

$$\Pi(w_1, \cdots, w_T) = \sum_{t=1}^{T} \beta^{t-1} n_t(w_1, \cdots, w_T)(q_t - w_t) \tag{2}$$

To simplify the firm's problem, the firm-specific wage schedule $w_1, \cdots, w_T$ is parametrized by 3,

$$\ln(w_t) = \varphi_0 + \varphi_1 \ln(t), \tag{3}$$

so the choice variables of the firm become φ_0, φ_1, representing starting wage rate and wage growth rate, respectively. The profit function 2 thus becomes 4.

$$\Pi(\varphi_0, \varphi_1) = \sum_{t=1}^{T} \beta^{t-1} n_t(\varphi_0, \varphi_1)(q_t - w_t) \tag{4}$$

The two first-order conditions to 4 are derived in 5.

$$\begin{aligned} \frac{\partial \Pi}{\partial \varphi_0} &= \sum_{t=1}^{T} \beta^{t-1} \left(\frac{\partial n_t}{\partial \varphi_0}(q_t - w_t) - n_t w_t \right) = 0 \\ \frac{\partial \Pi}{\partial \varphi_1} &= \sum_{t=1}^{T} \beta^{t-1} \left(\frac{\partial n_t}{\partial \varphi_1}(q_t - w_t) - n_t w_t \ln(t) \right) = 0 \end{aligned} \tag{5}$$

The wage markdown over the entire employment duration is defined as 6.

$$\text{Markdown} = \frac{\sum_t^T \beta^{t-1}(q_t - w_t)}{\sum_t^T \beta^{t-1} w_t} \tag{6}$$

Intuitively, n_t, the cumulative probability of working at the incumbent firm, serves as the individual labor supply function. If n_t is more responsive to φ_0 and/or φ_1, the recovered wage markdown should be lower.

3 Estimation

To obtain an estimate for the wage markdown in Equation 6, I follow three steps to recover the elements in the first order conditions in 5. First, I recover firm-specific wage coefficients $\widehat{\varphi_0}, \widehat{\varphi_1}$. Second, I estimate the derivatives of cumulative staying probability n_t with respect to the wage coefficients. Third, I solve the wage markdown.

3.1 Estimating Firm-specific Wage Coefficients

The first step is to estimate the firm-level heterogeneity in the two wage coefficients, aka the coefficients φ_0 and φ_1 in Equation 3. Following Abowd et al. (1999), the wage equation is decomposed into an individual component and a firm component. For worker i with job-specific experience t hired by firm j, the log wage

$\ln(w_{ijt})$ is determined by Equation 7.

$$\ln(w_{ijt}) = \underbrace{\alpha_0^i + \alpha_1^i \times t + \alpha_2^i \times t^2}_{\text{individual component}} + \underbrace{\varphi_0^j + \varphi_1^j \ln(t)}_{\text{firm component}} + \epsilon_{ijt} \tag{7}$$
$$\text{where } \alpha_1^i = \alpha_1(edu_i, occ_i, gender_i)$$
$$\alpha_2^i = \alpha_2(edu_i, occ_i, gender_i)$$

The individual component consists of a worker fixed effect, α_0^i, and a growth component where the coefficients in front of experience and experience squared depend on worker's education, occupation, and gender. The firm component of 7 consists of a firm fixed effect, φ_0^j, and a firm specific slope, φ_1^j. Denote the firm wage component by $\ln(w_{jt})$. Firms set wage schedules specific to worker characteristics.

I use the clustering approach of multidimensional heterogeneity suggested by Cheng et al. (2023) to assign two latent group memberships, g and h, to each firm. Firms belonging to the same g-type share the same intercept φ_0, and firms belonging to the same h-type share the same slope φ_1. Firm heterogeneity is therefore fully captured by a firm's (g,h) type. The firm wage component in Equation 7 thus becomes Equation 8, where $\mathcal{G}$ and $\mathcal{H}$ denote the finite set of all g types and h types, respectively.

$$\ln(w_{gh}) = \varphi_0^g + \varphi_1^h \ln(t),\ g \in \mathcal{G},\ h \in \mathcal{H} \tag{8}$$

The joint estimation of firm type assignment and the wage equation follows a recursive k-means clustering algorithm in Cheng et al. (2023). (Details can be seen in Online Appendix C.)

3.2 Estimating a Model of Employment Duration

The next step is to estimate the derivatives of the cumulative staying probability n_t with respect to φ_0 and φ_1, which appear in the first order conditions in 5. Following Bassier et al. (2022), the analyses limit that only the firm wage components affect worker job mobility, and that job separations are independent to wage schedules of other firms.

The cumulative staying function $n_{ijt}(\varphi_0, \varphi_1)$ is indeed a survival function, meaning

$$n_{ijt} = \Pr\left((\text{Duration of } i\text{'s job spell at } j) > t\right), \tag{9}$$

which takes the baseline exponential form 10.

$$n_{ijt} = \exp(-\lambda_{ijt} t)$$
$$\text{where } \lambda_{ijt} = \exp\left(\theta_0 \widehat{\varphi}_0^j + \theta_1 \widehat{\varphi}_1^j + \chi_{it}' \theta_\chi\right) \tag{10}$$

The worker-level control variables χ_{it} includes age, gender, education and occupation. After the duration model 10 is estimated, the derivatives can be recovered by averaging over all workers and firm types.

3.3 Recovering Cumulative Wage Markdown

After the derivatives $\frac{\partial n_t}{\partial \varphi_0}$ and $\frac{\partial n_t}{\partial \varphi_1}$ are recovered from the previous step, all terms in the first-order conditions 5 are recovered except for the evolution of MPL, $\{q_t\}_{t=1}^T$. With only two equations in 5, the entire path of MPL is under-identified. I parametrize the MPL evolution assuming a linear relationship in Equation 11 so that there are exactly two unknown parameters.

$$q_t = q_0 + \gamma t \tag{11}$$

The recovered path of MPL eventually identifies the wage markdown in Equation 6.

4 Data and Results

Table 1: Descriptive Statistics

Total observations	48,372,145			
Total workers	4,216,870			
Total establishments	3,043,416			
	Male No HS	**Male HS**	**Female No HS**	**Female HS**
Panel Data				
Total observations	17,283,921	8,060,547	14,862,529	8,165,148
Total persons	1,527,916	673,459	1,320,173	695,322
Non-full-time employment	0.199	0.195	0.308	0.269
Duration Data				
Spell duration (years)				
mean	3.200	3.187	3.316	2.963
sd	3.529	3.323	0.368	3.146
5% percentile	1	1	1	1
95% percentile	11	10	11	9

Notes. The selected sample consists of job histories of individuals from 1996 to 2018. "Panel Data" refers to the individual-year level panel data, while "Duration Data" refers to the rearranged data showing the duration (in integer years) of each employment spell.

Data This paper uses the Sample of Integrated Employer Employee Data (SIEED) administered by the German Institute of Employment Research. (Berge et al. (2020)). This dataset represents a 1.5% sample of all establishments in Germany and traces individual employment spells from 1975 to 2018. This paper further limits the sample to employment spells

- after 1996, a few years since the German Reunification in 1990, and

- of workers under the age of 50 to avoid the modeling of voluntary transitions into non-full-time employment.

Table 1 shows the descriptive statistics of the selected sample. There are over 3 million total individuals with over 48 million observations. Details about the dataset are documented in Online Appendix A.

Preset parameters The time discount factor β is set at 0.975. The numbers of firm types for intercepts and slopes are both set at 5. The two-digit occupation codes in the German system (KldB-2010) are clustered into 5 occupation categories based on similarity in task composition.[1] Education status is binary as any worker is characterized by with or without high school completion.

Wage equation Table 2 shows the estimation results for the wage equation 7, with two-dimensional grouped firm heterogeneity. The wage equations are run separately by the five occupation clusters. The "intercept-type" and "slope-type" shows the degree of wage heterogeneity along two dimensions: starting wages and wage growth rates.

Graphical relationship between firm wage components and job staying As a motivating analysis, I first show the relationship between cumulative earnings from firm-level wage components and job staying. I impute the firm-level wage component $\widehat{w}_{ght} = \exp(\widehat{\varphi}_0^j + \widehat{\varphi}_1^j \ln(t))$ from the estimated wage coefficients, and subsequently the present discounted value (PDV) of firm-level lifetime earnings:

$$\widehat{W}_{igh}^{PDV} = \sum_{\tau=t}^{T} \beta^{\tau-1} \widehat{w}_{gh\tau} \tag{12}$$

Figure 1 shows the binscatter plots of the relationship between imputed projected PDV of lifetime earnings and the job staying rates. It is shown that for all demographic groups, job staying rates increase if the firm provides a higher lifetime wage. In particular, the job staying rates of male workers are more responsive to wages compared to those of female workers.[2]

Duration model and cumulative wage markdown Table 3 shows the estimation results for the duration model and the implied cumulative wage markdowns. The signs of the estimated coefficients show the effect of the corresponding variables on the hazard rate (i.e. termination of the current employment spell), so negative coefficients mean that the variable lowers the chance of job separation. For firms that offer either higher intercepts (φ_0) or higher slopes (φ_1), they will expect a longer employment duration. The estimated coefficients can recover the wage markdowns following the first order conditions 5, the cumulative markdown formula 6, and the parametrization of the MPL path 11. It is estimated that the overall wage markdown is 34.1%, which is smaller than the literature has previously estimated for Germany. As a comparison, Bachmann et al. (2022) found the employer-specific labor supply elasticity in Germany to be between 0.9 and

[1]Details for the clustering approach can be found in the Online Appendix B.

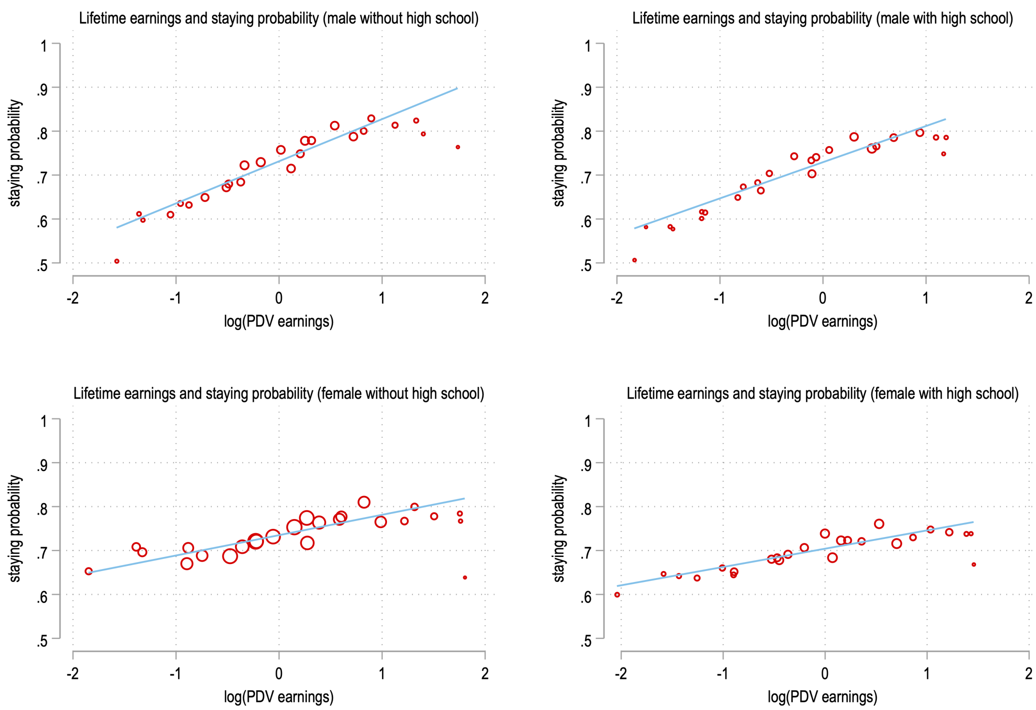
[2]A comparison between my specification and a static specification using the conventional approach is provided in Online Appendix E.

Table 2: 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)
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 Equation 7 with two-dimensional firm heterogeneity. Each firm is assigned an intercept-type and a slope-type. Experience and experience squared terms are controlled with gender and education specific coefficients. The full estimation results are shown in the online appendix D.

Figure 1: Job staying-Firm wage component relationship



Notes. These binscatter graphs shows the relationship between job staying (y-axis) and firm wage components (PDV of projected lifetime earnings computed from Equation 12, by gender and education. The marker sizes are proportional to the sample sizes.

1.6, corresponding to a wage markdown of between 63% to 111%. Women also experience much greater wage markdown than men, with a markdown of 97.1% compared to 14.1% for men. This is also consistent with the literature (see Sokolova and Sorensen (2021)). Wage markdown does not vary greatly with respect to education statuses.

Table 3: Duration Model Estimates and Implied Wage Markdown

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All Male	All Female	Male No HS	Male HS	Female No HS	Female HS
	Job duration	Job duration	Job duration	Job duration	Job duration	Job duration	Job duration
Firm Intercept	-0.365	-0.446	-0.248	-0.511	-0.304	-0.281	-0.201
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Firm Slope	-1.046	-1.313	-0.639	-1.417	-1.131	-0.676	-0.607
	(0.004)	(0.005)	(0.006)	(0.007)	(0.009)	(0.009)	(0.010)
Starting age	-0.010	-0.009	-0.010	-0.008	-0.012	-0.010	-0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.037						
	(0.001)						
High School	0.109	0.103	0.115				
	(0.001)	(0.001)	(0.001)				
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
θ_0	-0.038	-0.033	-0.059	-0.013	-0.084	-0.073	-0.018
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.002)
θ_1	0.295	0.252	0.432	0.237	0.280	0.404	0.465
	(0.368)	(0.000)	(0.003)	(0.001)	(0.002)	(0.004)	(0.006)
Markdown	0.368	0.166	1.010	0.172	0.124	0.960	1.025
	(0.004)	(0.004)	(0.016)	(0.005)	(0.008)	(0.018)	(0.027)
Log Likelihood	-7396495	-4257467	-3133586	-2921387	-1334377	-1956721	-1176587
Number Job Spells	5572296	3214648	2357648	2192524	1022124	1454658	902990

Notes. This table shows the estimation for the duration model in Equation 10. The signs and values of all coefficients should be interpreted as the effect on the hazard rate (end of a job spell), so negative coefficients imply an effect to keep the current employment spell longer. The wage markdown for each subsample is calculated from the first-order conditions 5, assuming the evolution of MPLs is linear. The standard errors of θ_0, θ_1 and Markdown are computed using Bootstrap with $B = 100$ samples.

5 Conclusions

This paper extends the literature on the estimation of labor market monopsony power by introducing a forward-looking model of worker job separation and firm wage posting. The estimates obtained from this model recovers an equilibrium wage markdown which is lower in magnitude than what the previous literature has found. This is an evidence that workers may be more responsive to future wage rates when making their job-switching decisions. As this paper exclusively focuses on job separations due to the lack of job application data, further research could extend on this margin by studying the firm hiring problem from a forward-looking perspective.

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Data Availability

The SIEED data used in this paper are provided by the German Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung, IAB). Researchers can apply for this data through IAB's official website.

Declarations of interest

None