The urban wage premium in imperfect labour markets*

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Abstract: Using administrative data for West Germany, this paper investigates whether part of the urban wage premium stems from fierce competition in thick labour markets. We first establish that employers possess less wage-setting power in denser markets. Local differences in wage-setting power predict 1.1–1.6% higher wages from a 100 log points increase in population density. We further document that the observed urban wage premium from such an increase drops by 1.1–1.4pp once conditioning on local search frictions. Our results therefore suggest that a substantial part of the urban wage premium roots in differential imperfections across local labour markets.

Keywords: urban wage premium, imperfect labour markets, monopsony, search frictions

JEL classification: R23, J42, J31

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* We thank Michael Burda, Dan Hamermesh, Peter Kuhn, Ismir Mulalic, Michael Pflüger, Claus Schnabel, Uta Schönberg, Jens Südekum, Gerard van den Berg, Rudolf Winter-Ebmer, and Thomas Zwick for very useful suggestions. We further appreciate comments by participants of the RES 2016, UEA 2015 and VfS 2015 conferences, the BGPE 2015 and DFG SPP 1764 workshops, as well as seminar participants in Hamburg, Lüneburg, Nuremberg, and Munich. We also gratefully acknowledge financial support from the Fritz Thyssen Foundation.

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1 Introduction

Following the seminal contribution by Glaeser and Maré (2001), a large empirical literature has investigated urban–rural differences in wages. The general finding of this literature is that a significant urban wage premium exists and that this premium consists both of a level effect that accrues directly upon arrival in the urban labour market and a growth effect that arises as workers gain urban work experience (Heuermann *et al.*, 2010). The conventional interpretation of this evidence is that the urban wage premium stems from higher worker productivity in thick markets rooted in agglomeration economies (Puga, 2010; Moretti, 2011). In this view, the wage level effect reflects a higher level of worker productivity in denser markets, and higher urban wage growth mirrors that worker productivity is also growing at higher pace in thick markets.

As this conventional interpretation attributes the urban wage premium to urban–rural differences in workers' marginal productivity, it implicitly views labour markets as competitive. Yet, as soon as one allows for imperfect competition in labour markets, wage differentials do not necessarily reflect productivity differentials. In imperfect labour markets, workers just receive part of the marginal product of labour, and the part of the marginal product accruing to workers, in turn, may depend upon the density of the local labour market. If thick labour markets are more competitive—say, because of less severe search frictions—, this will yield higher wages *on top of* the wage premium stemming from higher productivity in denser markets. Prior estimates of the urban wage premium may therefore exaggerate the part of the urban wage premium that is due to higher worker productivity and may instead partly reflect fiercer labour market competition in denser markets that does not affect worker productivity.

Against this background, we contribute to the literature as follows. In a first step of the analysis, we will establish that the wage elasticity of the labour supply to the single firm, which governs what part of the marginal product accrues to workers in imperfect labour markets with employer wage setting, is larger in denser markets. In a second step of the analysis, we will document that the urban wage (growth) premium is considerably lower once we condition on a measure of search frictions in the labour market. More specifically, we will demonstrate that the difference in employers' wage-setting power across local labour markets can account for the drop in the urban wage premium that occurs when conditioning on labour market frictions. Consequently, our findings will suggest that a substantial part of the urban wage premium roots in competition effects rather than merely reflecting productivity effects.

The remainder of this paper is organised as follows: In Section 2, we provide a short review of the relevant literature and build our hypotheses. Section 3 explains our empirical approach and Section 4 our data. Section 5 presents and discusses our estimates of employers' wage-setting power across local labour markets and the urban wage (growth) premium. Section 6 considers issues of robustness, and Section 7 concludes.

2 Review of the literature and theoretical considerations

Since the beginning of the new millennium, an increasing body of international evidence has established that workers earn significantly higher wages in urban than in rural labour markets. This urban wage premium has proven to be robust to controlling for unobserved worker heterogeneity by means of fixed-effects techniques (e.g. Glaeser and Maré, 2001; Yankow, 2006; D'Costa and Overman, 2014) and to endogenising workers' location decision in structural approaches (e.g. Gould, 2007; Baum-Snow and Pavan, 2012). The premium is thus unlikely to reflect mere worker sorting. As a general finding, the literature has documented that the urban wage premium stems both from a wage level and a wage growth effect (see, e.g., the survey by Heuermann *et al.*, 2010). In other words, urban experience–wage profiles have been found to possess both a larger intercept and a larger slope than rural profiles.

The standard explanation offered for these findings is that agglomeration economies raise marginal worker productivity in thick markets (Puga, 2010; Moretti, 2011), and these agglomeration economies are seen as rooted in sharing, matching, or learning mechanisms (Duranton and Puga, 2004). Along these lines, workers in denser markets are not only more productive (for instance, because they are employed by more productive firms or because worker–firm matches are of superior quality), but they also face faster productivity growth as they gain work experience than workers in sparsely populated markets (for example, due to faster human capital accumulation in thick markets).

While there is broad empirical evidence that agglomeration economies exist (see, e.g., the surveys by Rosenthal and Strange, 2004, or Combes and Gobillon, 2015), suggesting that worker productivity is indeed higher in denser markets, higher productivity in thick markets may be only part of the story behind the urban wage premium if labour markets are imperfect. In this case, employers possess some wage-setting power over their workers, so "that wages are … only proportional and not equal to labour productivity by a factor that depends on the local monopsony power of the firm" (Combes and Gobillon, 2015, p. 283). And the part of the marginal product accruing to workers, in turn, may depend upon market density. If thick labour markets were more competitive, as put forward by Manning (2010) and Hirsch *et al.* (2013), workers in denser markets would obtain a larger fraction of the marginal product, and we would observe an urban wage premium even if agglomeration economies were completely absent.

Yet, such a situation will be no equilibrium outcome once we consider firms' location decisions. Absent agglomeration economies, firms would have an incentive to flee high labour costs by relocating into sparsely populated markets. However, seen together, labour market imperfections and agglomeration economies could give rise to an urban wage premium with firms being compensated for higher urban labour costs by higher urban worker productivity. Consequently, the urban wage premium may reflect as well agglomeration economies boosting worker productivity as competition effects undermining employers' wage-setting power that simultaneously arise in thick labour markets.

Yet, why should we expect (denser) local labour markets to be (less) imperfect in the first place? In the last two decades, a growing literature has investigated the prevalence and causes of imperfect competition in the labour market (for recent surveys, see Ashenfelter *et al.*, 2010, or Manning, 2011). As this literature makes clear, employers may possess marked wage-setting power even in labour markets consisting of many competing firms. Potential reasons include search frictions, mobility costs, or job differentiation. All these factors are likely to impede workers' responsiveness to wages causing the labour supply curve to the single firm to be upward-sloping, rather than being horizontal as under perfect competition. In line with this prediction, numerous studies have found that the wage elasticity of the labour supply to the firm is limited (see Manning, 2011), suggesting that employers possess substantial wage-setting power and pay workers only part of the marginal product of labour.

Now, consider search frictions as the source of labour market imperfections, as in the search model by Burdett and Mortensen (1998), which can be thought of as a labour market model of monopsonistic competition (Manning, 2003).[1] In labour markets characterised by search frictions, workers possess incomplete knowledge on firms' wage offers. Therefore, at any point of time, they accept the highest wage offer available to them as long as it pays their reservation wage. By chance, some workers get only offers by low-paying firms and find themselves employed at a low wage, whereas some other workers receive and accept high wage offers. If workers, however, still search for better-paying jobs on the job, workers with low wages will be more likely to quit, thereby causing higher turnover and lower employment levels in low-paying firms. Thus, with on-the-job search the labour supply curve to the firm gets upward-sloping. What constrains employers' wage-setting power in this framework are

[1] Note that Burdett and Mortensen's model assumes that firms post wages and workers just decide on whether to accept or decline a firm's wage offer. This assumption of employer wage setting is in line with existing evidence for Germany documenting that wage posting is the predominant form of wage formation (see Brenzel *et al.*, 2014).

workers' on-the-job search activities, and the extent of on-the-job search frictions determines how hard it is for workers to move their way up the wage distribution by changing jobs.[2] As we suspect workers to generate more job offers in thick labour markets with many job opportunities nearby, search frictions should play less a role in denser markets, and we expect denser labour markets to be more competitive.[3]

3 Empirical approach

3.1 Estimating employers' wage-setting power in local labour markets

The first part of our empirical analysis will be to estimate differences in the wage elasticity of the labour supply to the single firm across local labour markets. To this purpose, we will adopt a two-step procedure similar in spirit to the approaches by Hirsch and Schumacher (2005), Combes *et al.* (2008), and De la Roca and Puga (2017). In the first step, we will fit individual-level separation equations controlling for several worker and employer characteristics to obtain estimates of the supply elasticity at the local labour market level. In the second step, we will regress these local elasticity estimates on local labour markets' population density to assess whether firms' wage-setting power is less pronounced in denser labour markets. Applying this two-step procedure is to avoid that our results are driven by the many individuals working in the small group of very large labour markets in our sample.

To identify the wage elasticity of the labour supply to the single firm, we will adopt the estimation approach by Manning (2003, pp. 96–104) building on search frictions as the

2 Absent on-the-job search, Diamond's (1971) paradox would apply and all workers would obtain their common opportunity costs of employment or, with worker heterogeneity, their respective opportunity costs (Albrecht and Axell, 1984).

3 One may wonder whether this argument is at odds with the general finding that aggregate matching functions exhibit constant returns to scale (see, e.g., the survey by Petrongolo and Pissarides, 2001). As demonstrated by Petrongolo and Pissarides (2006), though, increasing returns of market size at the "micro" level—showing up in higher job offer arrival rates—and constant returns in the matching function at the "macro" level can coexist on account of endogenous responses in workers' reservation wages.

source of labour market imperfections. Consider a firm paying some wage w at some point in time. We model the change in the labour supply to this firm $L(w)$ as

$$\dot{L}(w) = R(w) - s(w)L(w), \tag{1}$$

where $R(w) > 0$ denotes the number of recruits arriving at the firm at that point in time with $R' > 0$ while $0 < s(w) < 1$ denotes the separation rate of incumbent workers with $s' < 0$. Accordingly, we assume that the firm can increase its labour supply by increasing its wage and that the labour supply adjusts sluggishly over time.

Now consider a steady state with $\dot{L}(w) = 0$. Then, using equation (1) we arrive at

$$L(w) = R(w)/s(w) \tag{2}$$

with $L' > 0$.[4] From equation (2) we get the labour supply elasticity to the firm ε_{Lw} as the difference of the wage elasticity of recruitment ε_{Rw} and the wage elasticity of the separation rate ε_{sw}

$$\varepsilon_{Lw} = \varepsilon_{Rw} - \varepsilon_{sw}. \tag{3}$$

Using equation (3) to identify the supply elasticity, however, would require us to estimate the recruitment elasticity ε_{Rw}, which is a hard task given that one typically does not know the firm's recruitment pool.

To circumvent this problem, we follow the existing literature and impose more structure on the model. Making use of Burdett and Mortensen's (1998) search model with wage posting, which can be thought of as a dynamic steady-state model of monopsonistic competition with firm's employment given by equation (1), Manning (2003, p. 97) demonstrates that $\varepsilon_{Rw} = -\varepsilon_{sw}$, so that the labour supply elasticity gets

[4] Note that perfect competition is nested as the case with $L' \to \infty$, i.e. a horizontal labour supply curve to the firm, due to $s' \to -\infty$ and $R' \to \infty$ at the competitive wage that equalises supply and demand at the level of the labour market.

$$\varepsilon_{Lw} = -2\varepsilon_{sw}. \tag{4}$$

Intuitively, this result holds because in this model—as in alternative models of imperfect labour markets like Bhaskar and To (1999)—one firm's wage-related hire is another firm's wage-related quit. Hence, equation (4) allows us to identify the labour supply elasticity to the firm by just estimating the wage elasticity of incumbent workers' job separation rate.[5]

To obtain an estimate of the wage elasticity of incumbent workers' job separation rate in any local labour market, we fit in the first step a stratified Cox model for the separation rate of job m belonging to worker i employed by employer j in region r

$$s_m\left(\tau \middle| \log w_m(\tau), \mathbf{x}_i(\tau), \mathbf{z}_j(\tau)\right) = s_{0ir}(\tau)\exp(\theta_r \log w_m(\tau) + \mathbf{x}_i(\tau)'\boldsymbol{\beta} + \mathbf{z}_j(\tau)'\boldsymbol{\gamma}), \tag{5}$$

where τ is the job duration, $\log w_m(\tau)$ is the log wage, $\mathbf{x}_i(\tau)$ is a vector of worker characteristics, $\mathbf{z}_j(t)$ is a vector of employer controls, $s_{0ir}(\tau)$ is a worker–region-specific baseline hazard, and we treat all covariates as time-varying. In equation (5), the region-specific coefficient of the log wage θ_r provides us with an estimate of the local separation rate elasticity. Note that in the separation equation (5) the baseline hazard $s_{0ir}(\tau)$ is some arbitrary worker–region-specific function of job duration, thereby encompassing permanent unobservables at both the level of the worker and the level of the region. Controlling for worker unobservables is indispensable in our application because worker sorting on unobservables may simultaneously influence workers' wages, their location, and their job mobility.[6]

5 Previous studies, e.g. Booth and Katic (2011) or Hirsch and Jahn (2015), have applied a more sophisticated estimation approach distinguishing employment and non-employment as distinct labour market states. While our data include information on workers' previous and subsequent labour market states, distinguishing transitions from and to employment from those from and to non-employment is not viable in our application because of the limited number of jobs observed in small local labour markets.

6 Note that by allowing for a worker–region-specific baseline hazard the proportionality assumption inherent to the class of hazard rate models defined by equation (5) needs to hold only for jobs held by the same worker within a particular local labour market, but may well be violated across workers or regions without invalidating identification (see Kalbfleisch and Prentice, 2002, pp. 118/119). Furthermore, controlling for region unobservables in the separation equation alleviates concerns that quitting for the same wage is not comparable across local labour markets because of regional price or wage level differences, as permanent price and wage level differences are part of the baseline hazard and are thus accounted for.

To estimate the separation equation (5), we adopt the stratified partial likelihood estimator (see Ridder and Tunalı, 1999). This estimator allows us to sweep out the baseline hazard and, thus, permanent unobserved worker and region heterogeneity without the need of identifying them in a similarly convenient way as with the within estimator in linear fixed-effects models. As with the latter estimator, the stratified partial likelihood estimator rests identification on within-variation at the worker–region level, e.g. on wage variation occurring in multiple jobs held by the same worker within the same local labour market. In the stratified Cox model, we thus control for workers' wage relative to the outside offer available to him.

In the second step, we change to the level of the local labour market and regress the estimated labour supply elasticity to the single firm $\varepsilon_{Lw,r} = -2\theta_r$ on the centred time-average of local log population density

$$\varepsilon_{Lw,r} = \zeta_0 + \zeta_1 \log popdens_r + v_r \tag{6}$$

with v_r denoting the error term. In this second-step regression (6), we expect ζ_1 to have a positive sign, thereby indicating that employers possess less wage-setting power in denser labour markets with more elastic firm-level labour supply.[7] We will base our inference on standard errors coming from a block bootstrap at the worker level with 400 replications.

To assess the economic relevance of differential competition across local labour markets, we will use the fact that in imperfect labour markets with employer wage setting maximising steady-state profits yields

$$w_r = \frac{\varepsilon_{Lw,r}}{1+\varepsilon_{Lw,r}} \phi_r, \tag{7}$$

where ϕ_r denotes the marginal product of labour in region r. We next conduct a thought experiment and ask ourselves what the urban wage premium would be if we assumed away

[7] Note that our results do not hinge on using the average log population density as agglomeration measure in the second-stage regression. We will discuss alternative measures in Section 6.

agglomeration economies that yield different marginal products across regions. Hence, we set $\phi_r \equiv \phi$ in equation (7), and the predicted wage gap across any two local labour markets 1 and 2 gets

$$\frac{w_2 - w_1}{w_1} = \frac{\varepsilon_{Lw,2} - \varepsilon_{Lw,1}}{\varepsilon_{Lw,2}(\varepsilon_{Lw,1} + 1)}. \tag{8}$$

Based on the estimated ζ's from the second-step regression (6) and setting $\varepsilon_{Lw,1}$ to the average elasticity across local labour markets, we can calculate the predicted urban wage premium from differential local labour market competition (8) and confront it with estimates of the actual premium.

3.2 Estimating the urban wage premium

In the second part of our analysis, we compare the predicted urban wage premium from equation (8) to the reduction in the estimated premium that occurs when conditioning on the extent of search frictions in local labour markets. If these two numbers were of similar magnitude, this would suggest that this part of the urban wage premium reflects fiercer competition in denser labour markets.

To condition on the extent of search frictions faced by workers in local labour markets, we will use a simple measure of these frictions that has been used in an earlier study of employers' wage-setting power in local nursery labour markets by Hirsch and Schumacher (2005). As stressed in Section 2, frictions in on-the-job search cause workers in low-paying jobs to receive limited outside offers and thus restrain worker poaching by high-paying employers. To capture this notion of limited inter-employer mobility, Manning (2003, pp. 44–49) proposes to measure on-the-job search frictions by the share of hires from non-employment (as opposed to employment). Intuitively, the higher is this share, the less likely are incumbent workers wooed away by competing employers because jobs are more likely to be filled with workers who were previously unemployed or out of the labour force. This means that workers' threat to quit for a better-paying job becomes less effective and leads to higher wage-setting power for employers. As demonstrated by Manning, the share of hires from non-employment has a one-to-one correspondence to the extent of on-the-job search frictions in the Burdett and Mortensen (1998) model, and it is also likely to be a good proxy for employers' wage-setting power in various other models of imperfect labour markets.[8]

Calculating this measure for the local labour markets used in our later analysis (we will provide details on our data in Section 4) and plotting it against the time-average of log population density, we indeed find that new hires come less often from non-employment in denser markets (see Figure 1). Hence, it seems to be easier for workers to flee low-paying jobs through job-to-job moves in thick labour markets, and we suspect employers to possess less wage-setting power in these. In line with this expectation, a plot of workers' average local log wages against our measure of local search frictions reveals a strong negative relationship (see Figure 2). So part of the urban wage premium may indeed reflect fiercer competition in denser labour markets.

- FIGURES 1 AND 2 ABOUT HERE -

To estimate the urban wage premium, we will again adopt a two-step procedure. In the first step, we will run individual-level wage regressions controlling for several worker and employer characteristics to obtain estimates of local wage levels. In the second step, we will regress these wage levels on the local population density and the local share of hires from non-employment to get estimates of the urban wage premium.

To be more precise, the first step consists of running extended Mincerian wage regressions at the level of the individual worker

[8] Note that our results do not hinge on using the share of hires from non-employment as proxy for workers' on-the-job search frictions. In Section 6, we will demonstrate that we obtain the same results when using an alternative measure of search frictions proposed by van den Berg and van Vuuren (2010).

$$\log w_{ijrt} = \delta_r + \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \mathbf{z}_{jt}'\boldsymbol{\gamma} + u_{ijrt}, \tag{9}$$

where notation follows the same rules as before, δ_r is a region fixed effect, α_i is a worker fixed effect, and u_{ijrt} is an error term.[9] Our main point of interest in the wage equation (9) are the δ_r's which provide us with estimates of average local wage levels after controlling for observable worker and employer characteristics and permanent worker unobservables. As made clear by previous studies, such as Glaeser and Maré (2001) or Yankow (2006), it is important to include worker fixed effects in the wage equation to tackle the ability bias that would result if workers with higher abilities chose to live in denser labour markets.[10]

In the second step, we regress the estimated δ_r's obtained from the wage regression (9) on the centred time-average of local log population density

$$\hat{\delta}_r = \pi_0 + \pi_1 \log popdens_r + e_r, \tag{10}$$

where e_r denotes an error term and π_1 provides us with an estimate of the urban wage premium. Next, we add our measure of search frictions, the centred time-average of the local share of hires from non-employment $sharenemp_r$, as explanatory variable to the model

$$\hat{\delta}_r = \tilde{\pi}_0 + \tilde{\pi}_1 \log popdens_r + \tilde{\pi}_2 sharenemp_r + e_r. \tag{11}$$

In the second-step regression (11), we expect a negative sign for $\tilde{\pi}_2$ because a higher share of

9 Note that we do not correct workers' wages for differences in local labour markets' price levels because we are interested in the part of the urban wage premium that reflects workers' marginal productivity rather than differences in local price levels. As stressed by Heuermann *et al.* (2010, p. 752), "[t]he fundamental point in the debate on whether to use nominal or real wages is that, while spatial differences in nominal wages can be interpreted as productivity differences, regional differences in real wages reflect differences in workers' utility rooted in urban amenities." See Glaeser and Gottlieb (2009), Moretti (2011), and Combes and Gobillon (2015) for similar assessments.

10 Including worker fixed effects, however, means that the identification of local wage levels rests on workers who switch locations, and clearly switching locations may itself be endogenous. Hence, estimated regional wage levels may suffer from bias if worker unobservables and location changes are not orthogonal as is implicitly assumed when applying the fixed-effects approach. While instrumenting workers' location has proven difficult due to the lack of credible, strong instruments (Heuermann *et al.*, 2010) and has, in general, also made no big difference (Melo *et al.*, 2009), another approach chosen in previous studies has been to model worker mobility explicitly in a structural setting (Gould, 2007; Baum-Snow and Pavan, 2012). This structural approach, though, comes at the cost of strong functional assumptions and of excluding worker fixed effects from the wage equations.

hires from non-employment indicates more pronounced wage-setting power for local employers. We will then compare the estimated π_1 from equation (10) and $\tilde{\pi}_1$ from equation (11) and interpret a drop in regression (11) *vis-à-vis* regression (10) as an estimate of the part of the urban wage premium reflecting fiercer competition in thick labour markets. Again, we base our inference on standard errors coming from a block bootstrap at the worker level with 400 replications.

4 Data and descriptive analysis

To put our empirical approach into practice, we need detailed data on job durations, workers, and employers over a long period of time. Otherwise, the correction for worker unobservables by means of stratified Cox models and multiple jobs per worker within a local labour market could not be done convincingly. 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), which are both provided by the Institute for Employment Research (IAB). Since the information contained in these data is used to calculate social security contributions, it is highly reliable and especially suited for analyses on wages and job durations.

The data on job durations (at daily frequency), wages, and worker characteristics (education, experience, occupation, and nationality) come from a 5% random sample of the IEB (for details on the IEB, see Jacobebbinghaus and Seth, 2007). The IEB comprises all wage and salary employees registered with the German social security system, where about 80% of all people employed in Germany are part of the system. Note that the IEB dates back until 1975, so that we have information on workers' employment biographies from 1975 onwards. Note, however, that we will not use pre-1985 wage information in our analysis because of changes in the wage variable, which does not include bonus payments before 1985 but contains these from 1985 onwards. In the following, we will further restrict our sample to workers born no earlier than 1960, i.e. workers who were at maximum 15 years old in 1975 and for whom we thus have complete information on their real work experience.

The data on employers come from a quarterly version of the BHP which again consists of data from the German social insurances that are this time aggregated at the level of the plant at the end of each quarter (for details on the BHP, see Spengler, 2008). It contains information on plants' workforce composition, industry, size, and on plant location at the NUTS 3 level. We use this latter information to assign workers and their jobs to 103 local labour markets in West Germany identified by Kosfeld and Werner (2012) based on commuter links (rather than on mere administrative boundaries).

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. We will thus focus our analysis throughout on workers in West Germany (excluding Berlin) during the period 1985–2010 and will further restrict to males to circumvent selectivity issues regarding female employment.

To calculate the share of hires from non-employment at the local labour market level, we distinguish employment and non-employment as labour market states. Consequently, a new job may either start after a job-to-job move has taken place (i.e. the new job is with a plant that has a different plant identifier), or following a previous spell in registered unemployment or no spell in the data at all. The latter either means that before starting the new job the individual has been non-employed without receiving unemployment benefits or, for instance, a self-employed worker who is not included in the data.[11] While our data do not enable us to disaggregate this category of unknown origin, information from other German

[11] Note that separations to non-employment are ignored if the employee is recalled by the same plant within three months. Similarly, in classifying job-to-job moves we allow a gap of up to three months between two subsequent employment spells with different plants if no other labour market status, like registered unemployment, is recorded in the data.

data sets suggests that the vast majority of employees in this category have indeed started new jobs from non-employment.[12]

Whereas information on job durations and daily gross wages in the data are highly reliable, the data include no detailed information on the number of hours worked. Moreover, wages are top-coded at the social security contribution ceiling, which affects 7.6% 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 (though we will also include imputed wage observations in a check of robustness presented in Section 6). In addition, information on workers' education stems from employers and is for this reason inconsistent or missing for some workers. To alleviate this problem, we impute the missing information on education using a procedure proposed by Fitzenberger *et al.* (2006) that allows inconsistent education information to be corrected. After applying this imputation procedure, we have to drop only 1.5% of jobs due to missing or inconsistent information on education.

The merged data for the period 1985–2010 allow us to set up an inflow sample of 1,844,688 jobs held by the 581,724 workers. Out of these 1,844,688 jobs, 246,393 jobs (or 13.4%) have right-censored job durations. In our sample, the number of jobs varies markedly across the 103 local labour markets, with a minimum of 1,457 and a maximum of 102,329. Note that we observe multiple jobs within a given labour market for the majority (i.e. 57.4%) of workers. Hence, estimating stratified Cox models with worker–region-specific baseline hazards is viable, and we are able to precisely identify local separation rate elasticities—the θ_r's—in the first-step separation equation (5) with our data. For descriptive statistics on our sample, see Table 1.

- TABLE 1 ABOUT HERE -

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

When estimating the urban wage premium in the second part of our analysis, we will only use wage observations at the 30th of June of a year yielding a panel of 3,899,934 observations at yearly frequency. Again, the number of observations varies considerably across local markets, with a minimum of 3,525 and a maximum of 190,982. Notwithstanding, there are enough observations in every local labour market as well as enough movers across markets to precisely estimate local wage levels—the δ_r's—in the first-step wage equation (9).

Descriptively, we find a marked urban wage premium in our sample. Plotting average local log wages against the local time-average of log population density, we obtain a clear positive relationship (see Figure 3). The regression line in Figure 3 has a slope of 0.034, so that an increase in population density by 100 log points is associated with 3.4% larger wages on average. (Note that the standard deviation in log population density across local labour markets is 0.7, so that a rise by 100 log points is a reasonable point of departure.) This descriptive urban wage premium falls considerably once conditioning on local search frictions by regressing, respectively, wages and population density on the share hires from non-employment. Plotting the resulting wage and density residuals against each other more than halves the slope of the regression line to 0.015 (see Figure 4). Hence, the descriptive urban wage premium from a 100 log points rise in population density just amount to 1.5% once conditioning on local search frictions. This corresponds to a drop in the premium by 1.9pp.

- FIGURES 3 AND 4 ABOUT HERE -

5 Main results

5.1 Differences in wage-setting power across local labour markets

In this section, we will investigate whether the wage elasticity of the labour supply to the single firm is larger and thus whether firms' wage-setting power is smaller in denser labour markets. We will further use the difference in the elasticity across local labour markets to predict the urban wage premium that would result from differential competition absent any agglomeration economies affecting marginal worker productivity.

To arrive at local estimates of the labour supply elasticity, we adopt the two-step approach presented in Section 3.1. In the first step, we estimate stratified Cox models for incumbent workers' job separation rate controlling for several worker and employer characteristics as well as permanent unobservables at the region–worker level. Worker controls consist of real experience (linearly and squared) as well as groups of dummies for education (distinguishing low-skilled, medium-skilled, and high-skilled workers[13]), one-digit occupation, and non-German nationality. As employer controls we include the shares of part-time, high-skilled, low-skilled, female, and non-German workers among the plant's workforce as well as groups of dummies for plant size and two-digit industry. We finally add a full set of year dummies. We will then use the labour market-specific coefficients of the log wage in the separation equation to arrive at local estimates of the wage elasticity of the labour supply to the single firm and, in the second step, regress these estimates on the local average log population density. In the following, we will present estimates either with or without employer controls in the first-step separation equation because different employer characteristics may themselves root in the agglomeration economies that give rise to regional productivity and wage differences.[14]

For the sake of brevity, Table 2 presents only the second-step regression of our approach (with first-step estimates being available upon request). As the log population density is centred around its mean, the estimated regression constant represents the average elasticity

13 Low-skilled workers are workers with neither a vocational training nor an academic education, while medium-skilled workers possess a vocational training and high-skilled workers an academic education.

14 For instance, Manning (2010) shows that larger plant sizes in denser markets, which have been documented to explain part of the urban wage premium in Germany (Lehmer and Möller, 2010), are at odds with canonical models of agglomeration economies, which would predict the opposite to hold. Yet, he also demonstrates that larger plant sizes in denser markets may stem from stronger competition in these labour markets.

estimate across local labour markets. In Model I, the average elasticity amounts to 2.46, which is well within the range of previous estimates summarised by Manning (2011). This number implies that employers possess substantial, though not implausibly large wage-setting power over their workers. Based on equation (7), we expect workers in the average local labour market to receive 71.1% of the marginal product of labour.

- TABLE 2 ABOUT HERE -

In line with our expectations, the labour supply elasticity to the firm is significantly larger in denser labour markets. A 100 log points increase in population density comes along with a rise in the elasticity by 0.15 to 2.60. Based on our thought experiment conducted in equation (8) that imposes equal marginal worker productivity across local labour markets and thus abstracts from productivity effects through agglomeration economies, we would expect an urban wage premium of 1.6% to arise. Thus, employers' less pronounced wage-setting power in denser labour markets is also significant from an economic point of view.

The positive relationship between the elasticity and density reduces somewhat when controlling for employer characteristics in Model II. Including employer controls in the first-step separation equation both lowers the average elasticity, which now amounts to 2.25, and the slope of the elasticity with respect to density. It is unclear, though, whether controlling for employer characteristics is preferable given that local differences in these are likely to—at least partly—stem from agglomeration economies. A 100 log points rise in population density is now associated with an increase in the elasticity by 0.08 to 2.33, and based on equation (8) we expect workers to earn an urban wage premium of 1.1%.

Our estimates thus predict an urban wage premium from fiercer competition in thick labour markets by 1.1–1.6%. Remarkably, this prediction comes very close to the drop in the descriptive premium by 1.9pp that we found in Section 4 once conditioning on local search frictions. Our results thus suggest that a substantial part of the urban wage premium reflects differences in labour market competition. To pin this point down more thoroughly, we will next present estimates of the urban wage premium that condition on worker and employer characteristics as well as on permanent worker unobservables and thus account for worker sorting on these factors.

5.2 Estimates of the urban wage premium

To estimate the urban wage premium, we will adopt the two-step procedure described in Section 3.2. In the first step, we run wage regressions at the level of the individual worker, as shown in equation (9), to obtain estimates of average local wage levels controlling for various worker and employer characteristics. In the second step, we regress these local wage levels on, first, average local log population density as in specification (10) and, second, on the richer specification (11) that adds the average local share of hires from non-employment, our measure of the search frictions in local labour markets. We will show results obtained from estimating the first-step wage equation (9) either with or without worker fixed effects. In the wage equation, we include the same worker and employer characteristics as in the separation equation in the previous section and add a group of tenure dummies on top of these. As before, we will present estimates either without or with employer controls in the first-step wage equation and, for the sake of brevity, we will just show the results of the second-step regressions (with first-step results being available upon request).

Table 3 summarises our main results. Panel A presents the second-step regression (10) of local wage levels on log population density for various specifications of the first-step wage equation (9). When just controlling for observed worker characteristics (Model I) we arrive at a coefficient of log density of 0.028 that is lower than the descriptive estimate of 0.034 reported in Section 4. Hence, a 100 log points rise in population density is associated with a rise in local wages by 2.8%. When additionally controlling for employer characteristics in Model II, this number drops somewhat to 2.7%.

- TABLE 3 ABOUT HERE -

Yet, the main concern with these estimates is that workers in local labour markets of different density may differ in unobservables that affect their marginal productivity and wages. To account for permanent worker unobservables, we next include worker fixed effects to the first-step wage regressions. In these specifications, identification rests on workers moving across local labour markets. Estimating the first-step regression with worker fixed effects reduces the estimated coefficient by about a quarter, independently of whether we control for employer characteristics in the wage equation (Model IV) or not (Model III). In the specification without (with) employer controls, a 100 log points increase in population density now comes along with a 2.2% (2.1%) increase in wages.

Panel B in Table 3 shows the second-step regression (11) of Models I–IV which adds the local share of hires from non-employment as explanatory variable. In line with our expectations and the descriptive evidence from Figure 2, this measure of workers' on-the-job search frictions has a significantly negative impact on local wages in all specifications. In our preferred Models III and IV, in which the first-step regression includes worker fixed effects, a one standard deviation rise in the share of hires from non-employment, which amounts to 0.043 across local labour markets, is associated with a drop in wages by 1.9–2.6%.

As in the descriptive analysis in Figures 3 and 4, conditioning on local search frictions in the second-step regression markedly reduces the estimated urban wage premium by 1.1–1.6 log points, depending on specification. In our preferred Models III and IV, the drop amounts to 1.1–1.3 log points. A 100 log points rise in population density is now only associated with a 0.8–0.9% rise in wages, rather than the 2.2–2.3% previously found (see Panel A). We consider this fall in the urban wage premium by 1.1–1.3pp as a benchmark estimate of the part of the premium that reflects fiercer competition in thick labour markets. Remarkably, this drop is of the same magnitude as the predicted urban wage premium from differential competition across local labour markets from the previous subsection, which amounted to 1.1–1.6%.

To gain further insight into the role of search frictions on the urban wage premium, it is instructive to have a closer look at the difference in experience–wage profiles across local labour markets. To do so, we repeat our analysis of the urban wage premium and estimate region-specific coefficients of experience and its square in the first-step individual wage regression. Table 4 presents our main estimates based on a specification analogous to Model III in Table 2, i.e. with worker but without employer controls in the first-step wage equation, although we deviate from this specification in including worker–region fixed effects rather than worker fixed effects.[15] By adding worker–region fixed effects (rather than worker fixed effects) to the wage equation, we base identification on variation in wages that stems from workers gaining work experience within a local labour market, which is our point of interest at this stage. Note further that we centre the explanatory variables in the second-step regression around their means. Therefore, the estimated regression constants inform us on the average coefficients of experience and its square across local labour markets.

- TABLE 4 ABOUT HERE -

As before, Panel A in Table 4 presents second-stage regressions of the local coefficients of experience and its square on log population density only. The density coefficient for the linear experience component is significantly positive, so that labour market entrants experience higher wage gains from work experience in denser labour markets. In other words, there is an urban wage growth premium. Yet, as the density coefficient for the quadratic experience component is significantly negative, the rate of growth also slows down faster in denser labour markets. We thus find steeper and more concave experience–wage profiles in denser labour markets. As an illustration, Figure 5 plots the accumulated urban wage growth

[15] Results are robust to adding employer controls to the first-step wage equation.

premium relative to the average local labour market, i.e. the rise in the log wage from a 100 log points increase in population density over workers' labour market career. As is clear from Figure 5, there is indeed a substantial urban wage growth premium for labour market entrants that slows down over workers' career. As a consequence, the accumulated urban wage growth premium exceeds 2% after 13 years of labour market experience and takes on its maximum at about 20 years of experience.[16]

- FIGURE 5 ABOUT HERE -

Once we add the average share of hires from non-employment as explanatory variable to the second-step regressions, the density coefficient of the linear experience component drops by about a fifth whereas the density coefficient of the quadratic component remains unaltered. Thus, we still obtain steeper and more concave experience–wage profiles in denser markets, although these have a globally lower slope now. Consequently, the accumulated urban wage growth premium not only drops once conditioning on local search frictions, but the drop in the urban wage premium also widens over workers' career.

Taken together, these two findings suggest that the urban wage growth premium stems from two sources. On the one hand and in line with the previous literature, part of the higher wage growth in denser markets seems to stem from higher wage growth at the beginning of workers' careers likely to reflect an acceleration in workers' human capital acquisition due to learning effects. On the other hand, a substantial part of the urban wage growth premium seems to mirror faster search capital growth in more competitive, thick labour markets.

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[16] As stressed before, by including worker–region fixed effects in the wage equation we rest identification on variation in wages that occurs while workers gain work experience within a local labour market. In particular, the fixed effects control for workers' previous (time-invariant) work experience gained in other local labour markets. Hence, our approach is very similar in spirit to De la Roca and Puga's (2017), as are our findings that experience gained in denser markets gives rise to more pronounced wage growth. One possible concern, however, is that workers who repeatedly move between the same regions and who therefore gain work experience within a local labour market at different points of time in their employment biographies may blur our estimates. To rule this out, we redid our analysis for stayers who do not change regions at all. Reassuringly, this had no impact on our results.

6 Issues of robustness

To scrutinise our results further, we perform several checks of robustness along three dimensions. First, we repeat our analysis using different measures of agglomeration in the second-step regressions and, second, including imputed wages for top-coded wage observations. Third, we re-estimate the drop in the observed urban wage premium when conditioning on an alternative measure of local search frictions. Table 5 presents the key results from these checks and underscores the robustness of our findings.

- TABLE 5 ABOUT HERE -

In the first group of robustness checks, we explore how our results change when utilising alternative measures of agglomeration than the local time-average of log population density, which we used in our baseline specification. Using the local log population density in 1985, i.e. at the beginning of our period of observation, or in 2010, i.e. at the end of the observational window, rather than its time-average leaves our findings unchanged. Neither the slope of the wage elasticity of the labour supply to the firm, nor the predicted urban wage premium due to differential local labour market competition, nor the drop in the observed urban wage premium when conditioning on local search frictions change in any substantial way. The same holds when including log population and log size as separate explanatory variables in the second-stage regression or when using log employment density rather than log population density as agglomeration measure.

In our second check of robustness, we repeat our analysis including top-coded wage observations which we impute using a heteroscedastic single imputation approach developed by Büttner and Rässler (2008) for our data. We do so because top coding occurs at the contribution limit to the German social security system that is the same for all workers and thus independent of job location. As a consequence, top coding has a stronger bite in denser labour markets with higher wage levels, which may arouse some concerns. As Table 5 makes clear, our findings do not seem to suffer from this differential bite in top coding across local labour markets and are virtually the same when including imputed wage observations.

In a final group of robustness checks, we re-estimate the drop in the urban wage premium when conditioning on local search frictions using an alternative measure of these suggested by van den Berg und van Vuuren (2010), viz. the local share of job exits into non-employment (as opposed to employment). Like the share of hires from non-employment used in our baseline specification, the share of job exits into non-employment captures how hard it is for workers to move their way up in the local wage distribution by job-to-job moves. As the last column of Table 5 makes clear, the drop in the urban wage premium when conditioning on this alternative measure of local search frictions is almost the same as in our baseline specification. What is more, our results based on this alternative measure keep robust when using alternative agglomeration indicators and when including imputed wage observations.

7 Conclusions

Using administrative linked employer–employee data for West Germany comprising the years 1985–2010, we have investigated whether part of the urban wage premium stems from fiercer competition in thick local labour markets. In the first part of our analysis, we documented that the wage elasticity of the labour supply to the firm, which governs the part of the marginal product of labour that accrues to workers in imperfect labour markets with employer wage setting, is significantly larger in denser markets. While the average elasticity across local labour markets amounted to 2.25–2.46, depending on specification, an increase in population density by 100 log points came along with an increase in the elasticity by 0.08–0.15. Based on a thought experiment that abstracts from agglomeration economies that cause productivity differences across space, our estimates predict workers' wages to rise by 1.1–1.6%.

In the second part of our analysis, we found that a 100 log points increase in population density is associated with 2.1–2.2% higher wages when controlling for worker fixed effects and several worker and employer characteristics. However, once we conditioned on a measure of search frictions in local labour markets, the urban wage premium dropped considerably by 1.1–1.3pp. Remarkably, these numbers are of the same magnitude as the predicted urban wage premium from differential competition in local labour markets obtained in the first part of our analysis.

Thus, our findings are in line with the notion that a substantial part of the urban wage premium roots in fiercer competition in thick labour markets. Notwithstanding, our observation of a still sizeable urban wage premium and significantly steeper experience–wage profiles in denser markets when conditioning on local search frictions indicates that productivity effects are also present and non-trivial in magnitude. Our results therefore suggest that workers in denser labour markets not only obtain higher wages because they receive a larger part of the marginal product of labour, but also because the marginal worker productivity is greater and grows at higher pace in these markets.

That said, employers might still have no incentive to flee fierce competition in thick labour markets. Whereas lower wage-setting power in denser markets leaves them with a smaller part of a given marginal product of labour, agglomeration economies have a countervailing impact by raising marginal productivity. Our result of fiercer competition in thick labour markets thus points at another deglomerative force in employers' location decision that agglomeration economies have to overcome for agglomerations to come into existence. Since our results imply that denser labour markets are less imperfect, they suggest additional welfare gains from spatially concentrated economic activity. We leave it to future research to delve more deeply into the causes and consequences of fierce competition in thick labour markets.

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Figures

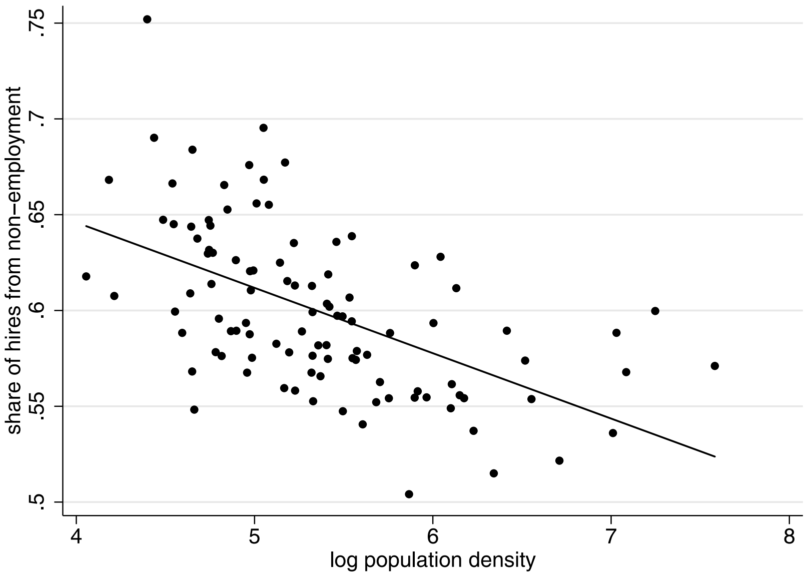

Figure 1: Local share of hires from non-employment and log population density

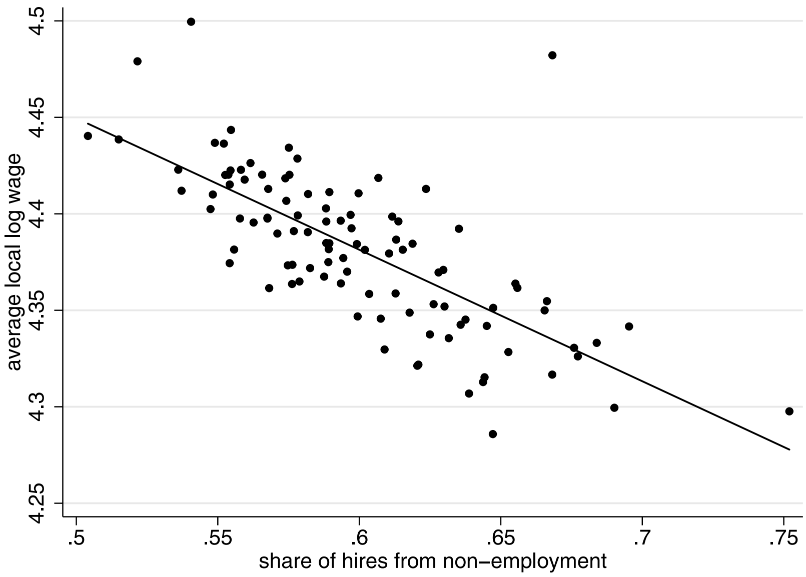

Figure 2: Local average wages and share of hires from non-employment

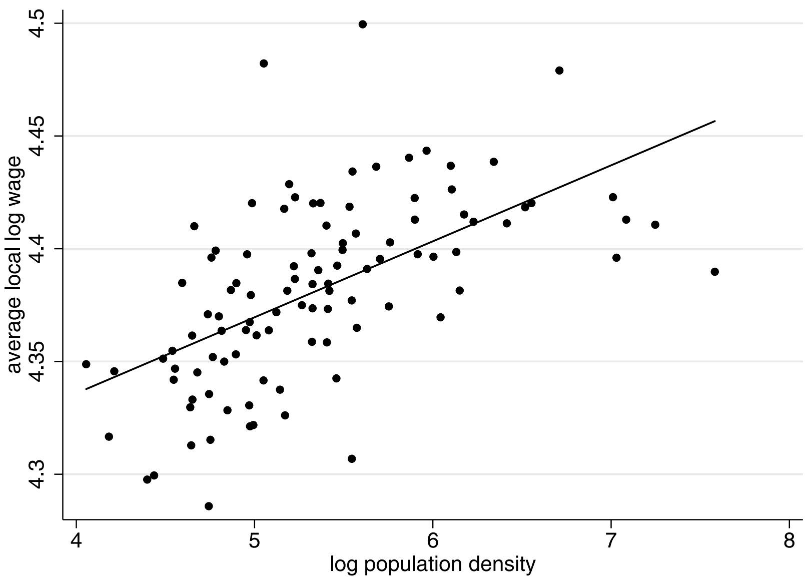

Figure 3: Local average wages and log population density

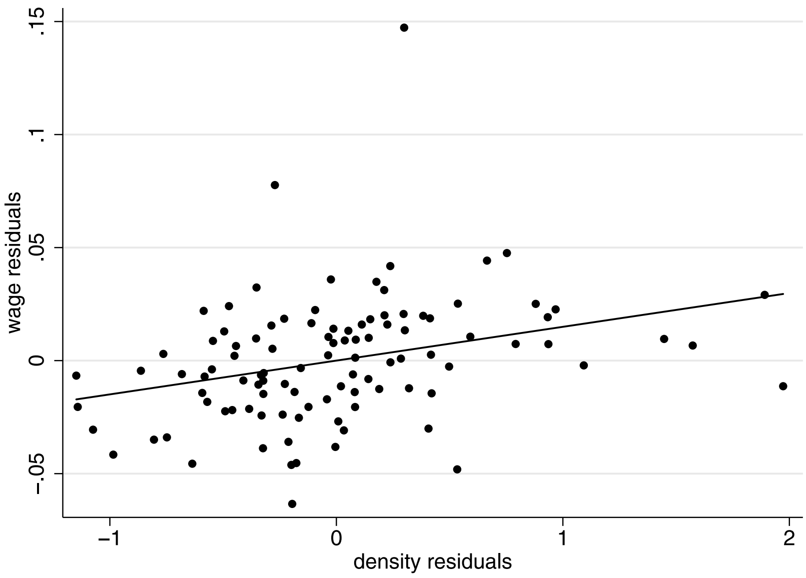

Figure 4: Local average wages and log population density when conditioning on the share of hires from non-employment

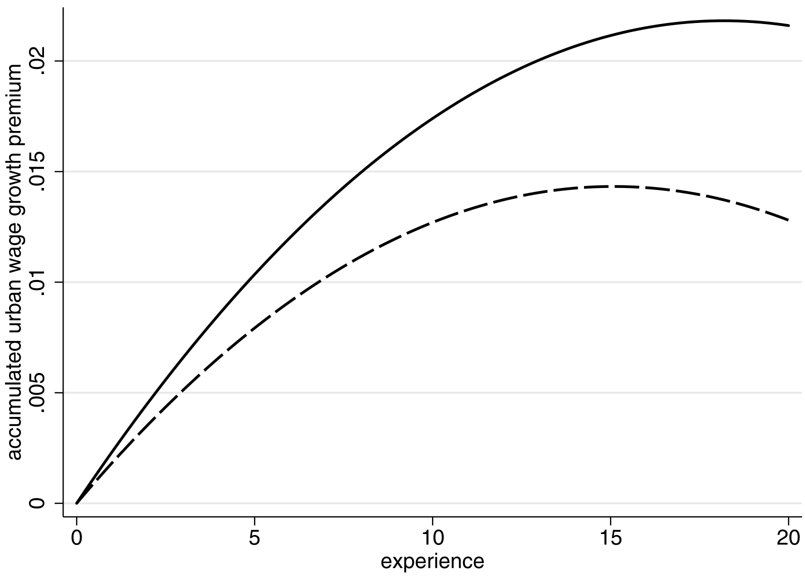

Figure 5: The rise in log wages from a 100 log point increase in population over workers' labour market experience (solid) and when additionally conditioning on the share of hires from non-employment (dashed)

Tables

Table 1: Descriptive statistics (means)

Log gross daily wage	4.368
Immigrant (dummy)	0.142
Low-skilled (dummy)	0.129
Medium-skilled (dummy)	0.797
High-skilled (dummy)	0.075
Experience (years)	9.493
Tenure (years)	3.538
Plant size below 11 (dummy)	0.157
Plant size 11–50 (dummy)	0.255
Plant size 51–200 (dummy)	0.245
Plant size 201–1000 (dummy)	0.211
Plant size above 1000 (dummy)	0.132
Share of low-skilled workers	0.201
Share of medium-skilled workers	0.613
Share of high-skilled workers	0.059
Share of female workers	0.168
Share of foreign workers	0.098
Share of part-time workers	0.116
Observations	17,861,643

Notes: IEB and BHP, 1985–2010.

Table 2: Local differences in the wage elasticity of the labour supply to the firm

First-step specification Second-step results (103 local labour markets)	Model I Stratified Cox model with worker but without employer controls	Model II Stratified Cox model with worker and employer controls
Log population density	0.1453	0.0814
	(0.0321)	(0.0318)
Constant	2.4577	2.2500
	(0.0232)	(0.0232)
Predicted urban wage premium from a 100 log points increase in population density based on equation (8) that abstracts from agglomeration economies, with $\varepsilon_{Lw,1}$ set to the average elasticity across local markets	1.6%	1.1%

Notes: IEB and BHP, 1985–2010. Estimates show the second-step regression (6). Log population density is centred around its mean. The dependent variable is the estimated wage elasticity of the labour supply to the firm obtained from the first-step separation equation (5), which we model as a stratified Cox model with a worker–region-specific baseline hazard. In the stratified Cox regression, worker controls consist of real experience (linearly and squared) as well as groups of dummies for education, one-digit occupation, and non-German nationality. Employer controls are the shares of part-time, high-skilled, low-skilled, female, and non-German workers among the plant's workforce as well as groups of dummies for plant size and one-digit industry. We further add year dummies. Standard errors come from a block bootstrap at worker level with 400 replications.

Table 3: Estimated urban wage premium

First-step specification Second-step results (103 local labour markets)	Model I OLS with worker controls	Model II OLS with worker and employer controls	Model III FE with worker controls	Model IV FE with worker and employer controls
Panel A: Estimates of the urban wage premium w/o conditioning on local search frictions				
Log population density	0.0282	0.0267	0.0215	0.0205
	(0.0007)	(0.0006)	(0.0013)	(0.0012)
Panel B: Estimates of the urban wage premium w/ conditioning on local search frictions				
Log population density	0.0132	0.0110	0.0083	0.0092
	(0.0007)	(0.0006)	(0.0014)	(0.0013)
Share of hires from non-employment	–0.5837	–0.6138	–0.5171	–0.4432
	(0.0153)	(0.0133)	(0.0302)	(0.0279)

Notes: IEB and BHP, 1985–2010. Panel A shows estimates for the second-step regression (10) and Panel B for the second-step regression (11). All second-step regressors are centred around their means. The dependent variable is the local wage level obtained from the first-step wage regression (9). In the first-step wage equation, we include real experience (linearly and squared) as well as groups of dummies for education, age, tenure, one-digit occupation, and non-German nationality as worker controls. Employer controls are the shares of part-time, high-skilled, low-skilled, female, and non-German workers among the plant's workforce as well as groups of dummies for plant size and two-digit industry. We further add year dummies. Standard errors come from a block bootstrap at worker level with 400 replications.

Table 4: Local differences in experience–earnings profiles

Dependent variable Second-step results (103 local labour markets)	Local coefficient of experience	Local coefficient of squared experience (times 100)
Panel A: Estimates of the urban wage growth premium w/o conditioning on local search frictions		
Log population density	0.0024	–0.0066
	(0.0002)	(0.0008)
Constant	0.0461	–0.0618
	(0.0004)	(0.0007)
Panel B: Estimates of the urban wage growth premium w/ conditioning on local search frictions		
Log population density	0.0019	–0.0063
	(0.0002)	(0.0009)
Share of hires from non-employment	–0.0220	0.0120
	(0.0051)	(0.0192)
Constant	0.0461	–0.0618
	(0.0004)	(0.0007)

Notes: IEB and BHP, 1985–2010. The dependent variables are the region-specific coefficients of real experience and its square, respectively, obtained from a first-step wage regression analogous to (9) including worker–region fixed effects. Panel A shows estimates for the coefficient-specific second-step regression (10) and Panel B for the coefficient-specific second-step regression (11). All second-step regressors are centred around their means. In the first-step wage equation, we include groups of dummies for education, tenure, one-digit occupation, and non-German nationality as worker controls but no employer controls. We further add year dummies. Standard errors come from a block bootstrap at worker level with 400 replications.

Table 5: Checks of robustness

Robustness checks / Estimate	Coefficient of the log of the agglomeration measure in the second-step regression for the labour supply elasticity	Predicted urban wage premium from an 100 log points increase in the agglomeration measure	Drop in the observed urban wage premium when conditioning on the local share of hires from non-employment	Drop in the observed urban wage premium when conditioning on the local share of job exits into non-employment
Baseline	0.1453	1.6%	1.3pp	1.6pp
	(0.0321)			
Alternative measures of agglomeration				
Log population density in 1985	0.1320	1.5%	1.2pp	1.5pp
	(0.0313)			
Log population density in 2010	0.1466	1.7%	1.4pp	1.7pp
	(0.0326)			
Log population (controlling for log size separately)	0.1393	1.6%	1.3pp	1.6pp
	(0.0338)			
Log employment density	0.1477	1.7%	1.6pp	1.6pp
	(0.0310)			
Including imputed wage observations	0.1206	1.5%	1.6pp	1.9pp
	(0.0302)			

Notes: IEB and BHP, 1985–2010. The first column shows the coefficient of the log of the agglomeration measure in the second-step regression (6), where the first-step separation equation includes worker controls but no plant controls and worker–region-specific baseline hazards—as in Model I in Table 2. The second column presents the predicted urban wage premium from a 100 log points increase in the respective agglomeration measure based on equation (8), with $\varepsilon_{Lw,1}$ set to the average elasticity. The third column gives the drop in the estimated urban wage premium when conditioning on the share of hires from non-employment, i.e. by moving from the second-step regression (10) to (11), where the first-step wage equation includes worker controls and fixed effects but not employer controls—as in Model III in Table 3. The last column re-estimates the drop in the urban wage premium from the third column using the ratio of job exits into non-employment to job exits into employment as an alternative measure of local search frictions. Standard errors come from a block bootstrap at worker level with 400 replications.