Monopsony power and the demand for low-skilled workers

Arnd Kölling

Supplemental files

Sample

The representative data used in the investigations comes from the IAB Establishment Panel and consists of observations about German establishments from 1996 to 2018. The Institute for Employment Research of the German Federal Labour Agency has conducted the IAB Establishment Panel since 1993 in Western Germany and since 1996 in the former eastern part of Germany. The population of the IAB Establishment Panel includes all German establishments with at least one employee covered by social insurance contributions. The survey is then a stratified random sample of 17 industries, 10 employment size classes and 16 regions (the Bundesländer) as particular strata of the total population. The survey shows a very high response rate of over 70% to 80% for establishments that have participated more than once. The data is unbalanced, however, as new establishments replace panel mortality through exits and non-response. In total, there are about 16,000 observations each year available for the investigation (Fischer et al. 2008, 2009). This data is augmented with information from the Establishment History Panel, which is official data from the social security system that provides detailed information about different qualifications and their respective daily remuneration in the observed firms (Eberle and Schmucker, 2017).

Supplemental tables

Table S1. Descriptive statistics of the data in the regressions (total)

Variable	Obs	Mean	S Dev	Min	Max
Wage share of low skilled	84.599	0.021	0.049	0.000	1.000
Log of wages for low-skilled per capita	84.599	4.079	0.399	2.714	4.982
Log of wages for medium-skilled per capita	84.599	4.178	0.360	3.124	4.935
Log of wages for high-skilled per capita	84.599	4.596	0.441	3.400	5.478
Log of mean Euribor in particular year	84.599	0.265	1.685	-4.000	1.573
Observation since introduction of statutory minimum wage 2015 (yes = 1)	84.599	0.157	0.363	0.000	1.000
Log of value added	84.599	14.082	2.177	5.945	22.705
Share of part-time workers	84.599	0.141	0.192	0.000	1.000
Share of temporary employed	84.599	0.047	0.117	0.000	1.000
Share of employed persons subjected to the social insurance scheme	84.599	0.842	0.196	0.000	1.000
Share of female workers	84.599	0.328	0.272	0.000	1.000
Share of foreign EU workers	84.599	0.024	0.076	0.000	1.000
Share of foreign non-EU workers	84.599	0.032	0.086	0.000	1.000
Share of workers older than 50	84.599	0.291	0.211	0.000	1.000
Share of workers younger than 25	84.599	0.095	0.128	0.000	1.000
Coverage by collected bargaining agreement	84.599	0.724	0.447	0.000	1.000
Western Germany	84.599	0.579	0.494	0.000	1.000
Herfindahl-Hirschman Index	84.599	0.021	0.057	0.000	1.000

Source: IAB Establishment Panel 1996 - 2018.

Table S2. Descriptive statistics of the data in the regressions (above 82nd percentile of residual wages)

Variable	Obs	Mean	S Dev	Min	Max
Wage share of low skilled	15.227	0.017	0.045	0.000	1.000
Log of wages for low-skilled per capita	15.227	4.600	0.125	4.444	4.982
Log of wages for medium-skilled per capita	15.227	4.471	0.327	3.128	4.935
Log of wages for high-skilled per capita	15.227	4.884	0.372	3.401	5.478
Log of mean Euribor in particular year	15.227	0.238	1.751	-4.000	1.573
Observation since introduction of statutory minimum wage 2015 (yes = 1)	15.227	0.170	0.376	0.000	1.000
Log of value added	15.227	15.349	2.454	5.945	22.705
Share of part-time workers	15.227	0.104	0.155	0.000	1.000
Share of temporary employed	15.227	0.036	0.080	0.000	1.000
Share of employed persons subjected to the social insurance scheme	15.227	0.892	0.177	0.000	1.000
Share of female workers	15.227	0.247	0.223	0.000	1.000
Share of foreign EU workers	15.227	0.027	0.059	0.000	1.000
Share of foreign non-EU workers	15.227	0.038	0.074	0.000	1.000
Share of workers older than 50	15.227	0.295	0.188	0.000	1.000
Share of workers younger than 25	15.227	0.077	0.094	0.000	1.000
Coverage by collected bargaining agreement	15.227	0.808	0.394	0.000	1.000
Western Germany	15.227	0.806	0.395	0.000	1.000
Herfindahl-Hirschman Index	15.227	0.032	0.081	0.000	1.000

Source: IAB Establishment Panel 1996 - 2018.

Table S3. Descriptive statistics of the data in the regressions (below 82nd percentile of residual wages)

Variable	Obs	Mean	S Dev	Min	Max
Wage share of low skilled	69.372	0.021	0.050	0.000	1.000
Log of wages for low-skilled per capita	69.372	3.964	0.343	2.714	4.443
Log of wages for medium-skilled per capita	69.372	4.113	0.334	3.124	4.935
Log of wages for high-skilled per capita	69.372	4.533	0.430	3.400	5.478
Log of mean Euribor in particular year	69.372	0.272	1.670	-4.000	1.573
Observation since introduction of statutory minimum wage 2015 (yes = 1)	69.372	0.154	0.361	0.000	1.000
Log of value added	69.372	13.804	2.007	6.123	21.320
Share of part-time workers	69.372	0.149	0.198	0.000	1.000
Share of temporary employed	69.372	0.050	0.123	0.000	1.000
Share of employed persons subjected to the social insurance scheme	69.372	0.831	0.198	0.000	1.000
Share of female workers	69.372	0.346	0.278	0.000	1.000
Share of foreign EU workers	69.372	0.023	0.079	0.000	1.000
Share of foreign non-EU workers	69.372	0.030	0.088	0.000	1.000
Share of workers older than 50	69.372	0.290	0.215	0.000	1.000
Share of workers younger than 25	69.372	0.099	0.135	0.000	1.000
Coverage by collected bargaining agreement	69.372	0.706	0.456	0.000	1.000
Western Germany	69.372	0.529	0.499	0.000	1.000
Herfindahl-Hirschman Index	69.372	0.019	0.049	0.000	0.990

Source: IAB Establishment Panel 1996 - 2018.

Table S4. Coefficients of fixed effects wage regressions / control function for endogeneity

	(a) Log of wages for low-skilled per capita	(b) Log of wages for medium-skilled per capita	(c) Log of wages for high-skilled per capita
Log of wages for low-skilled per capita	-	0.017** (0.003)	0.048** (0.009)
Log of wages for medium-skilled per capita	0.058** (0.009)	-	0.013** (0.005)
Log of wages for high-skilled per capita	0.016** (0.005)	0.018** (0.003)	-
Observation since introduction of statutory minimum wage 2015 (yes = 1)	0.276** (0.056)	0.167** (0.031)	-0.013 (0.055)
… interaction with log of wages for low-skilled per capita	-	-0.016** (0.006)	0.003 (0.010)
… interaction with log of wages for medium-skilled per capita	-0.046** (0.014)	-	0.007 (0.013)
… interaction with log of wages for high-skilled per capita	-0.006 (0.009)	-0.013* (0.006)	-
Log of mean Euribor in particular year	-0.015** (0.003)	-0.016** (0.002)	-0.004 (0.003)
Log of value added	0.002 (0.003)	0.007** (0.002)	0.003 (0.003)
Share of part-time workers	0.003 (0.013)	-0.012 (0.010)	0.008 (0.013)
Share of temporary employed	-0.037 (0.019)	-0.030* (0.013)	-0.040* (0.020)
Share of employed persons subjected to the social insurance scheme	-0.008 (0.015)	-0.078** (0.012)	-0.009 (0.017)
Share of female workers	-0.027 (0.016)	-0.037** (0.012)	0.007 (0.017)
Share of foreign EU workers	0.051* (0.024)	0.017 (0.021)	-0.017 (0.027)
Share of foreign non-EU workers	-0.011 (0.024)	0.023 (0.020)	-0.003 (0.026)
Share of workers older than 50	-0.007 (0.012)	0.015 (0.009)	0.002 (0.013)
Share of workers younger than 25	-0.037* (0.015)	-0.018 (0.011)	0.032* (0.015)
Coverage by collected bargaining agreement	-0.003 (0.005)	0.004 (0.003)	0.005 (0.005)

	(a) Log of wages for low-skilled per capita	(b) Log of wages for medium-skilled per capita	(c) Log of wages for high-skilled per capita
Local unemployment rate	-0.003* (0.001)	-0.005** (0.001)	-0.007** (0.001)
Herfindahl-Hirschman-Index	0.057 (0.032)	0.001 (0.016)	0.039 (0.031)
Western Germany	0.132 (0.159)	0.005 (0.010)	0.045 (0.109)
Adj-R²	0.3225	0.7719	0.5144
F-Test (df.1; df.2)	17.70** (90; 35,097)	42.77** (90; 35,097)	12.73** (90; 35,097)
Observations (establishments)	126,341 (35,098)	126,341 (35,098)	126,341 (35,098)

Source: IAB Establishment Panel 2007 - 2018.

Note: The model also includes the following dichotomous and auxiliary variables: establishment size (7 dummies), firm profitability (2), state of machinery (2), industry (42), year of founding (28), year of observation (21) and a constant. Robust standard errors adjusted for clustering on establishments in parentheses. ** and * denote significance at the .01 and .05 levels, respectively.

Theoretical model

The calculation of partial own-wage elasticities η_{ii} is given by the following expressions (Hamermesh, 1993: 35):

$$\text{(S1)} \quad \eta_{ii} = s_i \sigma_{ii}$$

with s_i as share of labour costs of groups i and j to total costs and σ_{ii} as:

$$\text{(S2)} \quad \sigma_{ii} = \frac{C \cdot C_{wiwi}}{C_{wi}^2}$$

where C is the cost function, and C_{wi} and C_{wiwi} are the first and second derivatives of C with respect to the wages w of group i. While s_i is the wage bill of a particular group of workers related to total costs, the σ_{ii} are similar to the partial elasticity of substitution between two factors of production

(Hamermesh, 1993: 35). Equation (S2) indicates that a particular cost function is needed to calculate a numerical solution for the elasticities. The translog cost function in its heterothetic form approximates the constant elasticity of substitution (CES) function by a second-order Taylor polynomial at the point where the CES equals the Cobb–Douglas case (Berndt and Khaled, 1979). Taking the first derivative of the cost function to wages and applying Shephard's lemma to labour input yields the following equation for each type of labour (Hamermesh, 1993: 40):

$$\text{(S3)} \quad s_i = a_i + b_{ii} \cdot \ln w_i + \sum_{i \neq j} b_{ij} \cdot \ln w_j + d_i \cdot \ln Y$$

where a_i, b_{ii}, b_{ij}, and d_i are the parameters, and $\ln Y$, $\ln w_i$, and $\ln w_j$ are the logarithms of the level of output Y, and the prices w for different types of inputs I, respectively. Equation (S3) is often used in empirical investigations since its formal structure, allows for the application of usual econometrical methods (cf. Lichter et al., 2015). It is now possible to calculate the own-wage elasticities. After some reformulation, we receive the usual expression for the own-wage elasticities from a translog cost function η_{ii} (Hamermesh, 1993: 41):

$$\text{(S4)} \quad \eta_{ii} = \frac{b_{ii}}{s_i} + s_i - 1$$

In the case of monopsony, we have to take into account that in a monopsonic labour market the wage costs depend on the number of attracted workers, which means that the supply of workers L_i increases with the size of w_i (Manning, 2003: 32):

$$\text{(S5)} \quad L_i = L_i^s(w_i), \; L'_i = \frac{\partial L_i^s}{\partial w_i} > 0$$

with L_i^s as labour supply and L'_i as the first derivative of L_i^s to w_i. While labour supply elasticities in competitive markets are positive infinite, the respective elasticities in imperfect labour markets are between zero and positive infinite. This has consequences for the calculation of s_i:

$$\text{(S6)} \quad s_i = \frac{w_i L_i^s(w_i)}{C}$$

As s_i in equation (6) only depends on w_i and C. The number of workers L_i results from the wage level w_i. Then, labour supply elasticities equal the right side of equation (4)[2]:

$$\text{(S7)} \quad \varepsilon_{Lw} = \frac{b_{ii}}{s_i} + s_i - 1$$

In a monopsony labour market, we will observe the labour supply elasticity instead of own-wage demand elasticities.

Calculation of own-wage elasticity

The total differential of s_i is defined as:

$$\text{(S8)} \quad \partial s_i = \partial w_i \frac{L_i}{C} + \partial L_i \frac{w_i}{C} - \partial C \frac{w_i L_i}{C^2}$$

Extending (S8) with (w_i/w_i) and (L_i/L_i) gives:

$$\text{(S9)} \quad \partial s_i = \frac{\partial w_i}{w_i}\frac{w_i L_i}{C} + \frac{\partial L_i}{L_i}\frac{w_i L_i}{C} - \frac{\partial C}{C}\frac{w_i L_i}{C}.$$

According to equation (S8) ∂s_i is then:

$$\text{(S10)} \quad \partial s_i = \left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial C}{C}\right) s_i,$$

Taking the partial derivative to $\ln w_i$ yields:

$$\text{(S11)} \qquad \frac{\partial s_i}{\partial \ln w_i} = \frac{\left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial C}{C}\right)}{\frac{\partial w_i}{w_i}} s_i = b_{ii},$$

with $\frac{\frac{\partial w_i}{w_i}}{\frac{\partial w_i}{w_i}} = 1$ and according to equation (2) $\frac{\frac{\partial L_i}{L_i}}{\frac{\partial w_i}{w_i}} = \eta_{ii}$.

Applying Shepard's Lemma $\left(\frac{\partial C}{\partial w_i} = L_i\right)$, then $\frac{\frac{\partial C}{C}}{\frac{\partial w_i}{w_i}} = \frac{w_i L_i}{C} = s_i$.

Then (S11) becomes equal to:

$$\text{(S12)} \qquad \frac{\partial s_i}{\partial \ln w_i} = \left(1 + \eta_{ii} - s_i\right) s_i = b_{ii}$$

Calculation of cross-wage elasticity

The partial derivative s_i to $\ln w_j$ is given by:

$$\text{(S13)} \qquad \frac{\partial s_i}{\partial \ln w_j} = \frac{\left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial C}{C}\right)}{\frac{\partial w_j}{w_j}} s_i = b_{ii},$$

with $\frac{\frac{\partial w_i}{w_i}}{\frac{\partial w_j}{w_j}} = 0$ because of the exogeneity of w_j and $\frac{\frac{\partial L_i}{L_i}}{\frac{\partial w_j}{w_j}} = \eta_{ij}$, the relevant elasticity.

Applying Shepard's Lemma $\left(\frac{\partial C}{\partial w_j} = L_j\right)$, then $\frac{\frac{\partial C}{C}}{\frac{\partial w_j}{w_j}} = \frac{w_j L_j}{C} = s_j$.

Then (S13) becomes:

$$\text{(S14)} \qquad \frac{\partial s_i}{\partial \ln w_i} = \left(\eta_{ij} - s_j\right) s_i = b_{ij}$$

$$\Leftrightarrow \qquad \eta_{ij} = \frac{b_{ij}}{s_i} + s_j$$

Calculation of output elasticity

Again, the total differential of s is defined as:

$$\text{(S15)} \qquad \partial s_i = \left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial C}{C}\right) s_i.$$

For the empirical work, I assumed that total costs C equal turnover Y. This yield:

$$\text{(S16)} \qquad \partial s_i = \left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial Y}{Y}\right) s_i.$$

Taking the partial derivative to $\ln w_i$ yields:

$$\text{(S17)} \qquad \frac{\partial s_i}{\partial \ln Y} = \frac{\left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial Y}{Y}\right)}{\frac{\partial Y}{Y}} s_i = d_i,$$

with $\dfrac{\frac{\partial w_i}{w_i}}{\frac{\partial Y}{Y}} = 0$, because of the exogeneity of Y, and $\dfrac{\frac{\partial L_i}{L_i}}{\frac{\partial Y}{Y}} = e_{LY}$,

the relevant elasticity, and $\dfrac{\frac{\partial Y}{Y}}{\frac{\partial Y}{Y}} = 1$.

Then (S17) becomes:

$$\text{(S18)} \qquad \frac{\partial s_i}{\partial \ln Y} = (e_{LY}-1)s_i = d_i,$$

$$\Leftrightarrow \qquad e_{LY} = \frac{d_i}{s_i} + 1.$$

Calculation of the supply elasticity

Again, the total differential of s is defined as:

$$\text{(S19)} \qquad \partial s_i = \left(\frac{\partial w_i}{w_i} + \frac{\partial L_i}{L_i} - \frac{\partial C}{C}\right) s_i.$$

In the case of a Monopsony, this yield:

$$\text{(S20)}\qquad \partial s_i = \frac{\partial w_i}{w_i} s_i + \partial w_i L'_i \frac{w_i}{C} - \frac{\partial C}{C} s_i \,,$$

Expanding the second term of equation (S20) with ${}^{w_iL_i}\!/\!_{w_iL_i}$ yields:

$$\text{(S21)}\qquad \partial s_i = \left(\frac{\partial w_i}{w_i}(1+\varepsilon_{Lw}) - \frac{\partial C}{C} \right) s_i \text{ with } \varepsilon_{Lw} = L'_i \frac{w_i}{L_i} > 0.$$

The ε_{Lw} is the wage elasticity of labour supply as the wage level determines the number of applicants and is always positive. In a monopsony, the number of applicants increase with the wage level. For small changes in L_i, the partial derivative of ∂s_i to $\partial \ln w_i$ is then approximately given by:

$$\text{(S22)}\qquad \frac{\partial s_i}{\partial \ln w_i} = (1 + \varepsilon_{Lw} - s_i)s_i = b_{ii}.$$

A reformulation of equation (S22) results in:

$$\text{(S23)}\qquad \varepsilon_{Lw} = \frac{b_{ii}}{s_i} + s_i - 1.$$

Empirical model

One way to estimate equation (6) using panel data is the fractional panel probit regression (Papke and Wooldridge, 2008). The Mundlak/Chamberlain device (Mundlak, 1978; Chamberlain, 1982) is used to control for the unobserved heterogeneity as a normally distributed variable conditional on the averages of the time-varying exogenous regressors. Wooldridge (2019) proposes a linear function of the time averages with different coefficients for each number of observations for an entity if unbalanced data is used. This yields the following empirical model:

(S24) $\left(s_{it}|\ln w_{it}, \ln w_{jt}, \ln Y_t, z_{it}\right) =$

$$\Phi\left(b_{ii}\cdot \ln w_{it} + \sum_{i\neq j} b_{ij}\cdot \ln w_{jt} + d_i\cdot \ln Y_{it} + \delta_i\cdot z_{it} + \Sigma_r\left(\psi_r + \bar{z}_i\xi_r\right) + a_i\right),$$

and the corresponding average partial effect (APE) is then:

(S25) $$\frac{\partial\left(s_{it}|\ln w_{it}, \ln w_{jt}, \ln Y_t, z_{it}\right)}{\partial \ln w_{it}} =$$

$$\frac{b_{ii}}{N}\sum_i \phi\left(b_{ii}\cdot \ln w_{it} + \sum_{i\neq j} b_{ij}\cdot \ln w_{jt} + d\cdot \ln Y_{it} + \delta z_{it} + \Sigma_r\left(\psi_r + \bar{z}_i\xi_r\right) + a_i\right),$$

with Φ as the standard normal cumulative distribution function (cdf), ϕ as the density function, N as the total number of observations, zit as additional exogenous variables of the model that are introduced later, $\bar{z}_i$ as averages of all time-varying zit including lnwi, lnwj, and lnYi, δ and ξ as additional parameters, r as the number of observations for each firm in the data and ψr becomes 1 if r observations are available for an establishment and zero otherwise. As equation (S25) denotes the average partial effect (APE), this outcome also has consequences for the calculation of the elasticities. In equation (S24), the parameters bii and si are firm specific, while the APE is the average for all establishments. Although it is possible to observe individual si, only the averages of the partial effects were estimated. Therefore, it is only possible to derive average elasticities.

If we want to identify the downward sloping labour demand curve in all parts of the labour market, one must take care of this probable endogeneity of the wage variables. Here, I apply a two-step control variable approach, where the residual of estimation on the first stage is used as an additional variable in the estimation of the model on the second stage (Wooldridge, 2015). The idea to add residuals of a first stage estimation to control for endogeneity was introduced by

Hausman (1978). Then, equation (3) is modified with the introduction of an additional exogenous variable in the z_{it} accordingly to introduce possible endogeneity. Due to the linear nature of the endogenous wage variables, a fixed effects model is applied on the first stage. Moreover, this procedure requires some additional exogenous variables that are not part of equation (3) to fit the exclusion restriction.

Determination of the threshold

The econometric work starts with identifying a threshold to detect firms with competitive and monopsonistic labour market conditions. Therefore, I estimate different versions of the model. The first goal is to find a threshold for a switching regression that has a larger validity compared with other thresholds. The second is to compare this estimation with a base model that does not contain interaction variables of a switching regression. While the relation of the latter is tested with a likelihood ratio (LR) test of the additional covariates, I cannot simply apply LR-tests when we look at the models with different thresholds as we change the level of the threshold but not the number of exogenous variables. As the model is not a linear regression, I cannot use the R^2 or adjusted R^2 for a decision. One possible way to indicate the validity of maximum likelihood (ML) estimations is the so-called Bayesian Information Criteria (BIC). Moreover, some authors suggest versions of the BIC for estimating pseudo likelihoods (Xu, Chen and Mantel, 2013; Gao and Carroll, 2017):

$$\text{(S26)} \quad BIC^{Pseudo} = F(N, k) - 2\ln(\widehat{L}^{Pseudo}),$$

with $\widehat{L}^{Pseudo}$ as the maximised value of the pseudo likelihood function and F as a function indicating the complexity of the model, ie. the number of observations N and covariates k. The estimation with the lowest BIC^{Pseudo} is then the favoured version of the regression. In our case, I like to compare switching regression models with different thresholds. This means the number of observations and the number of covariates do not change. Therefore, the value of F(N, k) is constant. If we take the differences of the BIC^{Pseudo}, the F(N, k) are excluded from the calculation. As the largest $\widehat{L}^{Pseudo}$ minimises the BIC^{Pseudo}, we can use the following criteria to determine model with highest validity:

$$\text{(S27)} \quad \Delta BIC^{Pseudo} = 2\ln(\widehat{L}_n^{Pseudo}) - 2\ln(\widehat{L}_{max}^{Pseudo}),$$

$\widehat{L}_n^{Pseudo}$ is the pseudo maximum likelihood of model n and $\widehat{L}_{max}^{Pseudo}$ as the largest pseudo likelihood in the estimated models. Because the $\widehat{L}^{Pseudo}$ are negative values, ΔBIC^{Pseudo} is zero if model n maximises the pseudo likelihood and positive otherwise.

An appropriate way to identify the optimal threshold of the switching regression would be an endogenous determination of the values. Unfortunately, these models are not available for nonlinear models like the fractional panel probit.[S1] Therefore, I exogenously choose values for thresholds and conduct several estimations of the model. As discussed before, a crucial variable that determines the threshold is the wage level. Hence, I use the percentiles of the wage distribution as possible threshold values. Dummy variables that become one for values below the threshold are multiplied with all exogenous variables to create interaction variables that are added to the regressions. Afterwards, I used the pseudo maximum likelihoods to calculate the differences in the BIC^{Pseudo}.

The model with the threshold at the 82nd percentile of wage distribution shows the highest pseudo maximum likelihood. As the data defines full-time as work with the usual hours in the particular entity and not according to a precise number of hours, it is not possible to calculate an exact hourly wage. Please note that all nominal values are discounted with the producer price index of 2015. If we use this value as a threshold, the gap to the maximum of BIC^{Pseudo} is zero. All other differences are positive according to equation (S27). Raftery (1995; 139) introduced a rule of thumb to assess the estimated differences in the BIC. Margins that are larger than 2 indicate a 'positive', larger than 6 'strong' and larger than 10 'very strong' evidence that the model with the larger likelihood has a higher validity. Therefore, I used a threshold value at the 6th decile of wage distribution to accomplish the subsequent empirical analysis. Moreover, I found a higher explanatory power of the threshold model compared to a base model without the interaction variables. An LR test of the interaction variables indicates a joint significance on the 1% level [$\chi^2(107) = 868.35^{**}$]. This outcome is in line with hypothesis I and confirms the need to consider a structural break in the regressions.

Monopsonies on labour markets

The labour demand curve is derived from profit maximising behaviour of the firms on the markets for their particular products. It reflects the combination of wages and labour where marginal production costs (including labour costs) equal the marginal revenues of the company. As it is normally assumed that the factors of production show a decreasing marginal productivity and therefore declining revenues if the number of workers is increased, the labour demand curve is normally downward sloping as a larger number of employed requires lower wages to fulfil the profit maximising condition. If the particular firm has no wage setting power, ie. the market wages are determined on the total labour market and each employee is willing to work at the given market wage, ie. the labour supply elasticity is infinite, we would observe a competitive labour market:

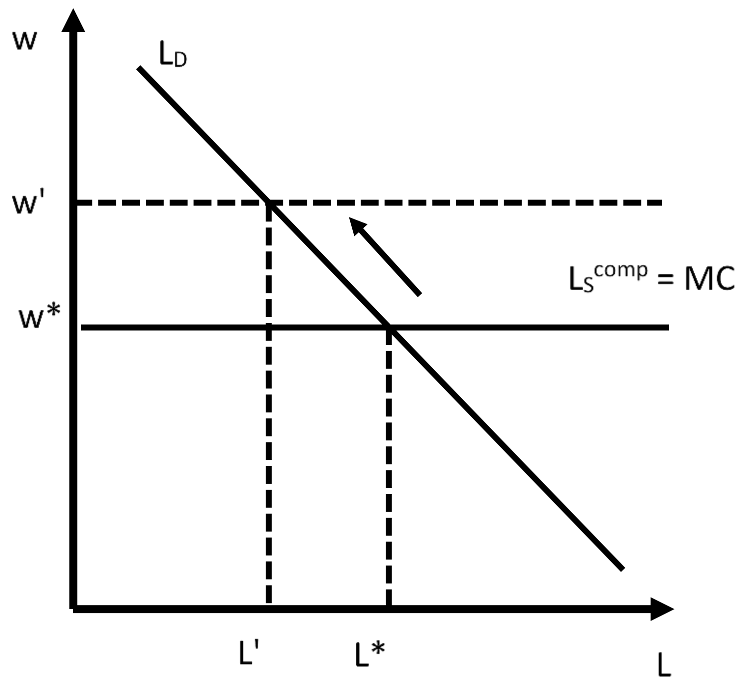

Figure S1. Competitive labour market

With L as labour, w as wages, LD as labour demand, L_S^{comp} as labour supply on a competitive market and * denotes optimal values. On a competitive market L_S^{comp} equals marginal costs of labour MC. If the market wages w* change, the firm will choose the number of workers according to its labour demand curve. If wages increase, the number of workers decrease and the observed labour demand elasticity, ie. the relative change of employment according to a relative change of wages is negative.

The situation changes if the firms have some wage setting power on the labour market and acts like a monopolist on the demand side. Then, each worker is willing to work if wages exceed their individual reservation wage and labour supply to the firm depends on the size of the remuneration. As said, the labour demand curve expresses profit-maximising behaviour where marginal revenue equals marginal costs. One source of marginal costs are changes in employment. Unlike the situation on a competitive labour market, marginal employment costs are not constant at w* but increase with the number of attracted workers as they have different reservation wages. This means that also the marginal costs of employments are increasing. Following the law-of-one-price, ie. paying equal wages to all employees leads to the classical model of monopsony:

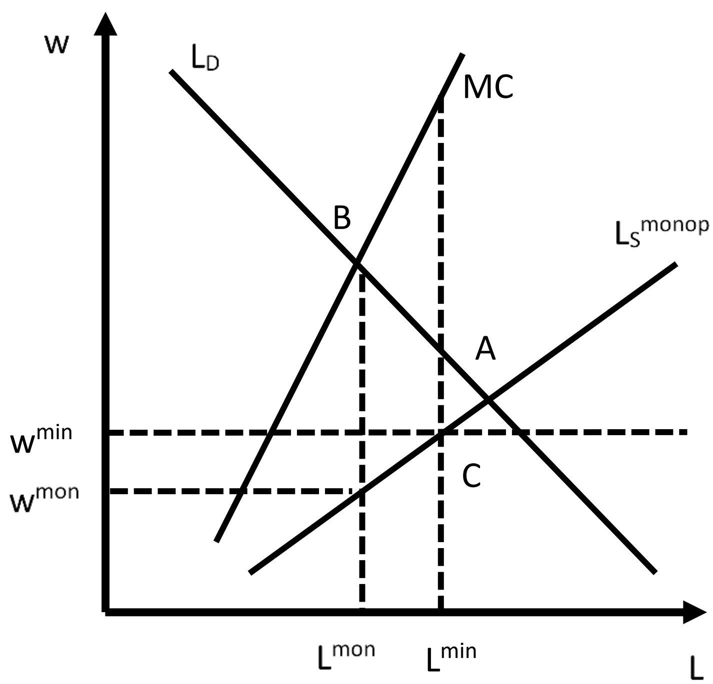

Figure S2. Monopsony

Marginal costs MC are larger than the wages if equal wages are paid for all employees, as the firms have to pay the wage of the additional worker and the differences between the old and the new wage for all other workers. Again, the profits are maximised when marginal costs equal marginal revenue. The labour demand curve indicates profit maximising on the goods market and taking into account the marginal costs from the labour market, intersection point B fulfils profit-maximising conditions for the goods and factor markets. Unlike on a competitive market, the firms do not have to pay the corresponding wages from the L_D curve. The number of required workers is attracted at the lower wage w^{mon}. The difference in the wages is the source of additional monopsonistic firm profits. If wages increase, eg. through the introduction of a minimum wage w^{min}, also the demand for labour increases; because marginal costs of labour are constantly given by w^{min} until point A is reached. If the firms want to attract more labour than L^{min}, the remuneration exceeds w^{min} and the marginal costs jump upwards to the MC-curve, crossing the profit maximising L_D-curve. Therefore, we would observe the labour supply curve until the market wage in point A is reached. Higher wages than in point A would lead to a lower employment according to LD. If we allow for more than one firm, ie. observe an oligopsony instead of a monopsony, wages should differ among firms and until a competitive market is established, wages and employment follow labour supply. Then, a larger degree of competition would increase both, wages and employment (Manning, 2021; Berger, Herkenhoff and Mongey, 2019). Wages that exceed the equilibrium of the market reduce the demand for labour. Coming from this, the observed labour demand of all firms on the market is the given by figure S.3:

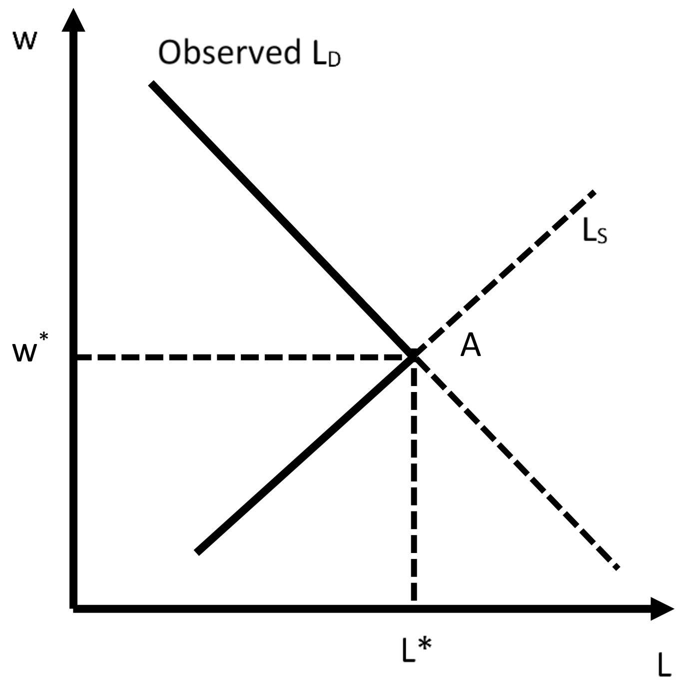

Figure S3. Observed firms' labour demand

Here we observe a relation of wages and employment with an upward sloping curve at the lower bound of the function, a downward sloping part if the firms pay higher wages and a turning point at the competitive market equilibrium A.

Supplement notes

1. The STATA commands 'movestay' for an endogenous switching regression and 'threshold' for a threshold regression only work with linear models. The latter also needs balanced panel data.

Arnd Kölling Monopsony power and the demand for low-skilled workers

Supplement References

Berger DW, Herkenhoff KF and Mongey S (2019) *Labour Market Power*. NBER Working Paper No. w25719. Cambridge, MA: National Bureau of Economic Research.

Berndt ER and Khaled MS (1979) Parametric productivity measurement and choice among flexible functional forms. *Journal of Political Economy* 87(6): 1220 - 1245.

Chamberlain G (1982) Multivariate regression models for panel data. *Journal of Econometrics* 18(1): 5-46.

Eberle J and Schmucker A (2017) The establishment history panel–redesign and update 2016. *Jahrbücher für Nationalökonomie und Statistik* 237(6): 535-547.

Fischer G, Janik F, Müller D et al. (2008) *The IAB Establishment Panel – from sample to survey to projection.* FDZ Methodenreport No. 01/2008. Nuremberg, Germany: Research Data Centre (FDZ), Institute of Employment Research (IAB).

Fischer G, Janik F, Müller D et al. (2009) The IAB Establishment Panel – things users should know. *Journal of Applied Social Science Studies* 129(1): 133 – 148.

Gao X and Carroll R J (2017) Data integration with high dimensionality. *Biometrika* 104(2): 251-272.

Hamermesh DS (1993) *Labour Demand*. Princeton, NJ: Princeton University Press.

Hausman JA (1978) Specification tests in econometrics. *Econometrica* 46(6): 1251–1271.

Lichter A, Peichl A and Siegloch S (2015) The own-wage elasticity of labour demand: A meta-regression analysis. *European Economic Review* 80: 94-119.

Manning A (2003) *Monopsony in motion: Imperfect competition in labour markets*. Princeton, MA: Princeton University Press.

Manning A (2021) Monopsony in labour markets: A review. *ILR Review*. 74(1): 3-26.

Mundlak Y (1978) On the pooling of time series and cross section data. *Econometrica* 46(1): 69-85.

Papke LE and Wooldridge JM (2008) Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics* 145(1-2): 121-133.

Raftery AE (1995) Bayesian model selection in social research. *Sociological Methodology 25:* 111-164.

Wooldridge JM (2015) Control function methods in applied econometrics. *Journal of Human Resources* 50(2): 420-445.

Wooldridge JM (2019) Correlated random effects models with unbalanced panels. *Journal of Econometrics* 211(1): 137-150.

Xu C, Chen J and Mantel H (2013) Pseudo-likelihood-based Bayesian information criterion for variable selection in survey data. *Survey Methodology* 39(2): 303-321.