The cyclical behaviour of employers' monopsony power and workers' wages*

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Abstract: This paper confronts monopsony theory's predictions regarding workers' wages with observed wage patterns over the business cycle. Using German administrative linked employer–employee data for the years 1985–2010 and an estimation framework based on duration models, we construct a time series of the long-run labour supply elasticity to the firm and estimate its relationship to the aggregate unemployment rate. In line with theory, we find that firms possess more monopsony power during economic downturns. We also show that this procyclicality is more pronounced in tight labour markets with low levels of unemployment. Both these findings are robust to controlling for time-invariant unobserved worker or plant heterogeneity. We further document that cyclical changes in workers' entry wages are of similar magnitude as those predicted under monopsonistic wage setting, suggesting that monopsony power should not be neglected when analysing wage cyclicality.

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1 Introduction

Whereas a quarter of a century ago most economists regarded the labour market as more or less perfectly competitive, many labour economists now have embraced the idea that employees (e.g. via unions) and employers have some market power in wage determination (see Booth, 2014). Lately, a number of studies has emerged that investigate the extent of employers' monopsony power in the labour market (Ashenfelter *et al.*, 2010). Other than classic accounts that saw employer concentration as the source of monopsony power, the recent literature makes clear that employers may readily possess marked wage-setting power in labour markets consisting of many competing firms. Potential reasons include search frictions, mobility costs, or job differentiation, all of which impede workers' responsiveness to wages. This causes the labour supply curve to the single firm to be upward-sloping, rather than being horizontal as under perfect competition (Boal and Ransom, 1997).

To assess the empirical relevance of monopsony power, a growing literature estimates the wage elasticity of the labour supply elasticity to the firm (Manning, 2003; Barth and Dale-Olsen, 2009; Falch, 2010, 2011; Hirsch *et al.*, 2010; Ransom and Oaxaca, 2010; Ransom and Sims, 2010; Staiger *et al.*, 2010; Booth and Katic, 2011; Hirsch and Jahn, 2012; Depew and Sørensen, 2013; Hotchkiss and Quispe-Agnoli, 2013; Webber, 2013*a*,*b*). The vast majority of these studies employ an estimation framework proposed by Manning (2003) that relies on a simple model of dynamic monopsony in which search frictions cause workers' labour supply to the firm to be imperfectly elastic. Imposing the structure of Burdett and Mortensen's (1998) search model and a steady-state assumption, these studies estimate the labour supply elasticity to the firm from the wage responsiveness of firms' labour flows. Overall, the resulting estimates of the elasticity turn out to be far from infinite, suggesting that the labour supply curve to the firm is upward-sloping (for a recent survey, see Manning, 2011). Yet, one has to keep in mind that 'evidence of upward sloping labor supply is not sufficient to infer monopsonistic outcomes' (Hirsch and Schumacher, 2005, p. 987).

It is, therefore, still an open question how substantial employers' monopsony power is, whether it varies over time, and whether firms actually exploit differences in their market power by adjusting wages accordingly. The case for monopsonistic labour markets could be strengthened by confronting monopsony theory's predictions regarding workers' wages with observed wage patterns. A case in point is the evolution of employers' market power and workers' wages over the business cycle. Monopsony power due to search frictions should be less felt by workers during economic upturns with many outside offers available to them compared to economic downturns with lingering outside opportunities.[1] Moreover, during bad times workers' preference for job security might induce them to be less wage-driven than during good times. We therefore expect the labour supply elasticity to the firm to move procyclically.

Up to now, however, there is no evidence on the evolvement of employers' market power over the business cycle, with the notable exception of a recent study by Depew and Sørensen (2013). Using Manning's (2003) steady-state estimation approach, Depew and Sørensen investigate the cyclical behaviour of the supply elasticity with data stemming from two large American firms for the years 1919–1940. They find that the elasticity is indeed moving procyclically. Estimates range from –0.5 during the Great Depression to 5.9 in the subsequent recovery and thus imply a substantially varying monopsonistic markdown on wages of 15 to 100 per cent.

We build on Depew and Sørensen (2013) by investigating the cyclical behaviour of the labour supply elasticity to the firm for West Germany using linked administrative employer–employee data encompassing the years 1985–2010. In doing so we improve on their contribution in several ways: (i) Our data set is based on a current representative sample of all workers covered by the German social security system and thus complements their findings based on two large firms' personnel files from the pre-war U.S. with recent results for a whole economy based on high-quality administrative data. (ii) Other than Depew and Sørensen, who use an estimation approach assuming a steady state and thus impose stationarity over the business cycle, we refine Manning's (2003) estimation

[1] Depew and Sørensen (2013) discuss this point in detail within Burdett and Mortensen's (1998) equilibrium search model and show that the labour supply elasticity to the firm is indeed lower in labour markets with a depressed job offer arrival rate and/or an increased job destruction rate.

approach allowing for a non-stationary environment. Also, the richness of our data set allows us to explicitly take into account hired workers' previous and separating workers' subsequent labour market status. Hence, we are able to use a more sophisticated estimation approach distinguishing transitions from/to employment from those from/to non-employment within a non-stationary labour market. (iii) The high frequency and long time span of our data further permits us to use hazard rate models on an inflow sample of jobs thereby accounting for left-truncation and right-censoring of job durations and – in two checks of robustness – to control for unobserved time-invariant worker or plant heterogeneity. (iv) What is more, the richness of our data allows us to confront the cyclical movements in employers' monopsony power with observed fluctuations in workers' wages and thus to relate predicted cyclical wage changes under monopsonistic wage setting to actual changes.

The remainder of this paper is organised as follows: Section 2 sets up our econometric approach that will be used to estimate the labour supply elasticity to the firm and its cyclical fluctuations from job transition data. The data used are described in Section 3. Section 4 presents and discusses the results of our preferred specification. Section 5 provides additional checks of robustness related to unobserved permanent worker and plant characteristics, and Section 6 concludes.

2 Econometric approach

2.1 Estimating the labour supply elasticity to the firm

The starting point of our econometric approach, which has been pioneered by Manning (2003), is a simple dynamic monopsony model for the labour supply to the firm. Consider a firm paying some wage w_t at time period $t \in \mathbb{N}$. We model the labour supply to this firm as

$$L_t = L_t(w_t, L_{t-1}) = R^e(w_t) + R^n(w_t) + [1 - s^e(w_t) - s^n(w_t)]L_{t-1}, \tag{1}$$

where $R^e > 0$ ($R^n > 0$) denotes the number of recruits hired from employment (non-employment) with $R^{e\prime}, R^{n\prime} > 0$ and $0 < s^e < 1$ ($0 < s^n < 1$) the separation rate to employment (non-employment) with $s^{e\prime}, s^{n\prime} < 0$ and the initial labour supply is some $L_0 > 0$.

It is straightforward to show that under dynamic monopsony the profit-maximising wage w^m satisfies

$$\frac{\phi - w^m}{w^m} = \frac{r}{1+r}\frac{1}{\varepsilon_{Lw}^{SR}} + \frac{1}{1+r}\frac{1}{\varepsilon_{Lw}^{LR}} \approx \frac{1}{\varepsilon_{Lw}^{LR}}, \tag{2}$$

where ϕ is the marginal revenue product of labour, r the firm's discount rate, and ε_{Lw}^{SR} (ε_{Lw}^{LR}) the short-run (long-run) wage elasticity of the labour supply to the firm (see, e.g., Boal and Ransom, 1997) and the latter approximation holds for small values of r. This approximation is reasonable in our application as we will make use of quarterly data, so that r represents the quarterly discount rate which is small enough for the approximation to hold sufficiently well. With $r \approx 0$ we thus get

$$w^m = \frac{\varepsilon_{Lw}^{LR}}{1+\varepsilon_{Lw}^{LR}}\phi \tag{3}$$

with workers just receiving a fraction of their marginal revenue product of labour and this fraction being smaller the smaller is the long-run supply elasticity.

To arrive at the markdown on productivity (3), we thus have to derive the long-run elasticity. To do so first involves determining the short-run elasticity, i.e. the elasticity of L_t with respect to w_t holding L_{t-1} fixed (see Boal and Ransom, 1997). Using (1) the short-run elasticity is

$$\varepsilon_{Lw}^{SR} = \frac{\partial L_t}{\partial w_t}\frac{w_t}{L_t} = \frac{R^e(w_t)}{L_t}\varepsilon_{Rw}^e + \frac{R^n(w_t)}{L_t}\varepsilon_{Rw}^n - \frac{s^e(w_t)L_{t-1}}{L_t}\varepsilon_{sw}^e - \frac{s^n(w_t)L_{t-1}}{L_t}\varepsilon_{sw}^n, \tag{4}$$

where ε_{sw}^e (ε_{sw}^n) denotes the separation rate elasticity to employment (non-employment) and ε_{Rw}^e (ε_{Rw}^n) the recruitment elasticity from employment (non-employment). Whereas it is straightforward (in principle) to estimate the separation rate elasticities and their weights in equation (4) from information on job durations available in many data sets, estimating the recruitment elasticities is a much harder task. For this would require the researcher not only to know the number and wages of firms' hires but also to know all the firms' applicants and the wages offered to these.

To avoid this problem, we follow the previous literature and simplify equation (4) by imposing more structure on the model. Following Manning (2003, pp. 96–100) we make use of Burdett and Mortensen's (1998) equilibrium search model. In this model, employed workers search on the job drawing job offers from the wage distribution F at a constant rate λ and are assumed to change employers whenever the offered wage is larger than the current one. Hence, the separation rate to employment and the recruits from employment are, respectively, given by

$$s^e(w_t) = \lambda[1 - F(w_t)], \tag{5}$$

$$R^e(w_t) = \lambda \int_{\underline{w}}^{w_t} L_t(x, L_{t-1})\, dF(x), \tag{6}$$

where $\underline{w}$ denotes workers' common reservation wage. Using (5) the separation rate elasticity to employment is

$$\varepsilon^e_{sw} = -\frac{\lambda F'(w_t) w_t}{s^e(w_t)}. \tag{7}$$

Making use of (6) and (7) the recruitment elasticity from employment becomes

$$\varepsilon^e_{Rw} = \frac{\lambda L_t F'(w_t) w_t}{R^e(w_t)} = -\frac{s^e(w_t) L_t}{R^e(w_t)} \varepsilon^e_{sw}. \tag{8}$$

Next, turn to the number of recruits from non-employment. These are given by

$$R^n(w_t) = \frac{1 - \theta_R(w_t)}{\theta_R(w_t)} R^e(w_t), \tag{9}$$

where $\theta_R = \frac{R^e}{R^e + R^n}$ denotes the share of hires from employment. Hence, the recruitment elasticity from non-employment is

$$\varepsilon^n_{Rw} = \varepsilon^e_{Rw} - \frac{\theta'_R(w_t)w_t}{[1-\theta_R(w_t)]\theta_R(w_t)} = \varepsilon^e_{Rw} - \frac{\varepsilon^R_{\theta w}}{1-\theta_R(w_t)} \tag{10}$$

with $\varepsilon^R_{\theta w}$ denoting the wage elasticity of the share of recruits hired from employment.

Combining (4), (8), and (10) yields

$$\varepsilon^{SR}_{Lw} = -\frac{s_e(w_t)[L_t + \theta_R(w_t)L_{t-1}]}{\theta_R(w_t)L_t}\varepsilon^e_{sw} - \frac{s^n(w_t)L_{t-1}}{L_t}\varepsilon^n_{sw} - \frac{R^e(w_t)+R^n(w_t)}{L_t}\varepsilon^R_{\theta w}. \tag{11}$$

To arrive at the long-run elasticity, we have to take into account that a change in the current wage also affects future employment levels, i.e. L_{t+1}, L_{t+2}, etc., because increased current employment will be inherited to future periods. Therefore, the long-run labour supply elasticity to the firm is

$$\begin{aligned}\varepsilon^{LR}_{Lw} &= \frac{\partial L_t}{\partial w_t}\frac{w_t}{L_t} + \frac{\partial L_{t+1}}{\partial L_t}\frac{\partial L_t}{\partial w_t}\frac{w_t}{L_t} + \frac{\partial L_{t+2}}{\partial L_{t+1}}\frac{\partial L_{t+1}}{\partial L_t}\frac{\partial L_t}{\partial w_t}\frac{w_t}{L_t} + \cdots \\ &= \varepsilon^{SR}_{Lw}\sum_{k=0}^{\infty}\prod_{l=0}^{k}\frac{\partial L_{t+l}}{\partial L_t}.\end{aligned} \tag{12}$$

With $w_t = w_{t+k}$ for all $k \in \mathbb{N}$, i.e. without changes in (expected) future wages, equation (1) yields $\prod_{l=0}^{k}\frac{\partial L_{t+l}}{\partial L_t} = [1 - s^e(w_t) - s^n(w_t)]^k$, so $\sum_{k=0}^{\infty}\prod_{l=0}^{k}\frac{\partial L_{t+l}}{\partial L_t} = 1/[s^e(w_t) + s^n(w_t)]$ and

$$\varepsilon^{LR}_{Lw} = \frac{\varepsilon^{SR}_{Lw}}{s^e(w_t)+s^n(w_t)}. \tag{13}$$

Combining (11) and (13) we thus arrive at

$$\varepsilon^{LR}_{Lw} = -\underbrace{\frac{\theta_s(w_t)[L_t + \theta_R(w_t)L_{t-1}]}{\theta_R(w_t)L_t}}_{\equiv a}\varepsilon^e_{sw} - \underbrace{\frac{[1-\theta_R(w_t)]L_{t-1}}{L_t}}_{\equiv b}\varepsilon^n_{sw} - \underbrace{\frac{R^e(w_t)+R^n(w_t)}{[s^e(w_t)+s^n(w_t)]L_t}}_{\equiv c}\varepsilon^R_{\theta w}, \tag{14}$$

where $\theta_s = \frac{s^e}{s^e+s^n}$ denotes the share of separations to employment. Equation (14) allows us to estimate the long-run labour supply elasticity to the firm from the two separation rate elasticities, ε^e_{sw} and ε^n_{sw}, the wage elasticity of the share of recruits hired from employment

$\varepsilon^{R}_{\theta w}$, and their respective weights, a, b, and c.[2]

Note that equation (14) nests the simpler approaches used in the previous literature to estimate the supply elasticity: Assuming a steady-state environment with constant employment for all firms, that is $\theta(w) \equiv \theta_R(w) \equiv \theta_s(w)$ and $L_t \equiv L$, equation (14) simplifies to

$$\varepsilon^{LR}_{Lw} = -[1 + \theta(w)]\varepsilon^{e}_{sw} - [1 - \theta(w)]\varepsilon^{n}_{sw} - \varepsilon^{R}_{\theta w} \tag{15}$$

as in Manning (2003, p. 100). Additionally restricting to an environment without transitions from and to non-employment, i.e. $\theta^R(w_t) \equiv \theta^s(w_t) \equiv 1$ and thus $\varepsilon^{n}_{sw} = \varepsilon^{R}_{\theta w} = 0$, equation (14) becomes

$$\varepsilon^{LR}_{Lw} = -2\varepsilon^{e}_{sw} \tag{16}$$

as in Manning (2003, p. 98). This is the steady-state approach chosen by Depew and Sørensen (2013) when investigating the cyclicality of employers' monopsony power.

2.2 Econometric specification

To estimate the long-run labour supply elasticity to the firm over the business cycle using equation (14), we have to estimate the cyclical movement of six components: (i) the separation rate elasticity to employment ε^{e}_{sw} and (ii) its weight a, (iii) the separation rate elasticity to non-employment ε^{n}_{sw} and (iv) its weight b, and (v) the wage elasticity of the share of recruits from employment $\varepsilon^{R}_{\theta w}$ and (vi) its weight c. In the following, we will use the aggregate unemployment rate as a measure of the business cycle.[3]

To arrive at estimates of the separation rate elasticities to employment and non-employment, we follow Manning (2003, p. 100–104) and Hirsch *et al.* (2010) and model

[2] Note that our way of estimating the long-run labour supply to the firm using equation (14) differs from Webber's (2013*a*,*b*) estimation approach who also tries to relax the steady-state assumption imposed by the previous literature. Apparently, however, Webber does neither take into account that a change in the firm's current wage both affects this firm's current and future employment growth nor distinguish short-run and long-run effects of such a wage change.

[3] Note that our findings are unchanged when using the lagged (by one year) aggregate unemployment rate as an alternative measure of the business cycle.

the separation rates of job spell i belonging to worker $m(i)$ as exponential models

$$s_i^\rho(\mathbf{x}_i^\rho(t), \upsilon_{m(i)}^\rho) = \exp(\mathbf{x}_i^\rho(t)'\boldsymbol{\beta}^\rho)\upsilon_{m(i)}^\rho \tag{17}$$

with route $\rho = e, n$, a vector of time-varying covariates $\mathbf{x}_i^\rho(t)$, a corresponding vector of coefficients $\boldsymbol{\beta}^\rho$, and unobserved worker heterogeneity $\upsilon_{m(i)}^\rho$, which is assumed to be independent of observed covariates $\mathbf{x}_i^\rho(t)$ and to follow a gamma distribution (as put forward by Abbring and van den Berg, 2007).[4] Note that by specifying separation rates as exponential models, we do not control for job tenure (i.e. we impose a constant baseline hazard on the model and thus restrict the separation rate to show no duration dependence). Of course, this puts a severe restriction on the models. Yet, we follow Manning (2003, p. 103) in arguing that under monopsony firms pay higher wages in order to reduce separations and increase tenure. Controlling for tenure would fail to attribute this indirect effect on the firm's labour supply to wages. In other words, job tenure would be a 'bad control variable', to use Angrist and Pischke's (2009, pp. 64–68) terminology, in that it is itself partly determined by wages, and controlling for it is expected to yield a downward bias (in absolute value) in the estimated separation rate elasticities.[5] To estimate the separation rate elasticities, we include the log wage and its interaction with the unemployment rate $u_i(t)$ as covariates in (17). So the respective separation rate elasticity is given by $\varepsilon_{sw}^\rho = \beta_w^\rho + \beta_{uw}^\rho \times u_i(t)$, and the estimated β_{uw}^ρ informs us on its cyclicality.

The wage elasticity of the share of recruits hired from employment is estimated from a random-effects logit model for the probability that a recruit comes from employment

[4] Assuming conditional independence of the separation probabilities to employment and non-employment Manning (2003, pp. 100/101) shows that they can be estimated separately by two univariate hazard rate models. When estimating the separation rate to non-employment all jobs are used. In contrast, when estimating the separation rate to employment only those jobs that do not end in non-employment are considered.

[5] This is exactly what is found in later checks of robustness (see Section 5) in which we estimate stratified Cox models that jointly control for job tenure and time-invariant unobserved worker or plant heterogeneity without imposing a random-effects assumption.

(as opposed to non-employment)

$$\Pr[y_i = 1|\mathbf{x}_i, \upsilon_{m(i)}] = \Lambda(\mathbf{x}_i'\boldsymbol{\beta} + \upsilon_{m(i)}), \tag{18}$$

where notation follows the same rules as before, y_i is an indicator for a hire from employment, Λ denotes the c.d.f. of a standard logistic distribution, and unobserved worker heterogeneity υ_m is Gaussian. Again, we include the log wage and its interaction with the unemployment rate as covariates in (17). As can be easily shown, $\beta_w + \beta_{uw} \times u_i$ gives the wage elasticity of the share of recruits hired from employment $\varepsilon^R_{\theta w}$ divided by $1 - \theta_R$.

Finally, the weights of the separation rate and recruitment elasticities are estimated from the data. That is, for every period a, b, and c are calculated using the period sample averages of L_t, L_{t-1}, θ_R, θ_s, R^e, R^n, s^e, and s^n.

Together, the period estimates of ε^e_{sw}, ε^n_{nw}, $\varepsilon^R_{\theta w}$, a, b, and c allow us to construct a time series of the long-run labour supply elasticity to the firm. In a next step of analysis, we relate this time series to the unemployment rate in the economy to see by how much the elasticity is moving over the business cycle. In a last step, we compare cyclical fluctuations in the elasticity to those in workers' wages to gain insight into the potential economic relevance of cyclical changes in employers' monopsony power.

3 Data

To put this approach into practice, we need detailed high-frequency data on job durations, preceding and subsequent jobs and periods of non-employment, as well as on workers and employers over a long period of time, ideally encompassing several business cycles. For our purpose, we combine two administrative data sets for the period 1985–2010: the Integrated Employment Biographies (IEB) and a quarterly version of the Establishment History Panel (BHP) provided by the Institute for Employment Research (IAB).

The data on job durations (on a daily basis), transitions, wages (deflated by the consumer price index), and worker characteristics come from a 5 per cent random sample of the IEB. The IEB comprises all wage and salary employees registered with the German social security system, where about 80 per cent of all people employed in Germany are covered by the system.[6] Since the information contained is used to calculate social security contributions, the data set is highly reliable and especially useful for analyses taking wages and job durations into account.

Information on employers comes from a quarterly version of the BHP which again consists of data from the German social insurances that are this time aggregated at the end of each quarter.[7] It not only contains information on plants' workforce composition and size but also on plant closures, which allows us to identify jobs in plants during their closing years.[8] Using turnover in these plants, however, is uninformative on the impact of wages on individual workers' separation decisions and may yield a spurious relationship between wages and separations. As a case in point, if receiving a low wage reflects low productivity and low-productivity employers are more likely to be driven out of the market, this will result in a negative correlation between wages and separations that is not driven by workers' labour supply behaviour. For this reason we exclude plants during their closing year.

Although our data contain observations for East German workers from 1992 onwards, restricting our analysis to the post-unification period would markedly reduce our period of observation and thus the scope of our investigation. Moreover, including East German data for the 1990s would mix up business cycle effects and those effects stemming from the transition of a socialist planned economy to a market economy. We will thus focus our analysis throughout on individuals working in West Germany (excluding Berlin) during the period 1985–2010 and further restrict it to males aged 18–55 years to circumvent selectivity issues regarding female employment and early retirement.

The merged data set allows us to build up an inflow sample of jobs starting between 1985 and 2010 taking into account workers' previous labour market status, the job duration, and – provided the job ended during our period of observation – workers' subsequent labour market status. In the following, we follow our theoretical model and

[6] For details on the IEB, see Jacobebbinghaus and Seth (2007).
[7] For details on the BHP, see Spengler (2009).
[8] Note that plant size does not comprise marginally employed workers as these are not consistently included in our data.

distinguish two labour market states: employment and non-employment. Consequently, a job may end with a transition to employment, which refers to a new job with another employer (i.e. a plant with a different plant identifier), or with a transition to non-employment, which refers to a subsequent spell in registered unemployment or no spell in the data at all.[9] The latter either implies that the individual has changed to non-employment without receiving unemployment benefits or that he has become, for instance, a self-employed worker not included in the data set. While our data do not enable us to disaggregate this category of unknown destination, information from other German data sets suggests that the vast majority of employees in this category have indeed moved to non-employment.[10]

Whereas information on job spells and daily gross wages included in the data are highly reliable, the data include no detailed information on the number of hours worked. Also, wages are top-coded at the social security contribution ceiling, which affects 9.6 per cent of our observations. To deal with the first drawback, we restrict our analysis to full-time workers. To cope with the second, we exclude jobs with wages above the ceiling. Besides, information on workers' education is provided by employers and therefore inconsistent or missing for some workers. To alleviate this problem, we impute the missing information on education by employing a procedure proposed by Fitzenberger *et al.* (2006) that allows inconsistent education information to be corrected. After applying this imputation procedure, only about 1.5 per cent of jobs are dropped due to missing or inconsistent information on education.

As can be seen from Table 1, our final data set comprises an inflow sample of 2,559,991 jobs belonging to 842,017 workers employed by 655,504 plants. Out of these jobs, 41.4 per cent start from employment and 58.6 from non-employment. Similarly, out of the 2,277,765 jobs terminated during our observation window, 1,020,812 or 44.8 per cent end with a separation to employment and 1,256,953 or 55.2 per cent end with a transition to non-employment. For further descriptive statistics on our sample, see Appendix Table A.1.

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9 Separations are ignored if the employee is recalled by the same plant within three months.

10 See, for example, Bartelheimer and Wieck (2005) for a transition matrix between employment and non-employment based on the German Socio-Economic Panel that allows stratification of the 'unknown' category into detailed categories.

— Table 1 about here —

4 Results

4.1 Cyclicality of the labour supply elasticity to the firm

To arrive at estimates of the long-run labour supply elasticity to the firm, we first of all estimate exponential models for the separation rates to employment and non-employment and a random-effects logit model for the probability that a recruit is hired from employment as opposed to non-employment. This provides us with estimates for the separation rate elasticities to employment and non-employment and the wage elasticity of the share of recruits hired from employment.

All these models include individuals' log wage and the interaction term of the log wage and the aggregate West German unemployment rate as main regressors to allow for varying elasticities over the business cycle. We further include six age, two education, and ten occupation dummies as well as an indicator for an immigrant worker to control for individual characteristics.[11] As plant controls we add four plant size dummies, the shares of low-skilled, high-skilled, female, immigrant, and part-time workers in the plant's workforce, the median age of the plant's workers, and 24 sector dummies. All estimations further include macro controls, namely year and quarter dummies, dummies for the type of region the firm is located in (i.e. rural, urban, or metropolitan), and the aggregate unemployment rate.

— Table 2 about here —

Fitting these models, the main results of which are presented in Table 2, we find that all three elasticities vary statistically significantly over the business cycle: If the unemployment rate is high, both the separation rate elasticities to employment and non-employment are lower in absolute value, whereas the wage elasticity of the share of recruits

[11] We follow Brücker and Jahn (2011) and count as immigrants all workers with non-German citizenship and so-called ethnic German immigrants, who possess German citizenship.

hired from employment gets larger. As can be readily seen from equation (14), every change in isolation as well as all changes together depress the long-run labour supply elasticity to the firm and thus raise firms' monopsony power.

To construct a time series of the elasticity, we next have to estimate the weights of the three separation rate and recruitment elasticities in equation (14), a, b, and c, from the data by combining quarterly information on employment flows. From the estimates of the separation rate and recruitment elasticities and the weights we obtain a quarterly time series of the long-run labour supply elasticity to the firm for the years 1985–2010. As is clear from Table 3 summarising our estimates, the long-run labour supply elasticity to the firm is varying markedly over our period of observation with estimates ranging from 1.43 to 3.34 and thus well within the range of the previous steady-state estimates surveyed by Manning (2011, Table 7). In particular, they come very close to the previous steady-state estimates for West Germany of 2.49–3.66 by Hirsch *et al.* (2010) obtained for the low-unemployment years 2000–2002. The aggregate unemployment rate also varies considerably from 5.8 to 11.8 per cent. A plot of both the elasticity and the unemployment rate time series (see Figure 1) is suggestive of a substantial procyclicality in the elasticity. Yet, the plot also reveals a strong seasonality in the elasticity series.

— Table 3 and Figure 1 about here —

To get rid of the seasonality and a potential trend in the labour supply elasticity, we run some simple regressions, regressing the elasticity on the unemployment rate, a group of quarter dummies, and a quadratic time trend (with all regressors centred around their sample means). As can be seen from Table 4, there is a significantly negative correlation between the estimated labour supply elasticity and the unemployment rate that hardly changes when controlling for seasonal and trend patterns. An increase in the unemployment rate by one percentage point is associated with a decrease in the long-run labour supply elasticity of about 0.11 in our preferred Model 3 that controls for both seasonality and trend components in the elasticity.

To get an impression about the economic relevance of this number, recall that under monopsonistic wage setting (with negligible discounting of future profits) workers' wage w^m is a fraction of their marginal revenue product ϕ that directly depends on the long-run labour supply elasticity to the firm,

$$w^m = \frac{\varepsilon_{Lw}^{LR}}{\varepsilon_{Lw}^{LR} + 1}\phi. \tag{19}$$

At the mean elasticity of our sample of 2.48 (see Table 3) this suggests that workers obtain just 71.3 per cent of their marginal product and thus implies a considerable extent of monopsony power. Now consider a marked economic downturn leading to an increase in the unemployment rate by, say, 2.5 percentage points. Using the results from Model 3 in Table 4, this decreases the elasticity by 0.27 to 2.21, and workers are thus expected to receive only 68.8 per cent of their marginal product. In other words, workers' wages are expected to decrease by 3.5 per cent if employers make full use of their additional monopsony power over their workers. Our results therefore are in line with theory in suggesting that the long-run labour supply elasticity to the firm moves procyclically and so in an economically significant way.

— Table 4 about here —

4.2 Cyclicality of firms' monopsony power and workers' wages

Although we have identified substantial and varying monopsony power over the business cycle, it remains unclear whether firms actually exploit cyclical changes in their monopsony power by raising wages during economic upturns and lowering them when economic activity is deteriorating. While employers are unlikely to (substantially) change ongoing wages, due to institutional constraints like collective bargaining or implicit contracts, entry wages have shown to be considerably responsive to the business cycle in Germany (for a survey and recent evidence, see Stüber, 2013). And changes in entry wages may be readily implemented by reducing the substantial wage cushion present in a large majority of West German firms (see Jung and Schnabel, 2011).

To relate our findings on the procyclicality of the long-run elasticity to cyclical fluctuations in workers' wages, we run some standard wage regressions regressing workers' entry wages on the aggregate unemployment rate and all the covariates included in the hazard rate and logit models controlling for personal and firm characteristics. The results shown in Table 5 confirm that entry wages respond significantly to changes in the unemployment rate.[12] In a standard OLS wage regression, an increase in the unemployment rate by one percentage point is associated with a significant decrease in the entry wage of about 1.2 per cent. When also including worker fixed effects, this effect even increases somewhat to 1.5 per cent.

— Table 5 about here —

As we previously saw, our results imply that under pure monopsonistic wage setting a severe economic downturn increasing the unemployment rate by 2.5 percentage points is expected to reduce workers' wages by 3.5 per cent. Our wage regressions document that workers' expected entry wages would sink by 3.0–3.8 per cent if such an increase in unemployment were to occur. Hence, cyclical changes in employers' wage-setting power are able to account for the procyclicality of workers' wages, though admittedly we cannot be sure that observed wage changes actually reflect cyclical changes in monopsony power. Nevertheless, our back-of-the-envelope calculation makes clear that the procyclicality of the long-run labour supply elasticity to the firm is of the magnitude needed to generate observed wage changes if employers were to fully exploit their wage-setting power. This contrasts with the earlier contribution by Depew and Sørensen (2013) who found cyclical fluctuations of the monopsonistic markdown that are magnitudes larger than those of workers' wages. One has to bear in mind, however, that Depew and Sørensen's study utilises pre-war data from two U.S. firms' personnel files that comprise the unprecedented slump during and the strong recovery following the Great Depression and thus a period of unique economic turmoil unlikely to compare to our period of observation.

[12] Note that, in line with our expectations, running similar regressions including incumbent workers' wages shows that ongoing wages are almost unresponsive to changes in the unemployment rate. The coefficient of the unemployment rate is only less than a tenth of the coefficient in the entry wage regressions.

4.3 Cyclicality and the prevailing level of unemployment

Up to now, we have found evidence that both the long-run labour supply elasticity to the firm and workers' entry wages move procyclically. What is more, we also saw that under monopsonistic wage setting cyclical changes in the elasticity would generate a procyclicality in wages that is of the same magnitude to the one observed in workers' entry wages. So far, we have restricted the impact of the aggregate unemployment rate on both the elasticity and entry wages to be independent of the current state of the labour market, i.e. independent of the prevailing level of unemployment. It is tempting, though, to conjecture that deteriorating labour market prospects are felt more by workers when the labour market is tight than in a situation with already poor outside opportunities. In other words, the impact of the aggregate unemployment rate on the long-run labour supply elasticity to the firm may be more pronounced for low levels of unemployment.

To check this conjecture, we now redo our analysis adding the squared unemployment rate and its interaction with the log wage as covariates to the exponential and logit models used to arrive at estimates of the separation rate and recruitment elasticities. We thus allow the impact of the aggregate unemployment rate on the respective elasticity to depend on the prevailing state of the labour market.

As is clear from Table 6, which presents the main results obtained from fitting the modified exponential and logit models, the coefficients of the interaction of log wage and the squared unemployment rate are statistically significantly negative in the two hazard rate models. So the unemployment rate indeed has a less pronounced adverse impact on both the separation rate to employment and to non-employment if the prevailing unemployment rate is high. Nevertheless, our estimates of the long-run labour supply elasticity to the firm (and its components) summarised in Table 7 are quantitatively very similar to those from our previous analysis shown in Table 3 in Section 4.1. Furthermore, a plot of the elasticity and the unemployment rate time series presented in Figure 2 is again suggestive of a procyclicality of the elasticity.

— Tables 6 and 7 and Figure 2 about here —

Regressing the elasticity on a group of uemployment rate dummies, a group of quarter dummies, and a quadratic time trend (see Model 3 in Table 8), we find that the elasticity is largest in a labour market with an unemployment rate of less than 7 per cent (which is the omitted reference group) and gets lower for larger levels of unemployment. An increase in the unemployment rate has a much stronger adverse impact on the elasticity for low levels of unemployment, and there is no further drop in the elasticity once unemployment exceeds 10 per cent.

— **Table 8 about here** —

Remarkably, workers' entry wages are also more responsive to a rise in the unemployment rate when the prevailing level of unemployment is low. Regressing workers' entry wages on a group of unemployment rate dummies (see Table 9) makes clear that increases in the unemployment rate are associated with considerable drops in workers' entry wages for low levels of unemployment. On the other hand, an increase in the unemployment rate has no further adverse impact on wages once the unemployment rate exceeds 10 per cent, which corresponds to the findings on the elasticity.

— **Table 9 about here** —

Taken together, these results point at the robustness of our main finding that both firms' monopsony power and workers' wages move procyclically. Even more, they make clear that the procyclicality is more pronounced in tight labour markets with low unemployment that in slack labour market where rising unemployment is unlikely to further deteriorate workers' search prospects much. In particular, there is no further adverse effect of a rise in unemployment on both the elasticity and entry wages once the unemployment rate reaches 10 per cent.

5 Issues of robustness

5.1 Robustness to unobserved worker heterogeneity

One legitimate concern regarding our findings is that transiting workers may differ considerably in terms of unobserved characteristics depending on the current state of the business cycle. As a case in point, a worker changing employers during bad times is arguably of much higher quality than a worker doing so during a boom. Therefore, our findings might suffer from bias if wages and workers' transition behaviour are correlated with unobserved worker quality.

A further concern is that our estimation approach to the separation rate elasticities assumes that wages are conditionally exogenous with respect to job duration to yield unbiased estimates. Yet, this assumption does not hold if high-ability (and thus high-wage) workers self-select into stable jobs (Altonji and Williams, 2005) or if incumbent workers' wages respond to their job opportunities (Pencavel, 1972). While we did not find any evidence that incumbent workers' wages respond in a significant way to changes in unemployment (see footnote 12), both these points should pose less a problem when controlling for permanent unobserved worker characteristics.

To scrutinise whether our findings suffer from bias stemming from unobserved worker characteristics, we redo our analysis from Section 4.3 estimating separation rate and recruitment elasticities from models that control for unobserved time-invariant worker heterogeneity allowing this heterogeneity to be correlated with observed covariates (i.e. relaxing the random-effects assumption employed in the previous exponential and logit models). More precisely, separation rate elasticities are estimated from Cox models statified at the worker level, i.e. the route-specific hazard rate is modelled as

$$s_i^\rho(t, \mathbf{x}_i^\rho(t)) = s_{0m(i)}^\rho(t)\exp(\mathbf{x}_i^\rho(t)'\boldsymbol{\beta}^\rho) \qquad (\rho = e, n), \tag{20}$$

where the baseline hazard $s_{0m(i)}^\rho(t)$ is some arbitrary worker-specific function of job duration thereby encompassing time-invariant unobserved heterogeneity at the level of worker $m(i)$. Adopting the stratified partial likelihood estimator allows us to sweep out the worker-specific baseline hazard without the need of identifying it and thus to estimate the covariates' coefficients while controlling for unobserved worker heterogeneity in a similarly convenient way as with the within estimator in linear fixed-effects models (cf. Ridder and Tunalı, 1999). That said, estimating stratified Cox models forces us to control for job tenure. As already said, the worker-specific baseline hazard $s_{0m(i)}(t)$ in equation (20) drops out of the partial likelihood function and does so without being constrained to be constant over job tenure t. By estimating stratified Cox models we thus not only control for unobserved worker heterogeneity but also for job tenure. And as discussed in Section 2.2, this introduces a bad control problem and should yield lower (in absolute value) estimated separation rate elasticities. We thus expect this exercise to result in considerably lower estimates of the long-run labour supply elasticity to the firm. Finally, the wage elasticity of the share of recruits hired from employment is estimated from a conditional logit model controlling for worker fixed effects.

As can be seen from Tables 10 and 11, estimates of the separation rate elasticities are indeed markedly lower when controlling for both unobserved time-invariant worker heterogeneity and job tenure by means of stratified Cox models. As a consequence, the estimates of the long-run labour supply elasticity to the firm are lower than in previous specifications that did not control for job tenure and thus did not suffer from the bad control problem that arises when doing so. Nonetheless, Figure 3 and Table 12 make clear that this has no effect on our central finding: The magnitude of the procyclicality of the long-run labour supply elasticity to the firm remains the same (compare Table 8). In general, an increase in unemployment is still associated with a significant drop in the elasticity for low levels of unemployment, whereas there is no further adverse effect once the unemployment rate exceeds 10 per cent.

— Tables 10–12 and Figure 3 about here —

5.2 Robustness to unobserved plant heterogeneity

A shortcoming of our administrative data is that we lack detailed information on plants other than plant size and workforce composition. This may pose a problem as we aim at identifying the impact of wages on individual workers' separation decisions and cannot distinguish voluntary quits from involuntary dismissals in our data. Part of the measured effect of wages on separations and hirings may be obviously demand-driven rather than a supply-side response and may for this reason not allow us to infer the labour supply elasticity to the firm from separation rate elasticities.[13] For instance, if being paid a low wage reflects low productivity of an employer and low-productivity employers are more likely to layoff workers, this may result in a negative correlation between separations and wages that is not driven by workers' supply behaviour and thus in too large (in absolute value) separation rate elasticities. It is, however, less clear to us whether this problem should matter for the procyclicality of the elasticity found in previous specifications.

As stated in Section 3, this is the reason why we exclude jobs terminated in plants' closing year from our sample as this sort of exogenous separations is obviously uninformative on the impact of wages on workers' quit behaviour. To further check whether our findings suffer from unobserved plant information, we redo our analysis along the lines of Section 5.1 fitting stratified Cox and conditional logit models that now control for time-invariant unobserved plant heterogeneity. Again, this comes along with controlling for job tenure and thus introduces the now familiar bad control problem expected to deflate estimated separation rate and supply elasticities. As is clear from Table 14, all these elasticities are indeed lower (in absolute value) than in our preferred specification from Section 4.3 (compare Table 7). As is visible from Figure 4 and Table 15, though, this has no impact on the procyclicality of the long-run labour supply elasticity to the firm. Still an increase in unemployment is associated with a marked drop in the elasticity for low levels of unemployment and no change in the elasticity once unemployment reaches 10 per cent.

[13] This point may be indeed be of importance as Hirsch *et al.* (2010) have documented that including detailed plant controls, like information on profitability or the industrial relations regime, has quite an impact on the estimated supply elasticity.

— Tables 13–15 and Figure 4 about here —

Taken together, these two checks of robustness make clear that the cyclical behaviour of the long-run labour supply elasticity to the firm documented in Section 4 is both robust to controlling for either permanent unobserved worker or plant heterogeneity. Notably, the magnitude of the procyclicality is almost unchanged across specifications. Given that our previous results from Section 4.3 do not suffer from the bad control problem involved when controlling for job tenure in separation equations inducing downward bias in the separation rate and supply elasticities, we regard them as our preferred specification.

6 Conclusions

Using administrative linked employer–employee data for West Germany comprising the years 1985–2010, this paper has investigated the cyclical behaviour of the long-run labour supply elasticity to the firm. In line with theoretical expectations, we found that the elasticity moves procyclically. The procyclicality of the elasticity found is pronounced enough to give rise to substantially higher monopsony power during economic downturns when workers are bereft of outside options and labour markets are therefore less competitive.

The long time horizon and high frequency of our data allowed us to substantially improve on Depew and Sørensen's (2013) earlier contribution by making use of a more sophisticated estimation procedure based on duration models. This allows us to relax their steady-state assumption, address left-truncated and right-censored job durations, distinguish employment and non-employment as distinct labour market states, and control, in two checks of robustness, for unobserved time-invariant worker and plant heterogeneity. What is more, we are able to use recent data for a whole economy whereas Depew and Sørensen base their evidence on pre-war data from personnel files of two large U.S. firms, a period including the considerably economic turmoil surrounding the Great Depression and thus unlikely to compare to our period of observation.

In our preferred specification, an economic downturn that causes an increase of the unemployment rate by 2.5 percentage points is expected to depress the supply elasticity in such a way that workers' wages under pure monopsonistic wage setting would drop by 3.5 per cent on average. This comes close to the observed cyclical pattern of workers' entry wages in our data, where actual wages are expected to decrease by 3.0–3.8 per cent following such an increase in unemployment. While we obviously cannot claim causality here, this finding points at the potential relevance of cyclical fluctuations of employers' wage-setting power for the cyclical change in workers' wages.

We additionally find that the procyclicality of the elasticity and workers' entry wages is more pronounced in tight labour markets with low levels of unemployment than in labour markets where the prevailing unemployment rate is high and search prospects are poor from the outset. In particular, further increases in unemployment have no adverse effect on both the elasticity and workers' entry wages once the unemployment rate reaches 10 per cent. In two checks of robustness, we also saw that the procyclicality of the elasticity is of very similar magnitude when controlling for either unobserved time-invariant worker or plant heterogeneity. So our findings are unlikely to be driven by unobserved worker or plant characteristics related to workers' wages and job mobility.

Following Manning (2003, p. 13) who argues 'that our understanding of labor markets would be much improved by thinking in terms of a model where the labor supply curve facing the firm is not infinitely elastic', we think the procyclicality of workers' wages to be another phenomenon a monopsonistic approach can shed light on. Of course, our findings present only a first indication of the possible relevance of cyclical fluctuations in employers' wage-setting power for the cyclical behaviour of workers' wages. To establish the causal link behind the comovement of workers' wages and the labour supply elasticity to the firm therefore seems to be a promising avenue for future research.

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Figures

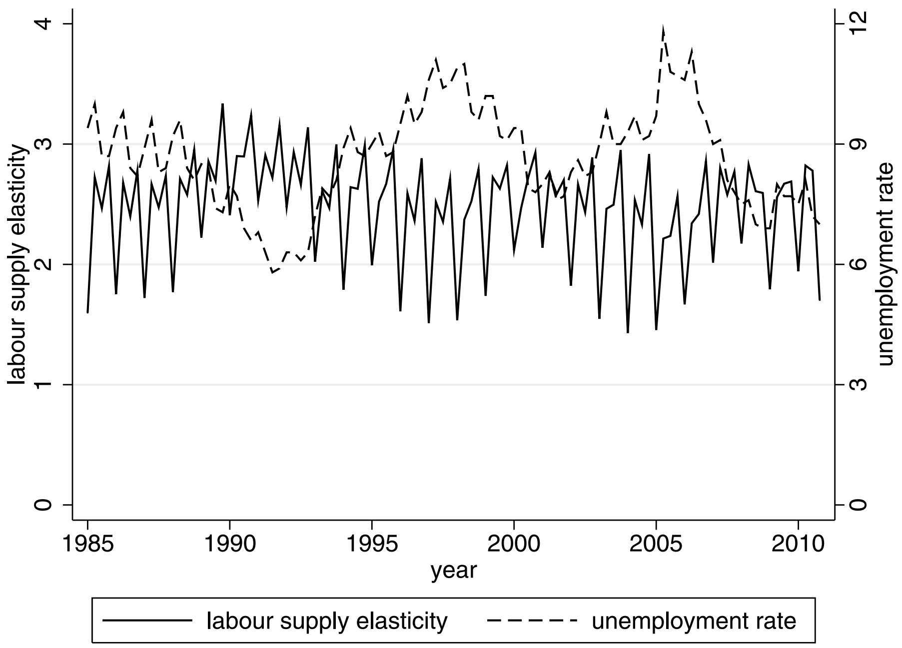

Figure 1: The unemployment rate and the estimated long-run labour supply elasticity to the firm

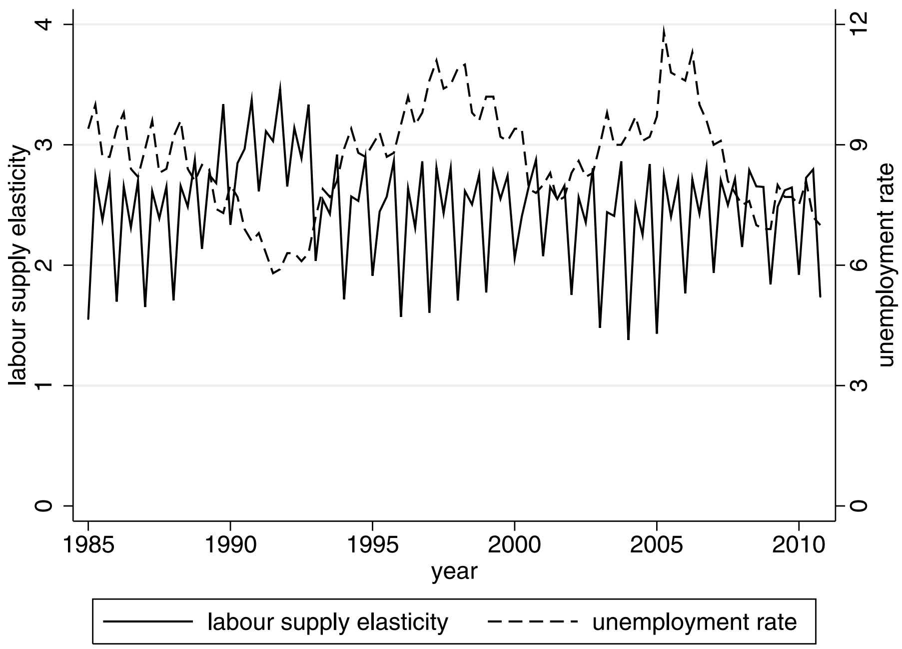

Figure 2: The unemployment rate and the estimated long-run labour supply elasticity to the firm when allowing interactions with quadratic unemployment

Figure 3: The unemployment rate and the estimated long-run labour supply elasticity to the firm when controlling for unobserved time-invariant worker heterogeneity

Figure 4: The unemployment rate and the estimated long-run labour supply elasticity to the firm when controlling for unobserved time-invariant plant heterogeneity

Tables

Table 1: Jobs and transitions

Jobs	2,559,991	
Workers	842,017	
Plants	655,504	
Hires from employment	1,059,284	(41.4)
Hires from non-employment	1,500,707	(58.6)
Separations to employment	1,020,812	(39.9)
Separations to non-employment	1,256,953	(49.1)
Right-censored job durations	282,226	(11.0)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. Percentages in parentheses.

Table 2: The cyclicality of the separation rate and the recruitment elasticities

Exponential model for the separation rate to employment	
log wage	–1.834** (0.019)
log wage × unemployment rate	0.040** (0.002)
Exponential model for the separation rate to non-employment	
log wage	–1.933** (0.016)
log wage × unemployment rate	0.034** (0.002)
Logit model for the hiring probability from employment	
log wage	0.500** (0.027)
log wage × unemployment rate	0.084** (0.003)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. Standard errors clustered at person level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Covariates included in the estimations are two education, six age, and three plant size dummies, quarter and year dummies, dummies indicating the size of the regional labour market, for an immigrant worker, one-digit occupation, and two-digit industry, the shares of low-skilled, high-skilled, female, immigrant, and part-time workers in the plant's workforce, the median age of its workforce, and the aggregate unemployment rate. Detailed results are available on request.

Table 3: The unemployment rate and the estimated elasticities and weights

	Mean	S.D.	Min	Max
Aggregate unemployment rate (per cent)	8.644	1.305	5.800	11.800
Long-run labour supply elasticity to the firm ($\hat{\varepsilon}^{LR}_{Lw}$)	2.479	0.439	1.430	3.337
Separation rate elasticity to employment ($\hat{\varepsilon}^{e}_{sw}$)	–1.492	0.052	–1.605	–1.367
Separation rate elasticity to non-employment ($\hat{\varepsilon}^{n}_{sw}$)	–1.635	0.045	–1.733	–1.527
Elasticity of the share of hires from employment ($\hat{\varepsilon}^{R}_{\theta w}$)	0.698	0.124	0.489	1.039
Weight of separation elasticity to employment ($\hat{a}$)	1.559	0.241	0.918	2.103
Weight of separation elasticity to non-employment ($\hat{b}$)	0.567	0.065	0.439	0.719
Weight of recruitment elasticity ($\hat{c}$)	1.096	0.349	0.445	1.685
Observations (quarters)		104		

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The separation rate and recruitment elasticities are estimated using the results from Table 2. The weights are calculated using quarterly sample averages. The long-run labour supply elasticity to the firm is estimated using equation (14).

Table 4: The partial correlation between the long-run labour supply elasticity to the firm and the unemployment rate when controlling for seasonality and trend

	Model 1	Model 2	Model 3
Unemployment rate	–0.116** (0.022)	–0.104** (0.019)	–0.108** (0.013)
2nd quarter (dummy)		0.812** (0.049)	0.814** (0.051)
3rd quarter (dummy)		0.632** (0.053)	0.630** (0.051)
4th quarter (dummy)		0.916** (0.074)	0.914** (0.072)
Year			0.018 (0.010)
Year^2 / 100			–0.094* (0.041)
Constant	2.479** (0.029)	2.479** (0.026)	2.479** (0.021)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regression sample is described in Table 3. The regressand is the long-run labour supply elasticity to the firm. Newey–West standard errors (with lag length four) in parentheses. **/* denotes statistical significance at the 1/5 per cent level. All regressors are centred around their sample means.

Table 5: Entry wage regressions

	OLS	Person FE
Unemployment rate	–0.012** (0.001)	–0.015** (0.001)
Immigrant (dummy)	–0.045** (0.001)	
Medium-skilled (dummy)	0.115** (0.001)	0.045** (0.001)
High-skilled (dummy)	0.234** (0.002)	0.245** (0.003)
Age 18–25 years (dummy)	–0.098** (0.001)	–0.025** (0.001)
Age 31–35 years (dummy)	0.049** (0.001)	–0.021** (0.001)
Age 36–40 years (dummy)	0.070** (0.001)	–0.076** (0.002)
Age 41–45 years (dummy)	0.077** (0.001)	–0.152** (0.002)
Age 46–50 years (dummy)	0.077** (0.001)	–0.240** (0.003)
Age 51–55 years (dummy)	0.065** (0.001)	–0.338** (0.004)
Plant size 11–50 (dummy)	0.060** (0.001)	0.046** (0.001)
Plant size 51–200 (dummy)	0.069** (0.001)	0.052** (0.001)
Plant size 201–1000 (dummy)	0.118** (0.001)	0.088** (0.001)
Plant size > 1000 (dummy)	0.161** (0.001)	0.121** (0.001)
Share of low-skilled workers	–0.073** (0.001)	–0.057** (0.001)
Share of high-skilled workers	0.326** (0.003)	0.229** (0.003)
Share of female workers	–0.146** (0.002)	–0.108** (0.002)
Share of immigrant workers	–0.128** (0.002)	–0.067** (0.002)
Share of part-time workers	–0.062** (0.002)	–0.046** (0.002)
Median age of workforce / 100	0.509** (0.004)	0.393** (0.004)
Observations	2,559,911	

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regressand is the log gross daily wage in the first observation of every job. Standard errors clustered at the person level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Further covariates included are dummies indicating the size of the regional labour market, dummies for one-digit occupation and two-digit industry, as well as quarter and year dummies.

Table 6: The cyclicality of the separation rate and the recruitment elasticities when allowing for interactions with quadratic unemployment

Exponential model for the separation rate to employment	
log wage	–3.673** (0.097)
log wage × unemployment rate	0.477** (0.023)
log wage × unemployment rate^2	–0.025** (0.001)
Exponential model for the separation rate to non-employment	
log wage	–3.648** (0.081)
log wage × unemployment rate	0.440** (0.019)
log wage × unemployment rate^2	–0.023** (0.001)
Logit model for the hiring probability from employment	
log wage	0.431** (0.142)
log wage × unemployment rate	0.100** (0.033)
log wage × unemployment rate^2	–0.001 (0.002)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. Standard errors clustered at person level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Apart from the squared unemployment rate, covariates included are the same as in Table 2. Detailed results are available on request.

Table 7: The unemployment rate and the estimated elasticities and weights when allowing for interactions with quadratic unemployment

	Mean	S.D.	Min	Max
Aggregate unemployment rate (per cent)	8.644	1.305	5.800	11.800
Long-run labour supply elasticity to the firm ($\hat{\varepsilon}_{Lw}^{LR}$)	2.479	0.455	1.379	3.461
Separation rate elasticity to employment ($\hat{\varepsilon}_{sw}^{e}$)	–1.491	0.074	–1.761	–1.433
Separation rate elasticity to non-employment ($\hat{\varepsilon}_{sw}^{n}$)	–1.635	0.068	–1.885	–1.583
Elasticity of the share of hires from employment ($\hat{\varepsilon}_{\theta w}^{R}$)	0.698	0.124	0.485	1.036
Weight of separation elasticity to employment ($\hat{a}$)	1.559	0.241	0.918	2.103
Weight of separation elasticity to non-employment ($\hat{b}$)	0.567	0.065	0.439	0.719
Weight of recruitment elasticity ($\hat{c}$)	1.096	0.349	0.445	1.685
Observations (quarters)		104		

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The separation rate and recruitment elasticities are estimated using the results from Table 6. The weights are calculated using quarterly sample averages. The long-run labour supply elasticity to the firm is estimated using equation (14).

Table 8: The partial correlation between the long-run labour supply elasticity to the firm and the unemployment rate when allowing for non-linear unemployment effects

	Model 1	Model 2	Model 3
Unemployment rate 7–8%	–0.361** (0.160)	–0.415** (0.133)	–0.344** (0.127)
Unemployment rate 8–9%	–0.447** (0.146)	–0.459** (0.110)	–0.443** (0.087)
Unemployment rate 9–10%	–0.635** (0.152)	–0.568** (0.115)	–0.551** (0.089)
Unemployment rate > 10%	–0.507** (0.149)	–0.499** (0.109)	–0.480** (0.089)
2nd quarter (dummy)		0.832** (0.051)	0.831** (0.054)
3rd quarter (dummy)		0.648** (0.055)	0.640** (0.052)
4th quarter (dummy)		0.924** (0.070)	0.919** (0.071)
Year			0.018 (0.010)
Year^2 / 100			–0.091* (0.043)
Constant	2.479** (0.029)	2.479** (0.025)	2.479** (0.022)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regression sample is described in Table 7. The regressand is the long-run labour supply elasticity to the firm. Newey–West standard errors (with lag length four) in parentheses. **/* denotes statistical significance at the 1/5 per cent level. All regressors are centred around their sample means.

Table 9: Entry wage regressions when allowing for non-linear unemployment effects

	OLS	Person FE
Unemployment rate 7–8%	–0.021** (0.001)	–0.018** (0.001)
Unemployment rate 8–9%	–0.029** (0.001)	–0.026** (0.002)
Unemployment rate 9–10%	–0.033** (0.002)	–0.033** (0.002)
Unemployment rate > 10%	–0.033** (0.002)	–0.034** (0.019)
Immigrant (dummy)	–0.045** (0.001)	
Medium-skilled (dummy)	0.115** (0.001)	0.045** (0.001)
High-skilled (dummy)	0.234** (0.002)	0.245** (0.003)
Age 18–25 years (dummy)	–0.098** (0.001)	–0.025** (0.001)
Age 31–35 years (dummy)	0.049** (0.001)	–0.021** (0.001)
Age 36–40 years (dummy)	0.070** (0.001)	–0.076** (0.002)
Age 41–45 years (dummy)	0.077** (0.001)	–0.152** (0.002)
Age 46–50 years (dummy)	0.077** (0.001)	–0.240** (0.003)
Age 51–55 years (dummy)	0.065** (0.001)	–0.334** (0.004)
Plant size 11–50 (dummy)	0.060** (0.001)	0.046** (0.001)
Plant size 51–200 (dummy)	0.070** (0.001)	0.052** (0.001)
Plant size 201–1000 (dummy)	0.119** (0.001)	0.088** (0.001)
Plant size > 1000 (dummy)	0.161** (0.001)	0.121** (0.001)
Share of low-skilled workers	–0.073** (0.001)	–0.057** (0.001)
Share of high-skilled workers	0.326** (0.003)	0.229** (0.003)
Share of female workers	–0.146** (0.002)	–0.108** (0.001)
Share of immigrant workers	–0.128** (0.002)	–0.068** (0.002)
Share of part-time workers	–0.062** (0.002)	–0.046** (0.002)
Median age of workforce / 100	0.509** (0.004)	0.392** (0.004)
Observations	2,559,911	

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regressand is the log gross daily wage in the first observation of every job. Standard errors clustered at the person level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Further covariates included are the same as in Table 5.

Table 10: The cyclicality of the separation rate and the recruitment elasticities when controlling for unobserved time-invariant worker heterogeneity

Stratified Cox model for separation rate to employment	
log wage	–2.599** (0.171)
log wage × unemployment rate	0.317** (0.040)
log wage × unemployment rate^2	–0.016** (0.002)
Stratified Cox model for separation rate to non-employment	
log wage	–2.604** (0.132)
log wage × unemployment rate	0.375** (0.030)
log wage × unemployment rate^2	–0.019** (0.002)
Conditional logit model for hiring probability from employment	
log wage	0.478** (0.179)
log wage × unemployment rate	0.032 (0.042)
log wage × unemployment rate^2	0.003 (0.002)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. Standard errors clustered at person level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Covariates included are the same as in Table 2. Detailed results are available on request.

Table 11: The unemployment rate and the estimated elasticities and weights when controlling for unobserved time-invariant worker heterogeneity

	Mean	S.D.	Min	Max
Aggregate unemployment rate (per cent)	8.644	1.305	5.800	11.800
Long-run labour supply elasticity to the firm ($\hat{\varepsilon}^{LR}_{Lw}$)	1.554	0.353	0.753	2.386
Separation rate elasticity to employment ($\hat{\varepsilon}^{e}_{sw}$)	–1.086	0.062	–1.301	–1.035
Separation rate elasticity to non-employment ($\hat{\varepsilon}^{n}_{sw}$)	–0.849	0.066	–1.084	–0.797
Elasticity of the share of hires from employment ($\hat{\varepsilon}^{R}_{\theta w}$)	0.559	0.110	0.378	0.882
Weight of separation elasticity to employment ($\hat{a}$)	1.559	0.241	0.918	2.103
Weight of separation elasticity to non-employment ($\hat{b}$)	0.567	0.065	0.439	0.719
Weight of recruitment elasticity ($\hat{c}$)	1.096	0.349	0.445	1.685
Observations (quarters)		104		

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The separation rate and recruitment elasticities are estimated using the results from Table 10. The weights are calculated using quarterly sample averages. The long-run labour supply elasticity to the firm is estimated using equation (14).

Table 12: The partial correlation between the long-run labour supply elasticity to the firm and the unemployment rate when controlling for unobserved time-invariant worker heterogeneity

	Model 1		Model 2		Model 3	
Unemployment rate 7–8%	–0.300*	(0.123)	–0.337**	(0.103)	–0.281**	(0.010)
Unemployment rate 8–9%	–0.395**	(0.106)	–0.401**	(0.086)	–0.387**	(0.067)
Unemployment rate 9–10%	–0.590**	(0.112)	–0.534**	(0.089)	–0.523**	(0.068)
Unemployment rate > 10%	–0.595**	(0.107)	–0.573**	(0.085)	–0.563**	(0.067)
2nd quarter (dummy)			0.542**	(0.032)	0.542**	(0.034)
3rd quarter (dummy)			0.450**	(0.041)	0.443**	(0.038)
4th quarter (dummy)			0.681**	(0.052)	0.676**	(0.053)
Year					0.017*	(0.008)
Year^2 / 100					–0.082*	(0.034)
Constant	1.554**	(0.023)	1.554**	(0.020)	1.554**	(0.018)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regression sample is described in Table 11. The regressand is the long-run labour supply elasticity to the firm. Newey–West standard errors (with lag length four) in parentheses. **/* denotes statistical significance at the 1/5 per cent level. All regressors are centred around their sample means.

Table 13: The cyclicality of the separation rate and the recruitment elasticities when controlling for unobserved time-invariant plant heterogeneity

Stratified Cox model for the separation rate to employment		
log wage	–3.855**	(0.197)
log wage × unemployment rate	0.531**	(0.046)
log wage × unemployment rate^2	–0.026**	(0.003)
Stratified Cox model for the separation rate to non-employment		
log wage	–3.547**	(0.148)
log wage × unemployment rate	0.397**	(0.034)
log wage × unemployment rate^2	–0.020**	(0.002)
Conditional logit model for the hiring probability from employment		
log wage	0.416*	(0.190)
log wage × unemployment rate	0.050	(0.044)
log wage × unemployment rate^2	0.002	(0.003)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. Standard errors clustered at plant level in parentheses. **/* denotes statistical significance at the 1/5 per cent level. Covariates included are the same as in Table 2. Detailed results are available on request.

Table 14: The unemployment rate and the estimated elasticities and weights when controlling for unobserved time-invariant plant heterogeneity

	Mean	S.D.	Min	Max
Aggregate unemployment rate (per cent)	8.644	1.305	5.800	11.800
Long-run labour supply elasticity to the firm ($\hat{\varepsilon}_{Lw}^{LR}$)	2.288	0.440	1.290	3.381
Separation rate elasticity to employment ($\hat{\varepsilon}_{sw}^{e}$)	–1.283	0.114	–1.665	–1.185
Separation rate elasticity to non-employment ($\hat{\varepsilon}_{sw}^{n}$)	–1.637	0.081	–1.914	–1.569
Elasticity of the share of hires from employment ($\hat{\varepsilon}_{\theta w}^{R}$)	0.575	0.113	0.385	0.905
Weight of separation elasticity to employment ($\hat{a}$)	1.559	0.241	0.918	2.103
Weight of separation elasticity to non-employment ($\hat{b}$)	0.567	0.065	0.439	0.719
Weight of recruitment elasticity ($\hat{c}$)	1.096	0.349	0.445	1.685
Observations (quarters)		104		

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The separation rate and recruitment elasticities are estimated using the results from Table 13. The weights are calculated using quarterly sample averages. The long-run labour supply elasticity to the firm is estimated using equation (14).

Table 15: The partial correlation between the long-run labour supply elasticity to the firm and the unemployment rate when controlling for unobserved time-invariant plant heterogeneity

	Model 1	Model 2	Model 3
Unemployment rate 7–8%	–0.414* (0.161)	–0.462** (0.132)	–0.404** (0.132)
Unemployment rate 8–9%	–0.561** (0.145)	–0.572** (0.114)	–0.560** (0.096)
Unemployment rate 9–10%	–0.796** (0.147)	–0.740** (0.116)	–0.725** (0.096)
Unemployment rate $>$ 10%	–0.779** (0.146)	–0.776** (0.112)	–0.759** (0.095)
2nd quarter (dummy)		0.725** (0.044)	0.724** (0.046)
3rd quarter (dummy)		0.572** (0.051)	0.566** (0.048)
4th quarter (dummy)		0.785** (0.061)	0.781** (0.063)
Year			0.013 (0.009)
Year^2 / 100			–0.069 (0.040)
Constant	2.288** (0.026)	2.288** (0.022)	2.288** (0.020)

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010. The regression sample is described in Table 14. The regressand is the long-run labour supply elasticity to the firm. Newey–West standard errors (with lag length four) in parentheses. **/* denotes statistical significance at the 1/5 per cent level. All regressors are centred around their sample means.

Appendix

Table A.1: Selected descriptives (means)

Gross daily wage (€)	83.782
Log gross daily wage	4.376
Unemployment rate (per cent)	8.623
Immigrant (dummy)	0.145
Low-skilled (dummy)	0.126
Medium-skilled (dummy)	0.804
High-skilled (dummy)	0.070
Age (years)	34.175
Age 18–25 years (dummy)	0.186
Age 31–35 years (dummy)	0.204
Age 36–40 years (dummy)	0.191
Age 41–45 years (dummy)	0.164
Age 46–50 years (dummy)	0.128
Age 51–55 years (dummy)	0.040
Tenure (years)	3.571
Plant size $\leqslant$ 10 (dummy)	0.157
Plant size 11–50 (dummy)	0.260
Plant size 51–200 (dummy)	0.247
Plant size 201–1000 (dummy)	0.209
Plant size $>$ 1000 (dummy)	0.127
Share of low-skilled workers	0.207
Share of medium-skilled workers	0.617
Share of high-skilled workers	0.055
Share of female workers	0.168
Share of foreign workers	0.098
Share of part-time workers	0.110
Median age of workforce (years)	37.587
Observations	25,155,743

Notes: The data sets used are a 5 per cent random sample of the IEB and a quarterly version of the BHP, 1985–2010.