Accumulating valuable work experience: the importance of large firms and big cities*

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Abstract

Using linked employer-employee data on employment biographies of workers in Germany, this paper analyzes where valuable work experience is primarily acquired. It distinguishes between learning effects related to firm size and city size. We show that wages increase with both the size of the cities and establishments in which experience was accumulated. Around one quarter of the dynamic agglomeration benefits can be attributed to gaining experience in large firms. We provide evidence on two potential explanations for the role of size: formal training increases with firm size and the frequency of job changes with city size.

Keywords: Dynamic agglomeration economies, work experience, firm size, learning, human capital, urban wage premium
JEL classifications: J31, R12, R23

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1 Introduction

Workers in large cities earn significantly more than employees in rural areas (see Melo et al., 2009 and Combes and Gobillon, 2015 for comprehensive surveys). Urban economic theory argues that an important factor behind these disparities is agglomeration economies. Learning, which is thought to be promoted by a dense urban environment, is one important channel that might give rise to a positive correlation between wages and city size (Duranton and Puga, 2004). Recent findings indicate that dynamic agglomeration benefits and learning might, in fact, be an important component of agglomeration economies (see, e.g., Glaeser and Maré, 2001; Baum-Snow and Pavan, 2012; De La Roca and Puga, 2017; Peters, 2020). These studies show that the wage premium a worker receives for individual work experience depends on the size of the labor markets in which the experience was acquired.

The importance of firms for learning effects is rarely considered in the urban economics literature, one exception being a study by Glaeser (1999) even though there is no explicit role for firms in the process of human capital accumulation in his model. However, he mentions that firms likely act as organizers of learning between workers. In labor economics, in contrast, the role of firms for skill acquisition of workers is highlighted (e.g., Mincer, 1962; Becker, 1964). Interestingly, size seems to matter for human capital accumulation at the firm level as well (see Oi and Idson, 1999). This might be of importance for the estimated size of learning benefits assigned to working in big cities as large firms are typically overrepresented in large urban areas (Manning, 2010).

This paper examines the accumulation of valuable work experience and distinguishes learning effects that arise at the firm level from those at the level of local labor markets. Our conceptual framework builds on Mincer's (1974) accounting-identity model which we combine with a learning function, capturing the assumption that returns to learning effort increase with the size of the firm and of the local labor market in which work experience is acquired. Using administrative linked employer-employee data for Germany with information on individual employment biographies dating back up to 1975, we quantify learning effects at the two levels and examine whether it matters, first and foremost, to gain work experience in a large establishment or whether a workplace in a large city makes the difference for future wages.

Our results indicate that wages tend to increase with both, the size of local labor markets *and* of establishments in which work experience was accumulated. We find that an important share of the dynamic benefits of working in large cities is related to working in large establishments rather than to labor market size itself. Based on a specification that omits the size of previous employers, we obtain a wage elasticity with respect to previous city size of 0.0288 for workers with a medium level of work experience. This elasticity declines by more than 26 percent to 0.0212 once we consider the size of previous employers in addition. The wage elasticity with respect to the latter is 0.0259 net of the city size effect. High ability workers and young employees benefit most from the advantages of size at the two spatial scales. After 14 years of work experience, wages of workers at the top of the ability distribution are more than 50 percent higher if they acquired work experience in large establishments located in big cities rather than in small establishments in small cities. However, the larger the firms in which experience is gained, the less important city size is for these workers.

Our analysis adds to a recent strand of research that investigates how workplace characteristics impact learning effects. Previous papers focus on either the firm level (Mion et al., 2020; Arellano-Bover, 2022a; Arellano-Bover, 2022b; Jarosch et al., 2021) or the city level (De La Roca and Puga, 2017; Peters, 2020). Thus, they cannot provide evidence on the relative importance of these different spatial scales although their results suggest that both levels likely matter. In a recent study, Porcher et al. (2023) consider both the firm level and the city level, examining whether *current* establishment size affects the urban wage premium. They conclude that current establishment size, i.e. taking-up employment in larger establishments, explains less than 5 percent of the medium-term benefits from working in large cities. However, lacking a measure of work experience in large and small firms, they cannot investigate how firm size influences learning in large cities. Our findings point to a prominent role of *previous* establishment size (i.e., work experience gained in large firms) when it comes to the learning benefits of big cities.

We also contribute to the urban economics literature that deals with the size, scale and nature of agglomeration economies. Findings by Glaeser and Maré (2001), Baum-Snow and Pavan (2012) and De La Roca and Puga (2017) suggest that an important percentage of the city size wage premium is caused by higher returns to work experience in larger cities. Our results confirm the importance of city size. However, they also show that the benefits of working in large labor markets are in part due to gathering experience in large firms. Our research is also related to a recent discussion about the spatial scale of agglomeration economies (Rosenthal and Strange, 2020). Baum-Snow et al. (2020) note that there is little evidence on the strength and composition of effects at the very small scale within cities. The significance of the firm level indicated by our results might partly explain the sharp attenuation of agglomeration effects that several studies detect (Rosenthal and Strange, 2008).

There is evidence that in particular high ability workers take advantage of (dynamic) agglomeration effects (Carlsen et al., 2016; De La Roca and Puga, 2017; Peters, 2020). Our results suggest that as regards learning benefits, this advantage is due to higher investments in human capital accumulation of more able workers. Moreover, for these workers city size is not important if they work in very large firms. (Internal) learning opportunities that these establishments may offer apparently compensate for lacking labor market size in smaller cities. Low-ability workers are, in contrast, not sheltered from lacking size of local labor markets by opportunities that large firms offer. This drawback that low-skilled workers face corresponds with a lower participation in employer-provided training compared to individuals at the top of the ability distribution.

While the urban wage (growth) premium and the importance of learning effects are robust findings in the literature, much less is known about specific mechanisms that give rise to agglomeration benefits in general and to learning effects in particular (see e.g. Combes and Gobillon, 2015). As regards learning, a study by Serafinelli (2019) that considers labor mobility is among the rare exceptions. We provide descriptive evidence on two potential mechanisms that link learning effects to firm and labor market size: a higher propensity of formal training in large firms and a higher frequency of local job changes in big cities. The results suggest that the high value of work experience acquired in large local labor markets is partly caused by a spatial sorting of firms that offer more formal training and of workers who invest more in training. Moreover, we detect a higher frequency of firm-to-firm mobility within big cities that likely facilitates the transfer of knowledge as argued by Serafinelli (2019) and Combes and Duranton (2006). Our findings thus lend support for the notion that learning benefits of big cities are due to different mechanisms which operate at different spatial scales.

We estimate augmented Mincer wage equations where the return on investments in human capital may vary depending on the size of former employers and the labor markets in which they are located. Our approach takes into account unobserved heterogeneity and selection. Detailed data on employment biographies of workers along with information on their workplaces enables us to consider a large set of covariates. Focusing on entry wages and excluding recalls, we rule out productivity and wage effects that will gain in importance as tenure increases. To account for unobserved heterogeneity, we include fixed effects for workers and establishments in our regression model. Furthermore, we use the variation of entry wages and work experience with respect to firm and labor market size within ten groups of workers with similar ability level to identify learning effects. Thereby, we take into account that there is a positive correlation between ability and size at the two considered scales, but not within sub-samples of workers with similar ability.

The paper proceeds as follows. We review the literature on learning and the role of cities and firm size in Section 2. In Section 3, we discuss our conceptual framework and introduce a learning function that is used to describe the accumulation of valuable work experience. In Section 4, we explain our empirical strategy and Section 5 describes the linked employer-employee data. We discuss our main regression results in Section 6 and provide evidence on two potential mechanisms in Section 7. Section 8 concludes.

2 Learning and size at different spatial scales

Urban economic theory emphasizes the role of cities as locations of human capital accumulation (e.g., List, 1838; Marshall, 1890; Glaeser, 1999; Peri, 2002). This literature ascribes the positive correlation between wages and local labor market size (Combes and Gobillon, 2015) to agglomeration economies with learning benefits being one important channel through which they operate. Glaeser (1999) and Berliant et al. (2006) argue that opportunities for face-to-face meetings and the rate of (new) contacts between workers which might give rise to knowledge exchange increases with city size. Davis and Dingel (2019) show that higher-ability workers who divide their time between producing tradable goods and learning sort into large urban areas since ability and local learning opportunities are assumed to be complements. As city size increases, the learning environment becomes more favorable because more talented workers move to large cities and they devote more time to the exchange of knowledge.

Empirical evidence indicates that learning benefits of bigger cities might, in fact, be an important component of dynamic agglomeration economies (Glaeser and Maré, 2001). Inter alia, De La Roca and Puga (2017) and Peters (2020) show that the wage premium a worker receives for individual work experience increases with the size of the labor markets in which the experience was acquired. Moreover, gains from acquiring experience in urban labor markets persist when workers relocate to less dense regions. This is interpreted as pointing to learning effects. The firm as a location of human capital accumulation is not considered in these studies.[1]

Rosenthal and Strange (2020) note that agglomeration economies operate at different levels of spatial aggregation, ranging from regions down to a scale even below local neighborhoods, including effects within buildings and organizations. Evidence on highly localized knowledge spillovers (e.g., Rosenthal and Strange, 2008; Liu et al., 2018; Helmers, 2017) suggests that for learning benefits size at a very low spatial scale might matter as the transfer of tacit knowledge and informal training call for familiarity between individuals and close proximity. This raises the question whether firms are actually the main locations of workers' skill acquisition. Our results indicate that the firm level in fact matters for learning benefits of big cities. However, we show that there are also important size effects beyond the firm level which operate at the level of local labor markets.

The role of firms for human capital accumulation is highlighted in labor economics (e.g., Becker, 1964, Mincer, 1962, Gibbons and Waldman, 2006). Acemoglu and Pischke (1998) note that firms are important sites of human capital accumulation because training and on-the-job learning takes place inside firms. It is noteworthy that size is also thought to influence human capital accumulation at the firm level. For instance, Barron et al. (1987) explain that especially large firms tend to substitute training for increases in the work force when monitoring costs incurred by employers rise with firm size. Rosen (1983) argues that workers might benefit from investing in specialized skills when learning involves fixed costs. But specializing on a narrow band of skills may only be feasible in large firms.[2] Theoretical arguments in labor economics, thus, directly refer to size as the relevant firm characteristic when it comes to learning effects.

Different studies indicate that the probability of receiving any kind of training (formal, informal, by coworkers or managers) increases with firm size (see Oi and Idson, 1999 for a survey of empirical evidence and corresponding theoretical arguments). Recent findings by Arellano-Bover (2022b) and Arellano-Bover (2022a) confirm the importance firm size for young workers who benefit from working in large firms both in terms of higher skill growth and wages. Other studies examine differences in the on-the-job learning potential between domestic and internationally active firms (Mion et al., 2020) or the role of highly skilled co-workers (Jarosch et al., 2021).

[1] Lehmer and Möller (2010) pay more attention to the firm level. They investigate wage growth effects caused by job changes that might also involve a change of the firm-size category and/or the region. They conclude that "there is overwhelming evidence that wage growth in urban areas is not tied to the firm level" (Lehmer and Möller, 2010, p. 51). However, the focus of their analysis is not on learning effects.

[2] Duranton and Puga (2004) propose a model in which an increase in the size of the workforce allows for a deepening of the division of labor between workers. But they refer to the extent of the local labor market and not to firm size.

The size of the local labor market might also influence the probability of firms to provide training for their employees. Brunello and Gambarotto (2007) explain that the impact of city size on the firms' decision to invest in human capital is ambiguous from a theoretical perspective. On the one hand, large local labor markets may enable firms to benefit from higher marginal returns of training. Trained workers might be more productive in urban areas because they can exploit positive knowledge spillovers when skills and knowledge are complements. On the other hand, there is a higher risk of poaching in large urban labor markets, which might reduce the incentive to provide training. Some empirical studies suggest that the poaching effect prevails: firms seem to provide less training in urban areas (Brunello and Gambarotto, 2007; Muehlemann and Wolter, 2011). Our results do not confirm a dominant poaching effect or more generally an important role of labor market size when it comes to formal training. While training provision clearly increases with firm size, there is no statistically significant correlation with labor market size once we control for firm characteristics.

Little is known about the mechanisms of knowledge transfer outside the firm at the city level. Charlot and Duranton (2004) investigate workplace communication between workers and show that communication external to the firm increases with region size. However, according to Charlot and Duranton (2006) there is no support for the hypothesis of a greater prevalence of face-to-face communication in cities as compared to rural areas. A significant percentage of communication takes place within firms and, interestingly, workers in large firms communicate more than workers in small firms.

Combes and Duranton (2006) propose job mobility as a channel through which knowledge is transmitted within local labor markets: Knowledge spillovers are linked to labor market pooling because knowledge is partly embodied in workers and its diffusion driven by labor turnover. They provide evidence that workers frequently change their employer and that these labor flows are mostly local in France. Serafinelli (2019) shows that learning externalities (partly) arise from job changes between firms in the Veneto region in Italy. Hiring workers with experience at high-productivity firms significantly increases the productivity of the recruiting firm. Atkin et al. (2022) combine knowledge spillovers through job changes with accidental meetings of workers in local labor markets. Their results indicate that knowledge flows between Silicon Valley firms are strongly correlated with random face-to-face interactions of their workers. However, learning does not primarily take place when workers meet accidentally outside the firm. Rather, job changes between neighboring firms seems to be the main mechanism. Our findings are in line with this assumption. We detect a higher frequency of firm-to-firm mobility within big cities that might promote the transfer of knowledge and learning at this spatial scale.

3 Conceptual framework

3.1 Accumulation of human capital

Our empirical analysis of the relationship between firm and labor market size and the value of work experience builds on Mincer's (1974) accounting-identity model, the origin of the classical Mincerian wage equation. In the model, workers accumulate human capital by spending each period a certain fraction of potential earnings to become more skilled (Heckman et al., 2003). Similar to Mincer (1974) and Arrazola and De Hevia (2004) – the latter consider human capital depreciation in the Mincerian framework – we assume that the accumulation of human capital of worker i can be described by the following function:

$$H_{i,t} = (1-\theta)H_{i,t-1} + \nu_{i,t-1}k_{i,t-1} \tag{1}$$

where $H_{i,t}$ is the stock of individual human capital at time t. $k_{i,t-1}$ denotes time-varying individual learning effort in terms of potential earnings devoted to acquire new skills one day before and $\nu_{i,t}$ is the corresponding rate of return, which is assumed to be constant in the original model. θ captures the depreciation of human capital (at a daily basis) which might be caused by, i.a., changes in the skill requirements of jobs due to technological change, shifts in the demand for particular occupations due to changes in the industry structure, or the loss of knowledge and skills due to insufficient use (De Grip and Van Loo, 2002).

Defining day $t = 1$ as the day of labor market entry, the day a worker starts to acquire skills at work, and assuming that human capital at labor market entry, $\eta_{edu(i)}$, is determined by the individual level of education, $edu(i)$, the stock of human capital at time t can also be expressed by (cf., Sydsæter et al., 2008):

$$H_{i,t} = (1-\theta)^t \eta_{edu(i)} + \sum_{\tau=1}^{t-1} (1-\theta)^{t-1-\tau} \nu_{i,\tau} k_{i,\tau}. \tag{2}$$

3.2 Learning and size

We adopt the concept of a learning function proposed by Duranton and Puga (2004) to integrate in the Mincer framework that learning prospects and, thus, human capital acquisition are thought to depend on characteristics of the environment, specifically on the size of establishments and labor markets in which learning takes place as discussed in Section 2. Duranton and Puga (2004) assume that the probability of becoming skilled in a city is a function of the local amount of (skilled) labor. Similarly, we hypothesize that the rate of return on the learning effort of worker i at day t is given by:

$$\nu_{i,t} = \gamma + \delta \ln(emp_{f(i,t),t}) + \rho \ln(emp_{r(i,t)-f(i,t),t}) + \omega \ln(emp_{f(i,t),t}) \times \ln(emp_{r(i,t)-f(i,t),t}). \tag{3}$$

Thus, it is assumed to consist of a constant term γ, a term capturing the size of firm f, i.e. employment (*emp*) of the establishments in which individual i is working at day t, and a term capturing the size of the local labor market in which firm f is located (without the firm itself).[3] Furthermore, we also consider the interaction of firm and labor market size taking into account potential complementarities between firm characteristics and labor market size observed by, e. g., Combes et al. (2012) and Gaubert (2018) with regard to firm productivity. $\nu_{i,t}$ is constant like in most applications of Mincer's model (cf., Heckman

[3] Arellano-Bover and Saltiel (2021) propose a similar approach in which the return on on-the-job learning differs across firm types, while Davis and Dingel (2019) focus on benefits of exchanging ideas that increase with city size.

et al., 2003) if δ, ρ and ω are set to zero.[4]

δ and ρ denote learning effects related to firm and labor market size, respectively and ω indicates whether the benefits of large firms and cities reinforce each other. In line with the assumption by Duranton and Puga (2004) that learning is increasing with city size, but at a decreasing rate, we consider the *logarithm* of size as typically done in the agglomeration economics' literature (cf. Combes and Gobillon, 2015).[5]

3.3 Wages and work experience

The wage a worker receives at day t, $w_{i,t}$, is equal to potential earnings $E_{i,t}$ minus fraction $k_{i,t}$ that is spent for learning:

$$\ln w_{i,t} \approx \ln E_{i,t} - k_{i,t}. \tag{4}$$

Potential earnings are assumed to be an exponential function of human capital with W being "the rental price per equivalent unit of capacity to obtain potential earnings" (Arrazola and De Hevia, 2004, p. 146):

$$E_{i,t} = Wexp(H_{i,t}). \tag{5}$$

The effort to acquire new skills, $k_{i,t}$, decreases by assumption linearly until it becomes zero if retirement age is achieved as is standard in the literature. In addition, we assume that a worker does not spend time on the acquisition of human capital if she is out of the labor market or unemployed. This is captured by an indicator function $I(O_{i,t} = 1)$ where $O_{i,t}$ is a dummy variable taking the value 1 if individual i is employed at day t and 0 else. $k_{i,t}$ is then given by (cf., Heckman et al., 2003):

$$k_{i,t} = \kappa \left(1 - \frac{t}{T_i}\right) I(O_{i,t} = 1), \tag{6}$$

with parameter κ referring to the fraction of time spent learning at labor market entry and T_i being the length of individual working life, i.e., the number of days between labor market entry and retirement. Equation (6) reflects the well-established result that human capital investments decrease with age because benefits become smaller as the payoff period declines (cf., Mincer, 1997).

[4] In the standard Mincer wage equation, where logarithmic wages are regressed on experience and its square, ν is not estimated explicitly, but it is part of the two estimated parameters describing the relationship between wage and experience (see Heckman et al., 2003). Equation (3) is an augmented version of the learning function applied by Peters (2020). A higher return on learning effort might either stem from a higher return per unit of acquired human capital or due to the acquisition of more units of human capital per unit of time in large cities or firms.

[5] Results by Peters (2020) confirm that dynamic benefits from city size increase at a decreasing rate and that workers in Germany gather valuable work experience even in the smallest local labor markets. However, we also consider a more flexible learning function in this study, i.e., $\nu_{i,\tau} = \gamma + \delta_{lin} emp_{f(i,\tau),\tau} + \delta_{sq} emp^2_{f(i,\tau),\tau} + \rho_{lin} emp_{r(i,\tau)-f(i,\tau),\tau} + \rho_{sq} emp^2_{r(i,\tau)-f(i,\tau),\tau}$ to test whether the benefits from firm and city size increase at a decreasing rate.

From Equations (2), (4), (5), and (6) we obtain:

$$\ln w_{i,t} \approx \ln W - \kappa\left(1-\frac{t}{T_i}\right) + \eta_{edu(i)}(1-\theta)^t + \sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\kappa\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\nu_{i,\tau} \qquad (7)$$

and if we, furthermore, substitute $\nu_{i,\tau}$ by Equation (3), $\ln w_{i,t}$ is approximately given by:

$$\begin{aligned}
&\ln w_{i,t} \approx \ln W + \kappa\left(\frac{t}{T_i}-1\right) + \eta_{edu(i)}(1-\theta)^t \\
&+\gamma\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1) \\
&+\delta\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right) \\
&+\rho\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right) \\
&+\omega\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right)\ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right). \qquad (8)
\end{aligned}$$

Hence, combing the Mincer model with a learning function which allows for an important role of firm and city size, our conceptual framework implies that the wage is a function of the size of all establishments a worker was employed at previously and the size of the labor markets where these establishments were located. Equation (8) is the basis of our regression model.

Our approach exploits the entire variation in the size of labor markets and establishments in which experience was gained to identify dynamic benefits from size, rather than focusing on experience gained in few (groups of) very large cities (or firms). However, we also estimate specifications applied by De La Roca and Puga (2017) and consider experience by categories of differently sized labor markets and firms to test the robustness of our main findings in this respect and increase the comparability to previous analyses (Appendix A2.2).

The specification given by Equation (8) explicitly considers, furthermore, *when* in the course of her individual working life a worker acquired work experience in specific firms and local labor markets. Usually, this is not taken into account when considering experience by city size or establishment size categories. However, *when* experience is gained in large firms and big cities might have an impact on future wages for at least two reasons. Firstly, where experience is acquired at the very beginning of an individual's working life is likely of particular importance for individual wage growth as learning efforts are high (Mincer, 1974) and because it might affect career paths (Arellano-Bover, 2022a). The fact that workers experience wage growth especially at the beginning of their working life is a typical result for standard Mincer wage equations. Moreover, De La Roca and Puga (2017) show that the marginal benefit from working in big cities decreases with the level of overall experience, i.e. workers at the beginning of their working life benefit more from an additional year of experience acquired in very large cities than more experienced employees.[6] Secondly, it is probably also more important for wages where the most recent experience was gathered compared to the location where experience was gained several years ago because human capital depreciates over time (De Grip and Van Loo, 2002; Arrazola and De Hevia, 2004; Dinerstein et al., 2022).

Our approach acknowledges that the benefits from size may vary over the course of an employee's career. Complementing our main results on the importance of firm and labor market size for the return on work experience, the estimates for κ and θ provide evidence on the role of size over the course of an individual's working life and the long-term nature of the associated wage effects.

4 Empirical strategy

4.1 Empirical model

Entry wages in new employment relationships

To investigate the wage effects of human capital accumulation in large firms and large local labor markets as described by Equation (8), we study wages in new employment relationships and to what extent they depend on where work experience brought into new employment was acquired. Recruiting usually involves that firms ascertain the productivity of applicants based on interviews, evidence of qualifications and screening devices (Pissarides, 1976). We assume that firms have no prior knowledge of the workers' skills and entirely rely on the information from the recruiting process. Previous work experience indicated by the application documents is an important source of information in this context and a factor that likely influences employers' expectation about the candidates' productivity and, thus, entry wages in new employment. We assume that recruiting firms use firm size and city size as signals pointing to the value of the work experience documented in the application papers because information on other relevant characteristics such as proximity of knowledgeable co-workers or productivity of previous employers might be more difficult to access.[7]

Empirical specification of entry wages

We estimate an augmented version of Equation (8) where $w_{i,t}$ is the wage of worker i in new employment taken-up t days after individual labor market entry:

$$\ln w_{i,t} = \alpha + \kappa\left(\frac{t}{T_i} - 1\right) + \eta_{edu(i)}(1-\theta)^t + \gamma\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)$$
$$+\delta\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right)$$

[6] Declining marginal returns on total experience and on big city experience are consistent with learning efforts that decline over a worker's career (cf., Mincer, 1997).

[7] Size could as act as a proxy for other important firm and city characteristics because it correlates with factors such as the qualification structure of the workforce, productivity, and wage setting (see Peters, 2020; Porcher et al., 2023). However, size likely matters also directly since it may influence the potential for specialization and presumably affects the likelihood to provide training (see Section 2).

$$
\begin{aligned}
&+\rho\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right)\\
&+\omega\kappa\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right)\ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right)\\
&+\mathrm{FE}_i\pi+\mathrm{FE}_{f(i,t)}\phi+\mu_{r(i,t),y(t)}+\mathbf{x}'_{i,t}\beta+\varepsilon_{i,t}. \qquad (9)
\end{aligned}
$$

FE_i and $\mathrm{FE}_{f(i,t)}$ are pre-determined worker and establishment fixed effects (henceforth labeled AKM referring to Abowd, Kramarz, and Margolis, 1999) that have been estimated by Bellmann et al. (2020). The AKM fixed effects base on the universe of all spells of employment that are subject to social security contributions in Germany and the largest connected set of establishments, i.e. all establishments that are linked by worker mobility (see Lochner et al., 2023). We include these estimates as continuous variables in our regression models to control for unobserved heterogeneity at the worker and the establishment level since with the sample at hand (see Section 5.1 and Appendix A1 for details) estimation of an AKM model is not feasible. This would require, inter alia, to observe at least two new employment relationships for every worker and every firm in the period between 2005 and 2011. The number of observations would dramatically decline giving rise a highly selective sample of workers.[8]

Furthermore, $\mu_{r,y}$ is a fixed effect for labor market region r, i.e., the region in which new employment is taken-up. Region fixed effects are allowed to vary across years y and refer to 141 functional labor market regions defined by Kosfeld and Werner (2012). $\mathbf{x}_{i,t}$ denotes a vector of observable characteristics of worker i (gender, qualification, pre-employment status, occupation), the hiring establishment (size, workforce composition, industry), the local industry the latter belongs to (local employment share and skill structure), and the local labor market in which the hiring establishment is located (skill-specific unemployment rates) with parameter vector β, and $\varepsilon_{i,t}$ is an error term. Since Equation (9) is non-linear in depreciation rate θ, we apply the Gauß-Newton-Algorithm[9] to determine the least squares estimators of its parameters (cf., Peters, 2020).

To allow for heterogeneous size effects, we estimate Equation (9) separately for ten distinct groups of workers that we define based on the deciles of the AKM worker fixed effects FE_i which we use as a proxy for unobserved individual ability (following, inter alia, Dauth et al., 2022). Thereby, we take into account that workers with different ability levels may benefit differently from acquiring experience in big labor markets and in large firms.

Interpretation of parameters

The two pivotal variables in our analysis are the size of the labor market $emp_{r(i,\tau)-f(i,\tau),\tau}$ and of the firm $emp_{f(i,\tau),\tau}$ in which work experience was acquired. Both are transformed such that they have zero mean (after taking the logarithm) to ease interpretation. Therefore, δ gives the effect of firm size on entry wages for previous employers that were located in average-sized labor markets (183.8 employees/km^2) and ρ refers to the effect of labor market size given that the size of previous employers equals average

[8] As a robustness check, we apply approaches used by Dauth et al. (2022) and Bonhomme et al. (2023) to account for the limited mobility bias that might affect the AKM estimates (see Section A1.3 in the Appendix).

[9] See, e.g., Green (2000, p. 421) for a description of this iterative procedure.

firm size (56.8 employees). γ is the return to experience acquired in an average sized firm located in an average sized labor market. The interpretation of ω does not change due to this transformation.

Furthermore, we use the estimates for $\gamma\kappa, \delta\kappa, \rho\kappa, \omega\kappa$ and θ to compute $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ as defined by Equations (10) to (13). In doing so, we address that the parameters in Equation (9) refer to the marginal benefit from acquiring one day of work experience (cf., Equation 3). Therefore, the size of the estimated effects is not immediately obvious.

$$\tilde{\gamma} \equiv \hat{\gamma}\hat{\kappa} \sum_{\tau=t-365}^{t-1} (1-\hat{\theta})^{t-\tau-1} \left(1-\frac{\tau}{T_i}\right) |_{T_i=16{,}099 \text{ days}, t=5{,}185 \text{ days}} \tag{10}$$

$$\tilde{\delta} \equiv \hat{\delta}\hat{\kappa} \sum_{\tau=t-365}^{t-1} (1-\hat{\theta})^{t-\tau-1} \left(1-\frac{\tau}{T_i}\right) |_{T_i=16{,}099 \text{ days}, t=5{,}185 \text{ days}} \tag{11}$$

$$\tilde{\rho} \equiv \hat{\rho}\hat{\kappa} \sum_{\tau=t-365}^{t-1} (1-\hat{\theta})^{t-\tau-1} \left(1-\frac{\tau}{T_i}\right) |_{T_i=16{,}099 \text{ days}, t=5{,}185 \text{ days}} \tag{12}$$

$$\tilde{\omega} \equiv \hat{\omega}\hat{\kappa} \sum_{\tau=t-365}^{t-1} (1-\hat{\theta})^{t-\tau-1} \left(1-\frac{\tau}{T_i}\right) |_{T_i=16{,}099 \text{ days}, t=5{,}185 \text{ days}} \tag{13}$$

$\tilde{\gamma}$ denotes the wage premium for the previous year of work experience acquired in an average sized firm located in an average sized labor market 5,185 days ($\approx$ 14 years) after labor market entry, assuming that a worker enters the labor market 16,099 days ($\approx$ 44 years) prior to retirement age.[10] $\tilde{\delta}$ and $\tilde{\rho}$ are the corresponding elasticities of the wage in new employment with respect to the size of the establishment and the local labor market where one year of experience was acquired. $\tilde{\omega}$, again, refers to the interaction effect of firm and labor market size.

4.2 Identification

Endogeneity might impair the estimates of the benefits from acquiring work experience in large firms and large local labor markets due to several reasons. First, a bias might be caused by unobserved heterogeneity at the worker level because more able workers might have acquired their experience primarily in large firms and urban labor markets. This correlation might be due to the sorting of workers into differently sized firms and cities (Combes et al., 2008), but also because workers are not perfectly mobile and more able workers were born more often in large labor markets due to the spatial sorting of their parents (Bosquet and Overman, 2019) or because big cities may provide better schooling (van Maarseveen, 2020). Second, due to the rather low mobility of labor, workers who gathered experience in large cities often continue to work in a large local labor market (Tables A4 to A6; see also Bosquet and Overman, 2019) which might be characterized by a high regional wage level, e.g., due to static agglomeration economies, reinforcing the positive correlation between entry wage and size of previous labor markets.

[10] 16,099 days is the sample mean of the number of days between observed individual labor market entry and retirement age as defined by German legislation. Depending on the month and year of birth, the latter varies between 65 and 67 years. 5,185 days is the sample mean of the number of days between individual labor market entry and the beginning of the new employment relationships considered in the analysis.

Moreover, workers might accept a lower entry wage in exchange for a high learning potential that the *new* workplace offers, giving possibly rise to a downward bias of the returns to previous firm and city size. Third, firms that pay higher wages for any reason (e.g., higher productivity, specific wage agreements) might show recruiting strategies which aim at hiring workers who obtained their skills predominantly in large firms and large cities. This might also apply to large firms that typically pay higher wages than small establishments causing a positive correlation between wage and the size of the labor markets and establishments in which experience was gained (cf. Porcher et al., 2023).

The estimated returns to firm and labor market size might thus be biased due to various forms of heterogeneity and it is important to account for observed and unobserved characteristics of workers, firms, and local labor markets. We do so by considering important observable characteristics of the worker, the hiring establishment and its location (see Table A1 and Table A8). A part of the value of work experience in large firms and cities might relate to higher quality jobs which are only accessible with this type of work experience. We include a number of variables to control for the quality of the current job (e.g., occupation, sector). These variables are bad controls if we perceive access to high quality jobs as a part of learning benefits in large firms and large labor markets. However, in line with Eckert et al. (2022), we interpret a positive correlation between the size of previous labor markets and firms and the quality of the current job as rather pointing to matching advantages than learning effects. Moreover, job mobility, the position on the job ladder and workers' bargaining power likely affect the wage in a new job. We try to account for these factors by including the number of previous employers and the employment status before the job starts (e.g. short- and long-term unemployment, employment, participation in a measure of active labor market).

As a robustness check, we interact the number of previous employers with all experience variables, thus allowing the pivotal parameters of the learning function to differ between workers at different stages of the job ladder. In this augmented specification, we only use the variation between workers with the same number of previous employers to identify the learning benefits of working in big cities and large firms. This enables us to examine whether matching advantages in large cities (Wheeler, 2006; Yankow, 2006; Dauth et al., 2022) impact on the benefits from acquiring experience in large cities and firms.

We include, furthermore, estimated AKM worker and establishment effects to account for unobserved factors, which correlate with work experience and influence entry wages. This implies that we apply a rather conservative approach because the pre-determined AKM effects correlate positively with the size of the firms and cities in which experience was gained (see Table 1, Column (1)). At the regional level, we include information on the local industry structure, industry-specific local human capital, and on skill-specific labor market conditions to reduce the risk of biased estimates. Furthermore, we also consider region-time fixed effects as well as the labor market density within 10 km around the center of the municipality in which the hiring establishment is located to account for the possible non-random sorting of workers into local labor markets. The region-time fixed effects will capture effects of competition in local labor markets (Manning, 2010).

Considering *entry* wages instead of wages at certain reference days, we address, furthermore, that workers will accumulate firm-specific skills and might receive promotion as tenure increases (cf., Topel, 1991). The importance of these factors for wages will likely increase with the length of an employment spell and some of these effects are time-varying, unobserved by the econometrician or hard to measure (Hamann et al., 2019). Hence, their omission will give rise to biased estimates of the learning effects if on the job training and promotion correlate with the previous work experience in large firms and large regions. However, we refrain from restricting our analysis to involuntarily displaced workers (see, e.g., Dustmann and Meghir, 2005) since we suspect that workers, who face a mass layoff, acquired experience in rather special firms which might impair the generalizability of the results.[11]

Furthermore, we also consider that workers, who – compared to other workers – learn fast (or accumulate more valuable knowledge), might have acquired work experience in larger firms and labor markets due to sorting. Including worker fixed effects in our model, we address this concern only partially because the individual fixed effect accounts for individual wage differentials that are constant over time, but not for different returns to experience resulting in faster individual wage growth (D'Costa and Overman, 2014). The significant positive correlation in Column (1) of Table 1 in fact indicates that higher ability workers, who presumably learn faster than other workers, acquire experience on average in larger firms and labor markets. However, by estimating Equation (9) separately for ten distinct sub-samples, we only use the variation between workers within deciles of AKM-worker fixed effects. This identification strategy rests on the observation that there is no significant correlation between individual ability level and previous firm and labor market size within these groups of workers (see Columns (2) to (11) in Table 1). This is in line with findings by Bacolod et al. (2009), Baum-Snow and Pavan (2012), Eeckhout et al. (2014) and De La Roca and Puga (2017) who observe that spatial sorting on ability is weak within broad groups of occupation or education. Recent results by De La Roca et al. (2022) suggest that this is due to a poor self-assessment of ability relative to people with the same education, particularly when workers are young. Furthermore, by exploiting the variation within groups of workers with comparable ability level, we address that the individual learning effort captured by κ is presumably correlated with the ability level since the expected return is arguably higher for more able workers (cf., Davis and Dingel, 2019).

[Table 1 about here]

5 Data

5.1 Sample of new employment relationships

To investigate the wage effects of learning benefits in large firms and large cities, we make use of linked employer-employee data for Germany for the period 1975–2011. It is based on the Integrated Employ-

[11] In recent studies by Mion et al. (2020) and Arellano-Bover and Saltiel (2021), the authors obtain very similar estimates for the return to experience acquired in different types of firms based on the respective full sample and displaced workers.

ment Biographies (IEB) of the IAB, which cover microdata on employment, job-search status, benefit receipt, and participation in active labor market policy measures.[12] The IEB contain information on individual employment biographies for all workers in Germany as long as they are not exempt from social security contributions, like civil servants and self-employed persons (about 12 percent of total employment in Germany). Based on mandatory notifications by the employer, the IEB provide information on wages and individual employment spells on a daily basis. An advantage of the IEB compared to other data is its administrative nature, ensuring that there is little measurement error in wages and work experience (Gathmann and Schönberg, 2010).

We use a 5 percent random sample of all employees in the IEB with at least one social security notification between 2005 and 2011. Workers for which we cannot observe the full employment biography are excluded from our analysis following Dustmann and Meghir (2005) (see Appendix A1 for details). For the remaining workers, we identify new employment relationships in the period 2005–2011 focusing on the first match of an establishment with a particular worker. The detailed information on individual labor market biographies enables us to identify transitions into new jobs and to check whether the worker has been employed in this establishment before. The wage associated with these new employment relationships is our dependent variable. By excluding recalls, we aim at minimizing the risk that the employer has information on the new worker gathered during previous employment spells and that the employee brings establishment specific human capital into the new employment relationship.[13] After imposing additional restrictions (see Appendix A1), we end-up with information on about 150,000 new employment relationships referring to about 100,000 workers.

5.2 Variables

Experience

Work experience brought into new jobs is our pivotal explanatory factor. In particular, we are interested in the time spent at previous employers, their size, and the size of the local labor market, in which they were located. The IEB include the exact start and end days of every employment relationship by establishment and municipality. We can link this information with data on the size of the establishments and the local labor markets and are, thus, able to precisely measure individual work experience on a daily basis with respect to these characteristics.[14] We only consider work experience that was acquired after a worker achieved the educational level that is reported with the new employment relationship, distinguishing between “no vocational training/university degree”, “vocational training degree” and “university (of applied sciences) degree”. Likewise, the date of individual labor market entry that is used to compute the expected length of the individual working life (T_i in Equation (6)) is defined as the day at which the worker

[12] For a detailed description of the IEB see Berge et al. (2013).

[13] It is not possible to identify whether different establishments belong to the same firm. Different units of one firm that are located in different municipalities are considered as independent establishments. Therefore, we cannot rule out that an employee acquired firm specific human capital at a different unit before joining the establishment which reports the new employment relationship. To improve readability, we use the term ‘firm’ as a synonym for ‘establishment’ throughout the paper.

[14] We only consider previous spells of employment subject to social security contributions because information on self-employment is not available.

is the first time observed with the respective educational level in the IEB.[15]

- **Establishment size:** Information on the size of previous employers in terms of number of employees is taken from the Establishment History Panel (BHP) of the IAB, which contains administrative data on each establishment in (West) Germany with at least one employee subject to social security notification at June 30 of each year dating back to 1975. Based on this information, we compute a three-year moving average of annual employment figures considering establishment employment reported for the years $t-1$, t and $t+1$ and merge this with the individual employment spells observed in year t using the establishment identifier available in the BHP and the IEB.[16]

- **Labor market size:** The BHP also provides information on the location of each establishment at municipality level. We use this information to merge characteristics of the local labor market, i.e. its size in terms of employment and, for an augmented specification (see Appendix), the number of establishments, with the individual employment spells. To define the local labor market in which a previous employer is situated, we take into account the attenuation of agglomeration benefits with distance (Di Addario and Patacchini, 2008; Rosenthal and Strange, 2008) and draw a circle of radius 10 km ($\approx$6.2 mi) around the geographic center of the municipality in which the establishment is located, similar to De La Roca and Puga (2017). In doing so, we also avoid discontinuities in local labor market density that inevitably arise if the latter is measured on the level of non-overlapping areas as discussed by Manning and Petrongolo (2017). Figure A1 in the Appendix illustrates in an exemplary way for 2011 the employment density used in our analyses and the original employment density at municipality level. We consider the size of the local labor market in which experience is acquired net of the size of the establishment in which the worker was employed in order to clearly differentiate between the value of work experience that is linked to the size of the local labor market and effects that relate to the size of the establishment.

Entry wage in new employment

Our dependent variable is the logarithmic gross daily wage associated with a new employment relationship, deflated by the German consumer price index. The wage information in the IEB is right-censored since establishments report earnings only up to the upper limit for social security contributions. We impute the wages above the threshold (approximately 7 percent of the considered entry wages) applying interval regression (see Appendix A1.2 for details).

Further variables

Information on additional control variables considered in the empirical analysis are provided in Table A1 in the Appendix. These include attributes of the *worker* (educational level, age, nationality, gender, employment biography), the hiring *establishment* (size, industry, location, workforce composition), the *local industry* the hiring establishment belongs to (industrial structure, human capital) and the *local labor market* (skill-specific unemployment rates).

[15] As an example, we do not consider periods of employment prior to graduation if we compute work experience and define labor market entry for a worker with a vocational training degree or a university degree.

[16] For more details refer to Table A1 in the Appendix. A detailed description of the BHP is provided by Eberle and Schmucker (2017).

6 Estimated returns to work experience

6.1 Baseline results

Table 2 summarizes the results that we obtain if we estimate Equation (9) based on the full sample of new employment relationships. The pivotal parameters of the learning function (Equation (3)) are expressed as described in Equations (10) to (13) to ease interpretation. They denote the return on the last year of work experience about 14 years after labor market entry which corresponds to the average time between entering the labor force and starting a new job in our sample. The results of the full specification in Column (4) suggest that the corresponding wage premium is 4.4 percent ($= (\exp(\hat{\gamma}) - 1) \times 100$ %) if experience was acquired in an average sized firm located in an average sized labor market as both are centered around their respective mean (see Section 4). Furthermore, the results indicate that firm size as well as labor market size positively affect the value of work experience. At the considered time in working life the wage elasticities ($\tilde{\delta}$ and $\tilde{\rho}$) are 0.00493 (previous firm size) and 0.00403 (previous city size) if they are evaluated at the corresponding sample mean.[17] An increase in the logarithmic size of the establishments and labor markets in which the previous year of experience was acquired by one standard deviation (see Table A2) is associated with a 0.820 percent ($= (\exp(0.00493 \times 1.656) - 1) \times 100\%$) and a 0.470 percent ($= (\exp(0.00403 \times 1.163) - 1) \times 100\%$) higher wage, respectively. Hence, the wage effect of the size of previous employers is about 74 percent larger than the effect of previous labor market size.

[Table 2 about here]

If we compare the results in Column (4) with the estimates reported in Columns (1) and (2) of Table 2, it becomes apparent that the effect of firm and labor market size is about 12 percent and 38 percent larger, respectively, when we omit size at the other scale. This is due to the positive correlation of firm and labor market size (see Figure A2 and Table A3 in the Appendix). If the source of this correlation are agglomeration economies, meaning that the latter *cause* firms in big cities to be larger than in small local labor markets, the advantage of acquiring experience in large firms in large cities can be perceived as part of the agglomeration benefit. However, Manning (2010) points out that there are theories on agglomeration predicting that firms should be smaller in large than in small cities. He discusses monopsonistic labor markets where competitiveness increases with labor market size, providing thus an alternative explanation for the positive correlation of firm and city size. Following this reasoning, it is important to control for firm size to avoid an upward biased dynamic effect of a dense urban environment.[18]

[17] Tables A9 and A10 in the Appendix summarize results that we obtain if we omit worker and firm fixed effects and results for different (sub-)samples. All specifications indicate that the reward for work experience is higher, the larger the firms and labor markets were in which experience was acquired. This finding is further confirmed by robustness checks that address the limited mobility bias in AMK estimates (Table A11), assume a different functional form for the learning function underlying the regression model (Table A12), and consider experience by city size and establishment size categories (Table A16), respectively.

[18] Table A13 in the Appendix summarizes the results for an augmented version of Equation (9) that considers these arguments by including the average firm size of all local labor markets in which experience was acquired as an additional explanatory variable. The results confirm the findings of the simpler model summarized in Table 2. We are grateful to Pierre-Philippe Combes for suggesting the alternative specification.

The significant positive coefficient for $\tilde{\omega}$ in Column (4) suggests, furthermore, that benefits from acquiring experience in large firms and in large labor markets complement each other. The estimate for the share of potential earnings invested in human capital acquisition at the very beginning of an individual working life, κ, is almost 44 percent and the estimated depreciation rate of human capital amounts to 20 percent per year. As regards the latter, it is worth noting that it refers only to the depreciation of human capital transferable to other firms. The rate indicates that in particular work experience accumulated in most recent years determines entry wages.

6.2 Results by ability level

We also estimate Equation (9) separately for ten distinct groups of workers which we define based on the worker fixed effects provided by Bellmann et al. (2020) that serve as a proxy for unobserved individual ability. This reduces the risk of biased estimates due to the positive correlation of the ability level and the size of firms and labor markets in which experience was acquired (see Section 4.2). Furthermore, it allows for heterogeneous wage-experience patterns across groups of workers. The results for the different sub-samples are summarized in Figure 1. Again, we consider the marginal return on one year of experience acquired in the middle of individual working life, indicated by $\tilde{\gamma}, \tilde{\rho}, \tilde{\delta}$ and $\tilde{\omega}$.

[Figure 1 about here]

The estimates are in line with results by De La Roca and Puga (2017) who observe that more able workers benefit more from acquiring work experience in general and from labor market size in particular (see $\tilde{\gamma}$ and $\tilde{\rho}$). As regards the latter, our results suggest that primarily workers at the very top of the ability distribution benefit more from labor market size. There is also a clear positive relationship between ability and the impact of firm size ($\tilde{\delta}$). For the two groups at the top of the fixed effects distribution, the reported elasticity is more than twice as high as for workers with fixed effects below the fourth decile. Only for the lowest ability category the establishment size effect is not statistically significant different from zero. Hence, particularly the high ability workers benefit from the advantages of larger firms when the acquisition of human capital is concerned. Furthermore, the acquisition of experience has a more long-lasting effect on entry wages for these workers than for those at the bottom and in the middle of the ability distribution. The annual depreciation rate θ varies roughly between 20 percent (10th decile) and 40 percent (2nd decile). In line with the model by Davis and Dingel (2019), the estimates for κ imply that more able workers also devote significantly more time to learning than those with lower ability. The differences in κ across ability categories might reflect, among other things, that high-skilled workers show a higher probability to participate in employer-provided training than low-skilled workers (see e.g. Wotschack, 2020; Fouarge et al., 2013).[19]

Figure A4 in the Appendix summarizes results of augmented specifications where the value of experience

[19] One reasonable concern might be that the investment rate in human capital varies by firm and labor market size since workers anticipate that they may acquire more skills in large firms and labor markets which likely would result in an upward bias of the firm and labor market effect on experience. Results in Figure A7 in the Appendix, however, suggest that κ is rather stable across types of firms and labor markets and varies predominantly between workers with different ability levels.

may not only vary depending on where it was acquired, but also depending on the size of the firm and of the labor market in which it is used. The estimates reveal that all considered types of hiring establishments – small, medium and large ones as well as those located in rural, medium sized and highly agglomerated labor markets – pay high ability workers an additional wage premium for experience that was acquired in large firms and large labor markets. The benefits of size are thus highly portable across differently sized firms and labor markets. Consistent with the reasoning by Glaeser and Maré (2001) and De La Roca and Puga (2017), this strongly suggests that it is learning which leads to the higher wage premium for work experience acquired in large firms and large labor markets.

This interpretation is also supported by additional results summarized in Figure A5 in the Appendix. They show that effects of city size and establishment size on the return on experience are fairly constant along the job ladder. We use the number of previous employers to approximate the individual position on the job ladder following Dauth et al. (2022). The results indicate that matching advantages, which give rise to stronger wage growth in large cities per job change, cannot explain the positive effect of big city experience on wages. This interpretation is also in line with Dauth et al. (2022) who note that the two mechanisms *matching* and *learning* do not necessarily reinforce each other.[20]

6.3 Variation of dynamic gains across different firm size and city size combinations

There are various combinations of firm size and city size in which experience is accumulated (see Table A3 in the Appendix). Figures 2 shows the corresponding range of wage effects for the full sample and selected ability categories. For the full sample relative entry wages vary, ceteris paribus, between 0.9 and 1.15 depending on where experience was gained (Figure 2a). However, the difference in the value of experience accumulated in large establishments located in big cities and work experience gained in tiny firms located in a sparsely populated rural environment varies across workers depending on their unobserved ability. For workers at the bottom of the ability distribution[21] the corresponding wage disparities are relatively small (0.96 to 1.04, Figure 2b), whereas for the most able workers they are larger than for the full sample (0.75 relative to 1.15, Figure 2d).

[Figure 2 about here]

Figures 2c and 2d also show that for high ability workers, the return on experience is virtually independent of labor market size if they acquire experience in large establishments with a workforce of more than 1,000 employees. In contrast, labor market size makes a difference for high ability workers who are employed in small establishments: their entry wage is more than 30 percent higher if the small firm is located in a big city rather than in a very small rural labor market (Figure 2d). Hence, the advantages

[20] We would expect that workers with many previous employers benefit more from big city experience than worker with few job changes (estimate for ρ should clearly increase with the number of previous employers) if dynamic matching advantages are primarily behind the positive impact of labor market size on the return on experience.

[21] We consider workers belonging to the 2nd decile of the worker fixed effects distribution because the effect of firm size is insignificant for the 1st decile.

offered by large labor markets apparently compensate (to some extent) for a lack of learning opportunities when high ability workers are employed in a small firm. Learning opportunities offered by large firms, in contrast, seem to be so substantial that the advantages of large labor markets apparently no longer matter for these workers.[22] More generally, the figures confirm that establishment size has a larger impact on the acquisition of valuable human capital than labor market size: the wages of high ability workers increase more strongly along the distribution of establishment size than with increasing city size.

Interestingly, low ability workers do not benefit in the same way from firm size as high ability employees. Firm size does not compensate for lacking city size for these workers at the bottom of the ability distribution (see Figure 2b). These differences between workers at the top and the bottom of the distribution might arise, inter alia, from a varying participation in training that in particular large firms offer (see Section 7.1). There is evidence that training participation of low-skilled workers is lower than participation of skilled worker in Germany (see e.g. Wotschack, 2020). Regarding the value of work experience, significant benefits from employer-provided training might thus shelter high ability workers in large firms from disadvantages of small labor markets.[23]

6.4 Benefits from size per day and at different stages of working life

In Figure 1, we have examined the returns on size on an annual basis, i.e. for one year of work experience. However, this approach hides useful information on potential mechanism which might give rise to the positive correlation between ability and the returns on experience and size. More precisely, to gain further insights on the role of individual learning effort for the benefits of size, we turn to the estimates of the parameters γ, δ, ρ and ω reported in Figure 3 that show the return to experience on a daily basis if the entire day would be spent for learning, i.e., κ equals one (see learning function: Equation (3)). Like in Figure 1, the baseline wage effect of experience as well as the effects of firm and labor market size are statistically significantly different from zero for almost all ability groups. However, we do not observe larger effects for high than for low ability workers in Figure 3. This suggests that it is the positive relationship between investments in human capital captured by κ and ability that explains why more able workers receive a higher return on one year of work experience and why they benefit more from acquiring experience in large firms and big cities than those with a lower ability level.

[Figure 3 about here]

Gains from learning at work accumulate over time and, thus, their contribution to wages in new employment relationships increases over the individual working life, even though the speed and the extent

[22] The differentiated role of size at the two scales is captured by the negative interaction effect $\tilde{\omega}$ for high ability workers in Figure 1. The city effect ρ and the interaction effect ω cancel out each other if establishment size amounts to 1150 workers $(= \exp(-\tilde{\rho}/\tilde{\omega}) \times$ av. establishment size $= \exp(-.006916/-.002299) \times 56.8$ workers).

[23] Unfortunately, there is no data that allows us to directly estimate the effect of training on the value of work experience. We lack information on participation of workers in advanced training in the IEB. At the establishment level, there is data on the provision of training for around 1 percent of all firms in the IEB beginning in 1999 (see Section 7.1).

of corresponding wage growth significantly differ between workers at the bottom and at the top of the ability distribution. For instance, entry wages of workers with the highest fixed effects more than double within the first 10 years after labor market entry, ceteris paribus, while entry wages of workers at the other end of the distribution grow by less than 20 percent in the same time span (Figure A3 in the Appendix).[24]

Likewise, the benefit from experience acquired in large firms and labor markets accumulates over time. To study this in more detail, we consider the elasticity of entry wage with respect to the size of all previous employers and their locations for different levels of experience in Figure 4. The accumulated benefit from size varies across different stages of working life and between workers with different ability level. On average, workers experience a steep rise in the wage elasticity with respect to firm and labor market size in the first years after labor market entry (Figure 4a), i.e. those years in which they undertake most human capital investments. Interestingly, we obtain an estimate of 0.0288 (Figure 4a) which is remarkably close to the dynamic agglomeration effect of 0.0287 estimated by De La Roca and Puga (2017) if we evaluate the wage elasticity with respect to previous labor market size at the same level of experience (7.72 years) and omit the firm effect. This elasticity drops by more than 26 percent to 0.0212 once we consider the size of previous employers in addition. The wage elasticity with regard to the latter is 0.0259 at this level of experience.[25]

However, not all workers benefit equally. It is particularly beneficial for workers at the top of the ability distribution to gain experience in large establishments and labor markets in the early phase of their career (Figure 4b). About ten years after entering the labor market, where the wage elasticities of the most able workers with respect to the size of previous employers and labor markets are both about 4.3 percent, the accumulated benefit of size starts to decline. At the very end of the working life, the returns to size are small for all types of workers.

[Figure 4 about here]

This inverted U-shaped relationship between gains from size and experience is also in line with results by De La Roca and Puga (2017) with regard to city size. Their estimates for the benefit from acquiring experience in the biggest Spanish cities describe a pattern over a 40-years period that is quite similar to the ones in Figure 4. However, when discussing earning-experience profiles, the authors focus on the first 10 years after labor market entry, where benefits from size are still increasing over time.

An explanation why accumulated gains from labor market and firm size may decline at a specific stage of working life is provided by our conceptional framework: Old workers invest little in the acquisition

[24] According to our underlying conceptual framework, a second reason behind wage growth is that the share of potential earnings that is spent on knowledge acquisition decreases in the course of working life.

[25] Porcher et al. (2023) who use the same data as De La Roca and Puga (2017) find a dynamic agglomeration effect of 0.0174 for workers with 7.7. years of experience in their baseline specification and an elasticity of 0.0166 if they estimate it conditional on the size of the establishment in which the experience is used, i.e. the size of the *current* employer. The authors do not consider the size of the establishments in which experience was acquired, i.e. *past* firm size as we do. For a discussion of the relative importance of current and past firm size for dynamic agglomeration effects see also Section A2.2 in the Appendix.

of human capital and due to a significant depreciation of human capital, workers nearing retirement do not benefit substantially from having worked in large firms or large labor markets in the early phase of working life when investment rates were high.[26]

7 Evidence on potential mechanisms

Various activities likely give rise to human capital accumulation. Learning might arise from informal training and interaction with co-workers within the same firm or from knowledge exchange with other workers outside the firm, but within the same local labor market. Moreover, specialized training departments in large firms or outside contractors from the local training sector may offer formal training separated from day-to-day work.

Our analysis does not provide direct evidence on the significance of these distinct activities for learning and whether they provide an explanation for the role of size. We focus on the importance of size at different spatial scales for the value of work experience. However, in this section, we present some descriptive findings on two potential mechanisms that may establish a link between learning benefits and size at the firm level and at the level of local labor markets. First, we examine whether the provision of training changes with establishment size and city size. Second, we investigate the relationship between the frequency of firm-to-firm mobility of workers and the size of local labor markets and firms.

7.1 Size and employer-provided training

In the literature dealing with the firms' decision to invest in training of their workers, there are arguments for an important role of size both at the firm and at the city level. Large firms may substitute training for recruiting new workers if monitoring becomes more costly as firm size increases (Barron et al., 1987) and benefits from investing in specialized skills might only be feasible in large firms or large labor markets (Rosen, 1983; Duranton and Puga, 2004). Moreover, both the returns to training and the risk of poaching likely increase with the size of the local labor market (Brunello and Gambarotto, 2007).

To study the correlation between a firm's decision to provide training and firm as well as labor market size (conditional on other covariates), we estimate logistic regressions and make use of additional (establishment level) panel data from Germany. We merge annual information on training available in the IAB Establishment Panel with information on different establishment characteristics in the IAB Establish-

[26] Our main analysis is restricted to workers who were 51 years old or younger during the 2005–2011 observation period. We obtain a very similar pattern for the evolution of accumulated learning benefits during working life if we also include workers born before 1960 in our analysis (see Figure A6). The older workers are dropped in our main analysis since we do not observe when and where these workers acquired experience prior to 1975 (see data description).

ment History Panel.[27] For our analysis we use about 190,000 year-establishment observations referring to the period 2000–2017 and about 52,000 establishments. The dependent variable is a binary variable indicating whether an establishment provided training in the respective year.

The results in Table 3 indicate a positive correlation between an establishment's probability to provide training and local labor market size. According to the (unconditional) odds ratio, the odds of providing training is 1.05 times larger if population density of the local labor market doubles [$= \exp(\ln(1.067) \times \ln(2))$]. If we address that larger firms may provide training more often than small firms (Column (2)), we obtain a smaller but still statistically significant effect for labor market density. Hence, as with our results for the benefit from acquiring work experience in large labor markets (Table 2), we observe that a higher chance of receiving training in a big city is to some extent related to larger firms being over-represented in these regions.

We include additional establishment characteristics in Column (3). The correlation between density and advanced vocational training disappears once we control for a number of additional observable characteristics. Thus, higher rates of training in large cities seem to be entirely driven by observable firm attributes. In contrast, the positive effect of establishment size turns out to be robust and economically meaningful. For instance, medium-sized establishments employing a workforce of 100 up to 199 workers are around 12 times more likely to provide training than very small establishments with less than 5 workers. The size of the effect increases steadily with the number of workers employed in the establishment.[28]

Furthermore, the results for the composition of an establishment's workforce indicate that employers with a high share of high-skilled workers are more likely to provide training than those with a high share of low-skilled workers, conditional on establishment size and other covariates. This is in line with the observation that skill groups in Germany participate differently in training (Wotschack, 2020). An increase in the establishment's share of high-skilled workers by ten percentage points is associated with an increase in the odds of training provision by 8 percent [$= \exp(\ln(2.211) \times 0.1) - 1 \times 100$ %], for instance. Insignificant interactions between labor market size and firm size categories in Column (4) indicate that small firms are less likely to provide training irrespective of the size of the local labor market in which they locate.

[Table 3 about here]

Altogether, the results of this complementary analysis are in line with the hypothesis that the benefit from acquiring work experience in large firms and large local labor markets might at least to some extent be related to the fact that large establishments and those in big cities generally provide more often training than small firms and firms located in small local labor markets. However, there is no support for the

[27] The former is a representative survey which covers about 16,000 establishments each year. The latter provides detailed administrative data and covers all establishments with at least one worker subject to social security. Eberle and Schmucker (2017) and Bechmann et al. (2021) provide detailed descriptions of the data sets.

[28] Our results are partly in line with findings by Brunello and Gambarotto (2007) and Muehlemann and Wolter (2011). They show that training is less frequent in economically denser areas in the UK and the Switzerland. In contrast, firm size increases the likelihood of workers' training participation.

hypothesis that an urban environment fosters the provision of employer-provided training. The results suggest that the high value of work experience acquired in large cities is partly caused by a spatial sorting of firms that offer more formal training.

The different importance of firm size and city size for employer-provided training might provide an explanation for the irrelevance of local labor market size as to the value of work experience of high ability workers who are employed in large establishments (see Figures 2c and 2d). Extensive training and other learning resources available in large firms might render city size insignificant. In addition, different patterns across ability groups illustrated by Figure 2 may be related to the fact that training opportunities offered by (large) employers or training participation seem to increase with the skill-level of a worker.

7.2 Frequency of establishment changes in large labor markets

Combes and Duranton (2006) argue that firm-to-firm labor mobility might be an important channel through which learning takes place within local labor markets. Several studies show that firms benefit from hiring workers from high productivity firms or multinationals (e.g. Balsvik, 2011; Stoyanov and Zubanov, 2012; Stoyanov and Zubanov, 2014; Poole, 2013). Whether these effects of labor mobility can explain agglomeration economies is, however, not considered in these studies. In contrast, Serafinelli (2019) examines learning benefits which arise from job changes between firms that are located in the same local labor market.

We use a 5 percent random sample of all employees in the IEB in the period 2005–2011 to investigate labor mobility, its spatial range and the role of firm and labor market size for job changes. The data includes more than 5.8 million worker-year-observations and enables us to identify whether a worker changes the establishment between two reference dates by comparing the establishment identifier of the corresponding IEB spells. The average share of establishment changes amounts to 8.8 percent of all worker-year-observations (see Table A14 in the Appendix). However, the percentage of changes increases with the density of the local labor market. While we observe a share of 7.9 percent in the second-lowest density category, establishment changes amount to 10.6 percent in the most dense areas. There is a similar pattern for workers with a university degree at a slightly higher level (average share of changes 9.9 percent).

To investigate whether the differences between the region types are primarily caused by a sorting of more mobile workers into large cities, we apply logistic regressions with a binary variable that indicates whether a worker changed the establishment between two reference dates as the outcome. The pivotal explanatory variable is the local employment density. Table 4 shows the results of different specifications. The unconditional correlation between labor market size and the probability of a job change is positive and highly significant (see Column (1) for the entire sample and Column (4) for the high-skilled in the upper panel of Table 4). Including a number of worker and establishment characteristics in Columns (2)–(3) and (5)–(6) reduces the correlation, indicating that some sorting takes place. However, workers who are employed in large cities show a higher probability of a job change even if we control for different characteristics of workers and the workplace (including firm size), suggesting that it is not simply sorting that gives rise to more frequent firm-to-firm mobility. The results by firm size categories (lower panels of Table 4) show that the positive relationship between labor market size and job switching also holds for firms of different size. The correlation is somewhat stronger for high-skilled workers in large establishments than for those working in small establishments.

[Table 4 about here]

The results in Table 5 indicate that these job changes tend to be highly localized, in particular in very large local labor markets. The share of job changes within a 25 km radius significantly increases as we move from the lowest to the highest density category. In the most dense areas almost 70 percent of all workplace changes take place within a 25 km radius. Interestingly, this share is high (63 percent) also among high-skilled workers whose mobility might be of above-average importance for learning benefits that large cities offer as discussed by, e.g., Davis and Dingel (2019). If these establishment changes involve in fact learning benefits, corresponding effects will be highly localized as well.[29]

[Table 5 about here]

Our analysis does not provide direct evidence on an above-average transfer of knowledge between firms that might result from worker mobility in large cities. However, it supports the hypothesis that learning effects in large cities rely on faster knowledge exchange, which is due to a higher frequency of localized firm-to-firm mobility of workers in dense labor markets. The positive correlation between local labor market size and the probability of firm-to-firm mobility together with the fact that distance acts as a strong barrier for mobility suggests that any learning potential induced by firm-to-firm changes is likely higher in large cities. Corresponding learning benefits that big cities potentially offer might be relatively important for workers in rather small establishments because the latter tend to have less internal resources to promote knowledge acquisition as indicated by the results on employer-provided training in Section 7.1. In particular high-ability workers, who devote significantly more time to knowledge exchange than lower ability workers, might be reliant on learning opportunities that the local labor market provides if they are employed in small firms in which internal training resources are scarce. The relative importance of labor market size for employees in small establishments might be reinforced by the fact that these firms are more likely to hire workers from the local labor market than large establishments (Table 6).

[Table 6 about here]

[29] Our results are only partly in line with the findings of previous studies. For instance, Bleakley and Lin (2012) report lower rates of job changing in more dense areas in the U.S., while results by Andersson and Thulin (2013) indicate that doubling the local employment density increases the probability of a job change by 0.2 percentage points in Sweden.

8 Conclusions

We examine where valuable work experience is primarily acquired and distinguish learning effects which are related to firm size and local labor market size. We quantify learning effects at the two spatial scales using administrative linked employer-employee data for Germany with information on individual employment biographies dating back up to 1975. The results indicate that wages tend to increase with both, size of local labor markets and of establishments in which experience was accumulated. However, the effect of firm size appears to be stronger. On average, more than a quarter of the dynamic benefits of working in large cities seem to be due to working in large firms rather than to labor market size.

High ability workers and young employees benefit most from the advantages of size. Our results suggest that this advantage is due to higher investments in human capital accumulation of more able and young workers compared to less able and older workers. Moreover, the importance of city size for the most able workers decreases with the size of the establishments in which they gain experience. (Internal) learning opportunities that large establishment may offer seem to completely compensate these workers for lacking labor market size in smaller cities. Low-ability workers are, in contrast, not sheltered from lacking size of local labor markets by opportunities that large firms offer.

Complementary analyses on potential mechanisms suggest that the high value of work experience acquired in big cities might at least partly be caused by a spatial sorting of (large) firms that offer training. High rates of employer-provided training in large cities can be ascribed to this sorting. Heterogeneous participation rates across ability levels might explain, furthermore, why low ability workers suffer from lacking city size even if they are employed by a large firm, in contrast to the most able workers. In addition, we observe that worker mobility between firms is higher in large than in small local labor markets. Therefore, labor market size might matter when it comes to the transmission of knowledge between firms that presumably increases the potential for learning in the recruiting firm. Worker mobility might thus be a key mechanism behind significant learning effects ascribed to workplaces in large urban areas. The findings suggest that learning benefits of big cities are due to different mechanisms which operate at different spatial scales.

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Tables and Figures

Table 1: Correlation between AKM-worker fixed effects and the average size of firms and local labor markets in which experience was acquired

	All workers	Deciles of AKM-worker fixed effects 1	2	3	4	5	6	7	8	9	10
	Correlation with individual AKM-worker fixed effect: Spearman's rank correlation coefficient										
ln(av. firm size)	0.2173	0.0324	0.0202	0.0061	0.0179	-0.0108	0.0202	0.0177	0.0275	0.0680	0.0743
ln(av. labor market size)	0.1686	-0.0308	0.0080	-0.0070	0.0100	-0.0085	0.0189	0.0306	0.0571	0.0616	0.0625
	Regression results, dependent variable: individual AKM-worker fixed effect										
ln(av. firm size)	0.114***	0.00534	0.00170**	0.000499	0.000394	-0.0000227	0.000562*	0.000134	0.000725	0.00540***	0.00268
	(0.00157)	(0.00527)	(0.000623)	(0.000325)	(0.000260)	(0.000246)	(0.000249)	(0.000306)	(0.000466)	(0.000808)	(0.00234)
ln(av. labor market size)	0.0879***	-0.0351***	0.000293	-0.000560	0.000299	-0.000380	0.000631	0.00150***	0.00411***	0.00712***	0.0174***
	(0.00213)	(0.00619)	(0.000788)	(0.000426)	(0.000349)	(0.000324)	(0.000356)	(0.000443)	(0.000675)	(0.00125)	(0.00364)
Constant	-0.843***	-1.491***	-0.677***	-0.402***	-0.227***	-0.0627***	0.0893***	0.275***	0.515***	0.902***	1.716***
	(0.0111)	(0.0344)	(0.00433)	(0.00231)	(0.00189)	(0.00173)	(0.00189)	(0.00236)	(0.00370)	(0.00705)	(0.0229)
N	147,614	14,762	14,761	14,763	14,761	14,761	14,762	14,761	14,761	14,761	14,761
R^2	0.0621	0.00228	0.000561	0.000232	0.000244	0.000102	0.000723	0.000900	0.00323	0.00689	0.00223

Notes: Average firm size and average labor market size are the geometric mean of the size of all previous employers in terms of employment and of the employment density of the local labor markets in which these establishments were located, respectively. In Column 1 all workers are included. In Columns 2-11, we consider sub-samples comprising about ten percent of the workers. Thresholds are the deciles of the AKM-worker fixed effects. ***, ** and * indicate significance at the 0.1, 1 and 5 percent level. Robust standard errors are given in parentheses. For some sub-samples, the regression results point to a statistically significant correlation between worker fixed effects and, in particular, labor market size. However, in a model with almost 15,000 observations and only 3 parameters the statistical significance of the slope coefficient is not particularly meaningful. More important, in each sub-sample the R^2 is far below 1 percent and, thus, virtually zero.
Source: IEB and Bellmann et al. (2020), own calculations.

Table 2: Baseline regression results for full sample

	(1)	(2)	(3)	(4)
general experience ($\tilde{\gamma}$)	0.0442***	0.0432***	0.0431***	0.0430***
	(0.00196)	(0.00172)	(0.00163)	(0.00164)
previous firm size ($\tilde{\delta}$)		0.00550***	0.00501***	0.00493***
		(0.000206)	(0.000213)	(0.000200)
previous city size ($\tilde{\rho}$)	0.00556***		0.00401***	0.00403***
	(0.000404)		(0.000402)	(0.000410)
prev. firm size × prev. city size ($\tilde{\omega}$)				0.000330**
				(0.000153)
learning effort (κ)	0.458***	0.438***	0.437***	0.437***
	(0.0117)	(0.0112)	(0.0112)	(0.0112)
depreciation rate (θ^y)	0.206***	0.201***	0.200***	0.201***
	(0.00944)	(0.00713)	(0.00762)	(0.00768)
N	147,614	147,614	147,614	147,614
$R^2_{adj.}$	0.705	0.707	0.708	0.708
R^2	0.708	0.710	0.710	0.710
RSS	10866.805	10794.975	10768.821	10767.957

Note: Dependent variable is the log daily wage. $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the results for Equation (9) which are summarized in Table A7. The results refer to the value of the previous year of work experience as reflected in the entry wage about 14 years (5,185 days) after labor market entry for a worker who entered the labor market 45 years (16,266 days) prior to retirement age. Depreciation rate θ is expressed in years. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 labor market regions. All regressions include control variables (see Table A8), pre-determined AKM-worker and AKM-establishment fixed effects estimated by Bellmann et al. (2020) as well as industry, occupation, and region-year fixed effects.
Source: IEB, own calculations.

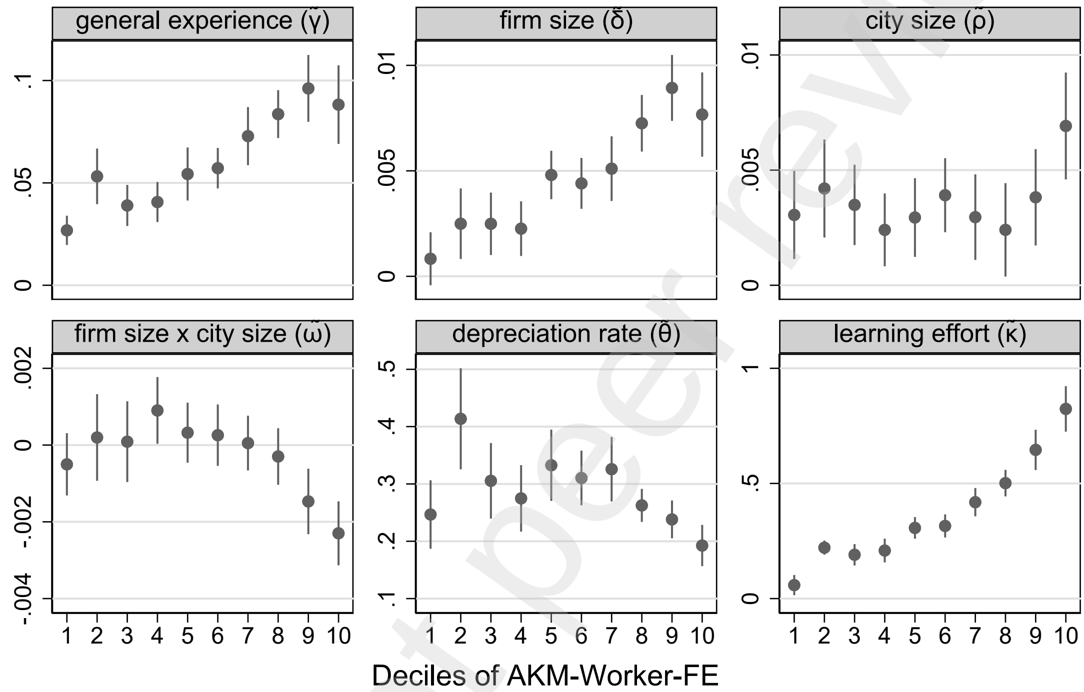
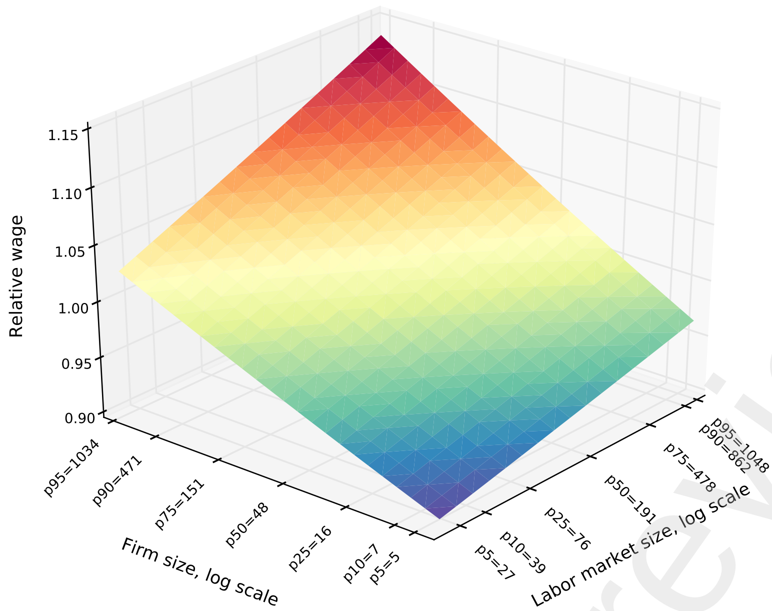
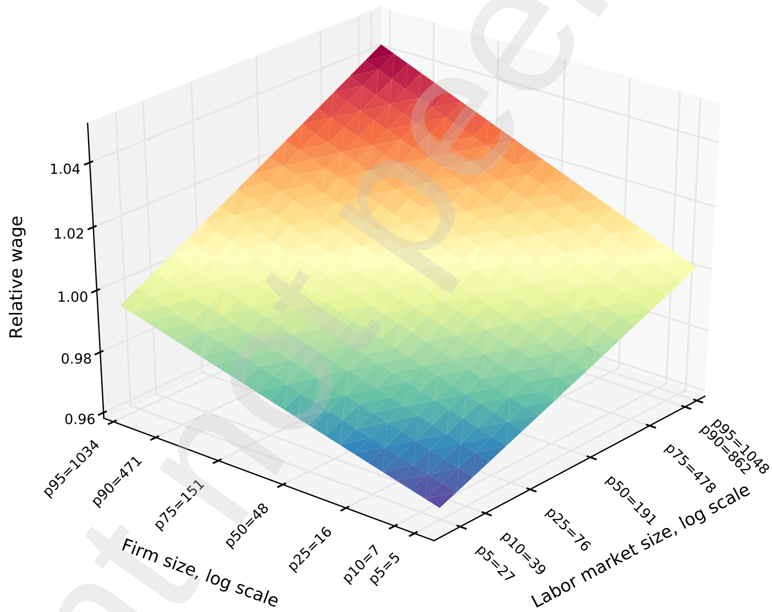


Figure 1: Heterogeneous effects across ability levels

Notes: The figure summarizes the results of ten separate regressions of Equation (9) where we distinguish between workers according to the AKM-worker fixed effect estimated by Bellmann et al. (2020). Thresholds of the ten sub-samples are the deciles of AKM-worker fixed effects. Results for the full sample are given in Column (4) of Table 2. $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the parameter estimates reported in Figure 3. The results presented here refer to the value of the previous year of work experience as reflected in the entry wage 14 years (5,185 days) after labor market entry for a worker who entered the labor market about 45 years (16,266 days) prior to retirement age. Depreciation rate θ is expressed in years.
Source: IEB, own calculations.

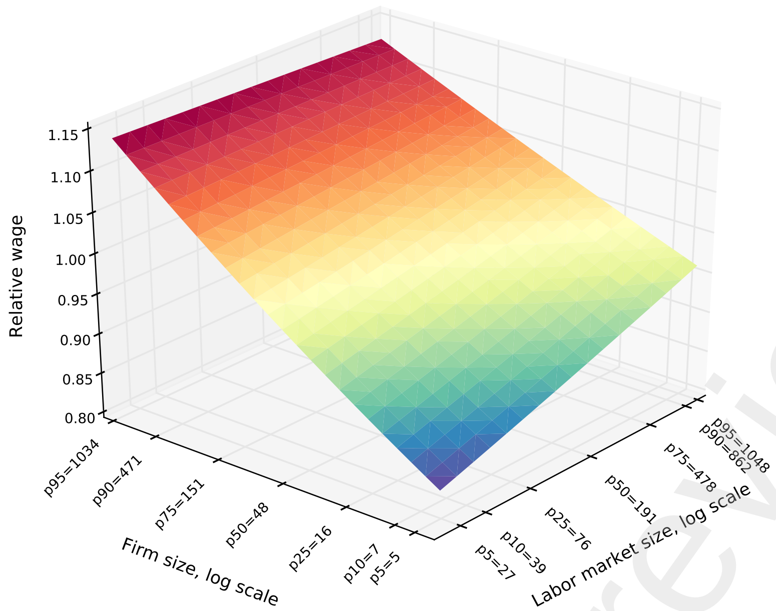


(a) Full sample

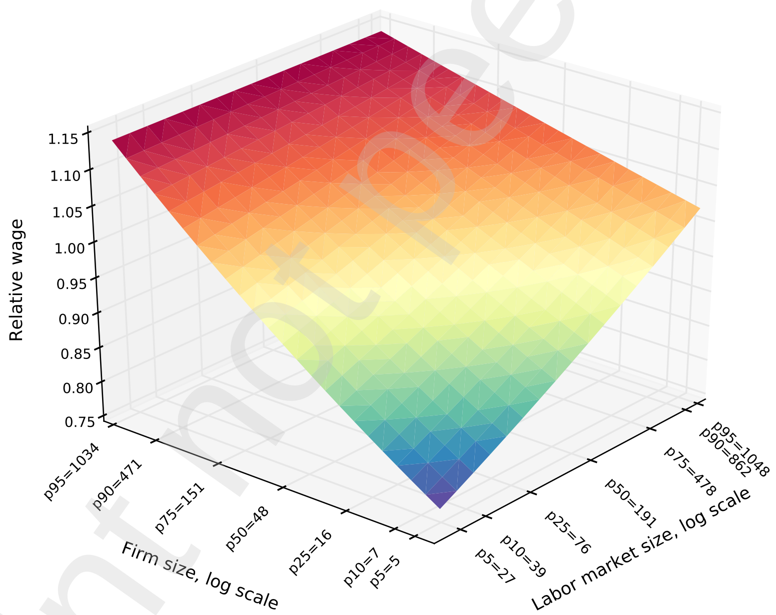


(b) Workers with an AKM-worker fixed effect between the 10th and the 20th percentile

Figure 2: Relative wage after 14 years of work experience depending on where experience was acquired (continues on next page)



(c) Workers with an AKM-worker fixed effect between the 80th and the 90th percentile



(d) Workers with an AKM-worker fixed effect higher than the 90th percentile

Figure 2: Relative wage after 14 years of work experience depending on where experience was acquired (continued)

Notes: The value of work experience has been computed based on the parameter estimates reported in Column (4) of Table A7 (Figure a) and Figure 3 (Figures b-d). The reference worker gathered 14 years of work experience in an average-sized establishment (57 employees) located in an average-sized labor market (184 employees/km^2). For the length of individual working lives (T) 45 years (16,266 days = sample mean) is assumed. Furthermore, it is assumed that a worker was never unemployed since the beginning of working life. The percentiles of firm size (employees) and labor market size (employees/km^2) refer to the distribution of the considered new employment relationships across previous employers and labor markets, respectively.
Source: IEB and Bellmann et al. (2020), own calculations.

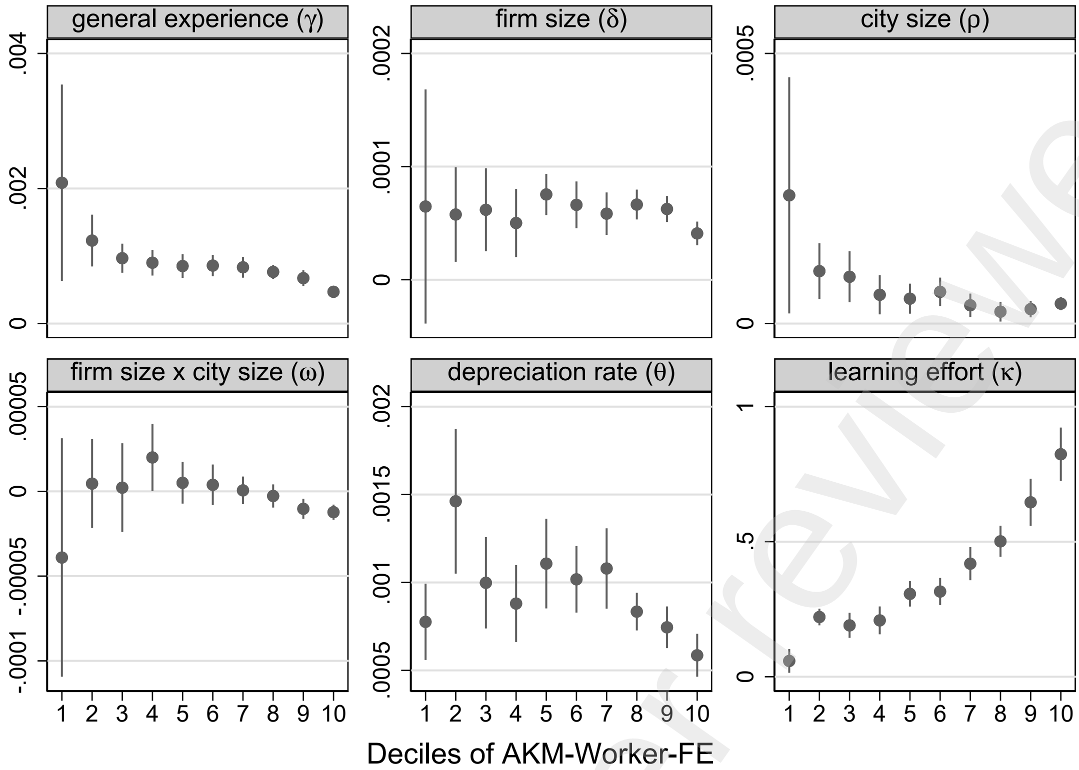
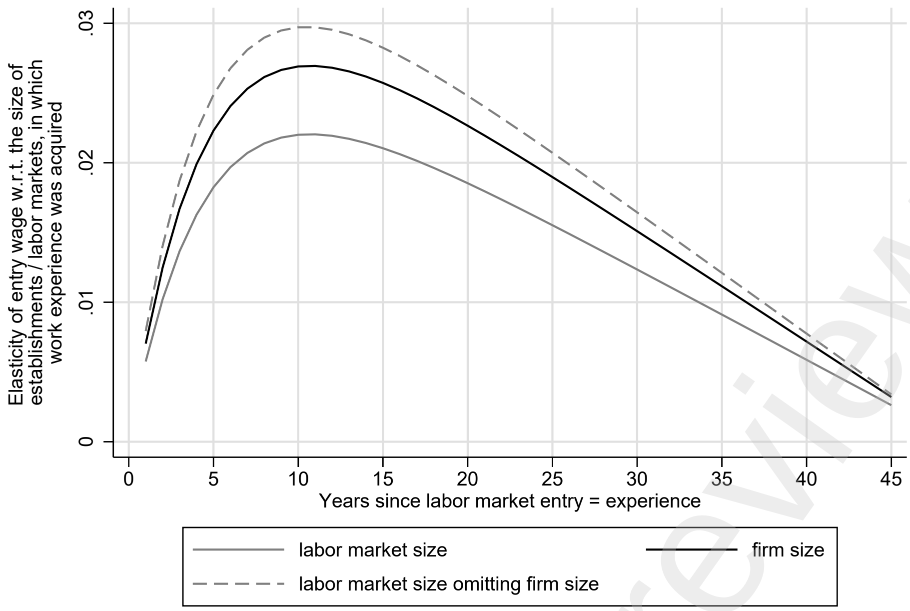
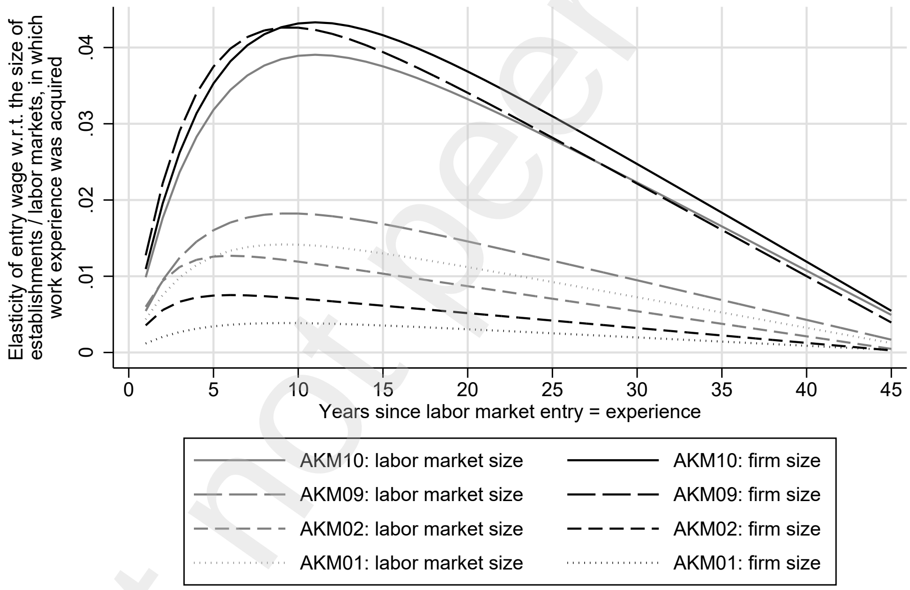


Figure 3: Parameter estimates by ability level

Notes: The figure summarizes the results of ten separate regressions of Equation (9) where we distinguish between workers according to the AKM-worker fixed effect estimated by Bellmann et al. (2020). Thresholds of the ten sub-samples are the deciles of AKM-worker fixed effects. Results for the full sample are given in Column (4) of Table A7. The parameters reported here were used to compute the effects reported in Figure 1, inter alia.
Source: IEB, own calculations.



(a) Full sample



(b) Distinct groups of workers with low / high ability levels

Figure 4: Elasticity of entry wage w.r.t. the size of the establishment and of the local labor market in which experience was acquired

Notes: (a) is based on the parameter estimates reported in Columns (1) and (4) of Table A7. (b) is based on the results summarized in Figure 3. For the evaluation of the effect of firm size, it is assumed that experience was acquired in a labor market with an average size so that the interaction of firm and labor market size is zero. For the evaluation of the effect of labor market size, it is assumed that experience was acquired in firms with an average size. AKM01 and AKM02 refer to the two groups of workers with the lowest AKM-fixed effect estimated by Bellmann et al. (2020) and AKM09 and AKM10 denote the two groups of workers with the highest AKM-fixed effect. Thresholds of the sub-samples are the deciles of AKM-worker fixed effects. In each case the length of individual working life (T) is assumed the be almost 45 years (16,266 days = sample mean) and it is assumed that a worker was never unemployed since the beginning of working life. Entry wages are only observed up to 36 years after labor market entry (p99: 29 years, p95: 24 years). Results for a sample that also includes workers with more than 36 years of experience are summarized in Figure A6.
Source: IEB and Bellmann et al. (2020), own calculations, illustration based on Peters (2020).

Table 3: Correlation between training provision, establishment size and local labor market size – results from a logistic regression

	(1)	(2)	(3)	(4)
ln(employment density)	1.067***	1.043***	0.989	1.012
	(0.008)	(0.008)	(0.008)	(0.019)
Establishment size – reference: less than 5 workers				
5 - 9 workers		2.292***	2.234***	2.233***
		(0.062)	(0.062)	(0.062)
10 - 19 workers		3.489***	3.356***	3.355***
		(0.102)	(0.105)	(0.105)
20 - 49 workers		6.077***	5.325***	5.323***
		(0.165)	(0.169)	(0.169)
50 - 99 workers		10.727***	7.940***	8.179***
		(0.381)	(0.335)	(0.377)
100 - 199 workers		19.011***	12.199***	12.562***
		(0.818)	(0.620)	(0.671)
200 - 499 workers		34.041***	18.485***	19.002***
		(1.772)	(1.157)	(1.246)
500 - 999 workers		76.765***	34.944***	35.160***
		(8.379)	(4.083)	(4.962)
1000 - 4999 workers		143.461***	56.839***	57.200***
		(27.875)	(11.664)	(10.985)
Qualification of establishment's workforce				
Share high-skilled workers			2.211***	2.211***
			(0.124)	(0.124)
Share low-skilled workers			0.504***	0.504***
			(0.029)	(0.029
Labor market size $\times$ establishment size – reference: 50 - 499 workers				
ln(employment density) $\times$ establishment size $<$ 50 workers				0.973
				(0.020)
ln(employment density) $\times$ establishment size $\geq$ 500 workers				0.979
				(0.087)
Constant	1.761***	0.341***	0.327***	0.324***
	(0.034)	(0.009)	(0.027)	(0.027)
Establishment-year observations	192,371	192,371	192,371	192,371
Industry fixed effets	No	No	Yes	Yes
Indicator variables for legal form and work council	No	No	Yes	Yes
Indicator variables for the type of establishment	No	No	Yes	Yes
Information on workforce composition	No	No	Yes	Yes

Note: Exponentiated coefficients are reported and robust standard errors adjusted for establishment clusters are given in parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent level. All models include year fixed effects. Employment density is the number of inhabitants per km^2 at county level. The information on the workforce composition in Modell (3) comprise the share of low-skilled and high-skilled workers, of part-time workers, of females and of different age groups. Workers with a university degree / degree in applied sciences are considered high-skilled. Workers who have neither a university degree nor a vocational training degree are considered low-skilled.
Source: IAB-Establishment Panel, own calculations.

Table 4: Correlation between the probability of job change and local labor market size

	(1)	(2)	(3)	(4)	(5)	(6)
	full sample					
	all workers			high-skilled workers		
ln(labor market size)	0.00431***	0.00386***	0.00452***	0.00463***	0.00330***	0.00371***
	(0.000100)	(0.000105)	(0.000107)	(0.000308)	(0.000333)	(0.000347)
N	4,458,873	4,458,873	4,458,873	602,952	602,952	602,952
pseudo R2	0.001	0.090	0.091	0.001	0.060	0.062
	workers employed by a small firm (< 50 workers)					
	all workers			high-skilled workers		
ln(labor market size)	0.00506***	0.00461***	0.00483***	0.00754***	0.00339***	0.00335***
	(0.000186)	(0.000188)	(0.000191)	(0.000633)	(0.000668)	(0.000690)
N	1,496,297	1,496,297	1,496,297	140,145	140,145	140,145
pseudo R2	0.001	0.075	0.075	0.002	0.059	0.059
	workers employed by a medium-sized firm (50-249 workers)					
	all workers			high-skilled workers		
ln(labor market size)	0.0110***	0.00368***	0.00497***	0.00901***	0.00281***	0.00378***
	(0.000190)	(0.000195)	(0.000201)	(0.000598)	(0.000637)	(0.000672)
N	1,357,435	1,357,435	1,357,435	164,969	164,969	164,969
pseudo R2	0.005	0.099	0.102	0.002	0.068	0.070
	workers employed by a large firm ($\geq$ 250 workers)					
	all workers			high-skilled workers		
ln(labor market size)	0.00780***	0.00390***	0.00475***	0.00436***	0.00386***	0.00433***
	(0.000163)	(0.000178)	(0.000186)	(0.000460)	(0.000510)	(0.000539)
N	1,605,053	1,605,053	1,605,053	297,565	297,565	297,565
pseudo R2	0.004	0.089	0.091	0.001	0.059	0.061

(1) + (4) without control variables
(2) + (5) conditional on individual and establishment characteristics (age and its square, tenure at the current job and its square, average tenure in previous jobs and its square, experience of the worker and its square as well as indicators for age and size of the establishment) and fixed effects for year, industry, occupation, gender and educational level
(3) + (6) like (2) + indicator variables for AKM-firm fixed effects estimated for the period 1998-2004 and the establishment's share of high- and low-skilled labor
Notes: The table summarizes results of 24 logistic regressions. The reported coefficients are marginal effects. Robust standard errors are given in parentheses. *** indicates significance at the 1 percent level. The dependent variable is an indicator variable which is one if a worker changed the establishment from one to another year in the period 2005 to 2011 (reference date: June 30) and zero if she stayed at the establishment. Labor market size refers to the number of employees per km^2 10 km around the center of the municipality of an establishment's location.
Source: IEB, own calculations.

Table 5: Job changes by distance and labor market size

Category of labor market size	Distance between the former and the new workplace (at municipality level) at most...							
	all workers				high-skilled workers			
	25 km	50 km	75 km	100 km	25 km	50 km	75 km	100 km
1 (lowest)	61.4%	78.5%	83.9%	86.9%	41.7%	62.4%	70.8%	76.0%
2	63.2%	79.9%	84.7%	87.3%	45.3%	65.4%	72.7%	76.6%
3	64.5%	79.6%	84.6%	87.5%	46.1%	63.4%	70.8%	76.5%
4	64.4%	78.7%	83.6%	86.2%	45.8%	62.6%	69.7%	74.4%
5	64.7%	77.5%	82.7%	85.6%	48.0%	61.6%	68.9%	73.5%
6	65.6%	76.5%	81.3%	84.1%	52.0%	63.5%	69.7%	73.7%
7	64.6%	75.6%	80.8%	83.4%	51.8%	63.0%	69.4%	72.9%
8	66.2%	76.4%	81.2%	83.5%	54.9%	66.0%	71.9%	74.9%
9	67.8%	75.2%	79.1%	81.2%	58.2%	65.9%	70.4%	72.9%
10 (highest)	69.8%	76.0%	78.8%	79.9%	63.3%	68.7%	71.7%	72.9%
Total	65.4%	77.3%	81.9%	84.3%	53.5%	65.0%	70.6%	73.9%

Notes: The table is based on information about 518,873 workers who changed the establishment from one to another year in the period 2005-2011 (reference date: June 30). Workers with a university degree / degree in applied sciences are considered high-skilled (N=75,362). Labor market size refers to the number of employees per km^2 10 km around the center of the municipality in which the former establishment was situated. The ten categories are defined such that all worker-year observations – those of mobile and immobile workers – are equally distributed across groups.
Source: IEB, own calculations.

Table 6: Distance between the former and the new workplace by size of hiring establishment

Category of firm size	Distance in km at municipality level					
	all workers			high-skilled workers		
	p50	p75	p90	p50	p75	p90
1 (lowest)	10.3	28.9	122.9	16.7	72.0	284.5
2	11.2	31.0	128.9	17.2	71.5	254.5
3	12.2	35.3	157.5	20.5	90.0	304.7
4	13.3	39.6	181.0	21.6	103.7	311.4
5	13.7	43.5	192.5	21.7	111.2	304.3
6	13.8	47.6	199.0	22.5	112.4	316.3
7	14.3	52.8	225.4	23.9	130.0	327.0
8	13.9	54.7	233.4	23.3	130.5	321.8
9	13.4	57.3	247.5	23.3	123.0	318.3
10 (highest)	10.2	56.9	254.5	17.6	128.5	328.1
Total	12.4	42.2	194.7	20.6	112.6	312.7

Notes: The table is based on information about 489,377 workers who changed the establishment from one to another year in the period 2005-2011 (reference date: June 30). Workers with a university degree / degree in applied sciences are considered high-skilled (N=69,504). Firm size refers to the number of employees of the hiring establishment. The ten categories are defined such that the hires are equally distributed across groups.
Source: IEB, own calculations.

Online Appendix

Contents

A1 Additional information on data

A1.1 Definition of the sample of new employment relationships

Following Peters (2020), we focus on workers with German nationality that were born in 1960 or later. For individuals born between 1960 and 1977, we require observing a period of employment in West Germany before re-unification (1990). These conditions reduce the risk of underestimating experience. The IEB do neither contain information about work experience acquired abroad, which would particularly be an issue if foreign workers were considered, nor provide information on work experience acquired in West Germany before 1975. Valid information on employment in East Germany is only available from 1993 onwards.[a] We further reduce the sample to be able to control for unobserved heterogeneity at the level of workers and the hiring establishments by means of worker and establishment coefficient estimates from an AKM (Abowd, Kramarz, and Margolis, 1999) regression provided by Bellmann et al. (2020) (see Section A1.3 for detailes). We exclude new employment relationships for which these fixed effects are not available.[b]

For the remaining workers, we consider all new employment relationships in the period 2005–2011 referring to regular employment subject to social security outside the public sector and outside the temporary employment industry with a length of at least 7 days. We focus on full-time employment since wages are only available on a daily basis and information on contract hours is not available. In addition, we only consider the first match of an establishment with the respective worker and exclude a new employment relationships if

- it is the first spell of employment in a person's life,
- there is a previous employment relationship that ends more than 7 days after the new employment relationship begins,
- it starts at the same time as another new employment relationship,
- it starts within 7 days before or after the beginning of certain active labor market policy measures that point to a subsidized employment relationship,
- the gross daily wage is below two times the marginal part-time income threshold of €13.15 in most of the considered years,
- information on the location of a previous workplace (firm or region) or the size of a previous

[a] As a robustness check, we also consider workers born between 1940 and 1960, although we cannot consider work experience acquired prior to 1975 and do not observe the date of individual labor market entry. Workers born before 1940 are excluded because they retire before 2005 (statutory retirement age: 65 years).

[b] With respect to most variables used in the analyses, the composition of the reduced sample is fairly similar to the larger sample that includes observations for which no AKM worker/establishment effects are available. However, young workers with few years of work experience are excluded relatively often: The mean of work experience increases from 7 years to 10 years (Table A2). The inclusion of the AKM fixed effects reduces our sample from about 350.000 to about 150.000 observations.

employer (in the year of employment) is missing,

- we cannot precisely measure the employment density of a local labor market in which experience was acquired[c],

- there is a missing value in one of the control variables.

A1.2 Imputation of missing values

Entry wage

Firms report earnings only up to the upper limit for social security contributions (2011: 66,000 € per year in West Germany, 57,600 € in East Germany). Therefore, the wage information in the IEB is right censored and we impute an uncensored value for each censored observation similar to, e.g., Card et al. (2015) and Dauth et al. (2021). Specifically, we follow Reichelt (2015) and apply an interval regression to estimate the wages above the threshold (about 7% of the considered entry wages in new employment) and add an error term to the estimates, i.e., a random value from a normal distribution. As the wage information is right censored, the interval regression is equivalent to a tobit regression. The random variable is drawn from a truncated distribution as suggested by Gartner (2005) to ensure the estimated wage is larger than the censoring limit. For the imputation we use information about sex, age, nationality, educational level, industry and the region in which the establishment is located. Logarithmic entry wage is the dependent variable in our regression analysis.

Industry

In 2008, a new classification of industries was introduced in Germany. To address this, we apply the two-step procedure proposed by Eberle et al. (2011) and transfer the assignment of an establishment to an industry in 2008 to new employment relationships with the respective establishment in earlier years. Likewise, we replace single missing values in the period 2008–2011 using information from other years in which corresponding information is available. If an establishment does only exist until 2007, we use the correspondence tables provided by Eberle et al. (2011) and merge the 2008 industry classification to the individual employment spells using information on the assignment of an establishment to an industry according to the 2003 industry classification. In the regression analysis, we use the industry identifier to include industry fixed effects and to merge information on the industrial composition of regional economies where new employment is taken-up.

Skill level

In the IEB, some spells do not contain information on the individual educational level. If so, we transfer the information from previous employment spells using the code provided by Fitzenberger et al. (2005). In the regression analysis, we use this information to include fixed effects for educational attainment and

[c] Valid information on employment in East German municipalities is only available from 1993 onwards. Hence, for West German municipalities along the former inner German border it is not possible to determine the local labor market density within 10 km for the years 1990–1992.

to define the day of individual labor market entry.

A1.3 Worker and establishment fixed effects

To account for unobserved heterogeneity, we include coefficient estimates of worker and establishment fixed effects as continuous variables in our regression model that have been estimated by Bellmann et al. (2020) based on the universe of all workers and establishments covered by the IEB and the largest connected set of movers, i.e. all establishments that are connected via mobile workers (Lochner et al., 2023; Lochner et al., 2020). We use these fixed effects since it is not feasible with our sample to estimate a corresponding AKM model because of our focus on wages observed for new employment relationships. Controlling for unobserved heterogeneity at the worker level applying the standard within estimator, we could only consider workers who take up a new job at least twice in the period 2005 to 2011. This approach would considerably reduce our sample to a probably highly selective group of workers. The same problem applies to unobserved heterogeneity at the establishment level. It is also not an option to estimate the complex non-linear model given by Equation (9) using the entire IEB to guarantee unbiased estimates of the fixed effects.

To decompose wages, Bellmann et al. (2020) applied the empirical strategy proposed by AKM (Abowd, Kramarz, and Margolis, 1999) which provides additive fixed effects for workers and establishments. The underlying regression model is given by:

$$\ln w_{i,t} = \zeta_i + \eta_{J(i,t)} + \mathbf{x}'_{i,t}\beta + \upsilon_{i,t}. \tag{A1}$$

where $w_{i,t}$ is the daily real wage of worker i in year t and $\upsilon_{i,t}$ is the error term. The model is estimated for different time intervals (1985-1992, 1993-1999, 1998-2004, 2003-2010, 2010-2017). The worker fixed effect ζ_i can be interpreted as a reward for ability and other (unobserved) factors that does not differ across firms and is constant during the corresponding time interval. The establishment fixed effect $\eta_{J(i,t)}$ with $J(i,t)$ indicating the establishment that employs worker i in year t captures a pay premium (or discount) that is paid by establishment J to all workers who are employed in the establishment in the corresponding time interval. As argued by Card et al. (2015), η_J might reflect rent-sharing, an efficiency wage premium, or strategic wage posting behavior of firms. $\mathbf{x}_{i,t}$ denotes time-varying observable worker characteristics, i.e. quadratic as well as cubic terms in age which are fully interacted with the educational attainment of the worker, as well as year dummies.

To avoid potential endogeneity, we use lagged worker and firm coefficient estimates for the period 1998–2004 in our regressions so that the estimation of the fixed effects does not include the new employment relationships starting in the period 2005–2011 which we analyze. We exclude new employment relationships for which these fixed effects are not available. Furthermore, we drop workers (about 3%) for which we observe a significant increase in the AKM worker fixed effect estimated by Bellmann et al. (2020) for the periods 1998–2004 and 2003–2010, respectively. More precisely, we drop all workers who are in the first or second decile of the 1998–2004 AKM worker fixed effect distribution, but in the upper half of the 2003–2010 AKM worker fixed effect distribution. We presume that the estimated AKM effect is not a good proxy for individual ability for these workers.

Limited mobility bias

A concern with respect to AKM fixed effects is the risk of a limited mobility bias. The firm-specific parameters in the AKM model are solely identified from mobile workers, i.e., employees who switch between firms. A limited mobility of workers across firms might impair the wage decomposition and result in significantly biased estimates of AKM fixed effects (Abowd and Kramarz, 2004; Andrews et al., 2008; Bonhomme et al., 2023). To address this issue, we apply two different approaches. The first one is to exclude small establishments with less than (i) 10 workers, (ii) 25 workers and (iii) 50 workers from the analysis as discussed by Bonhomme et al. (2023). This is supposed to increase the number of movers per firm assuming that in particular small establishments are characterized by only few entries and exists.

The second approach is to consider grouped fixed effects rather than a fixed effect of each plant (see Bonhomme et al., 2019; Bonhomme et al., 2022; Dauth et al., 2022). The underlying rationale is that there is much more mobility between clusters of establishments than between individual firms. To estimate group fixed effects, we make use of an annual worker panel that has been constructed based on all spells of employment subject to social security at June 30 in Germany. As with the AKM establishment fixed effects provided by Bellmann et al. (2020), we focus on the period 1998–2004 and allocate all establishments covered by the panel into 100 groups with similar wage structures using a k-means cluster analysis and considering 40 wage percentile for each establishment similar to Dauth et al. (2022). For each cluster, we estimate a fixed effect similar to the AKM model given by Equation (A1). The obtained grouped-fixed effects are then used as control variable in our main regression analysis (Equation (9)).[d] Table A11 summarizes the regression results of the different specifications which address the limited mobility bias in the AKM model.

[d] We are grateful to Luisa Braunschweig, Wolfgang Dauth, and Duncan Roth for providing the code for estimating grouped fixed effects models.

A1.4 Variables, descriptive statistics and analyses

Table A1: Variables - definitions and sources

Variable	Definition	Source
Gross daily wage	Daily wages are calculated by dividing the reported total earning from an employment spell by the length of the spell. The first employment spell in the IEB of a new employment relationship ends, at the latest, by December 31 of the year in which the new employment relationship starts. Information on actual working days or contract hours is not available. Wages above the upper limit for social security contributions are imputed (see Section A1.2).	IEB
Work experience and location of human capital accumulation	Length of previous employment spells subject to social security measured on a daily basis. Marginal employment is not considered, nor employment spells that refer to measures of active labor market policies. We also consider the size of establishments and local labor markets in which experience was acquired in terms of employment (see below).	IEB
Size of local labor market in which experience was acquired	Based on municipality data, we compute the number of workers at June 30 of the respective year (1975-2011) within a circle with a radius of 10 km (≈6.2 mi) around the geographic center of a municipality (Figure A1). If a municipality encompasses both areas inside and outside the circle of 10 km, we assume that employees and firms are evenly distributed across space within the municipality and assign a corresponding fraction of employment and firms to the considered local labor market.	IEB
Size of establishments in which experience was acquired	Based on data from the Establishment History Panel (BHP) of the IAB, we compute a three-year moving average of annual employment for every establishment considering employment reported for the years $t-1$, t and $t+1$ (referring to June 30) and merge this with the individual employment spells observed in year t. If an employment relationship ends before June 30 of year t, we only consider employment in the establishment at the reference days of years $t-1$ and t. Likewise, we consider employment at the reference days of years t and $t+1$ only if an employment relationship starts after June 30 in year t.	IEB
Tenure	Length of the new employment relationship in months. The corresponding employment spell ends at the latest by December 31 of the year in which the new employment relationship starts.	IEB
ln(Number of previous employers)	Number of unique establishment identifiers until the new employment relationship of the workers starts.	IEB
Educational level of the worker	Categorical variable that combines information about the highest schooling level attained, completed vocational training, and university degree/degree in applied sciences. For some spells of employment this information is missing. If so, we use the information from previous employment spells following Fitzenberger et al. (2005).	IEB
Gender	Dummy variable distinguishing male and female workers.	IEB
Length of non-employment	Number of days between the beginning of the new employment relationship and the end of the previous employment spell.	IEB
Pre-employment status	Dummy variables referring to the period 28 days before the considered transition to employment - unemployment benefits (Arbeitslosengeld I) - unemployment assistance (Arbeitslosengeld II / Arbeitslosenhilfe)	IEB

Table A1 continued

Variable	Definition	Source
	- unemployed and registered as a job seeker - not unemployed, but registered as a job seeker - participating in active labour market policy programms.	
Characteristics of hiring firm	Number of employees, share of workers with a university degree or degree in applied sciences, share of workers with no completed vocational training, share of workers aged 30 to 49 years, share of workers 50 years old or older. The information refers to the last reference date (June 30) before the considered transition.	Establishment History Panel (BHP)
Employment density	Number of workers within a circle with a radius of 10 km around the geographic center of the municipality in which the hiring establishment is located.	IEB
Industry share	Logarithm of the share of industry (2-digit level: 88 industries) in total employment in local labor market.*	Employment statistics of the Federal Employment Agency (FEA)
Industrial diversity	Logarithm of the inverse Herfindahl index based on the shares of industries in total employment in local labor market. The own industry is excluded when the inverse Herfindahl index is calculated as suggested by Combes and Gobillon (2015).*	FEA
Human capital in local industry	Share of workers with a university degree or degree in applies sciences in total employment in industry j in region r, and corresponding share of workers without completed vocational training/university degree.*	FEA
Skill-specific unemployment rate in local labor market	Share of unemployed in local labor force by skill level (university degree or degree in applies sciences, completed vocational training, no completed vocational training/university degree/degree in applied sciences). Logarithmic unemployment rates are set to zero if a worker does not belong to the considered skill group.*	(Un-)employment statistics of FEA
Industry fixed effects	Fixed effects for 88 industries (2-digit level according to classification from 2008), for details see, Section A1.2.	IEB
Occupation fixed effects	Fixed effects for 335 occupations.	IEB
Region-year fixed effects	Time varying fixed effects for the location of the establishment in which a person starts to work. The location refers to one of 141 functional labor market regions which are defined according to commuting intensity between counties (NUTS-3-regions) (see Kosfeld and Werner, 2012).	IEB

* The information refers to June 30th of the previous year and to local labor markets (N=141) as defined by Kosfeld and Werner (2012).

Note: Description based on Hamann et al. (2019) and Peters (2020).

Table A2: Summary statistics

	Initial sample (N=347,894)				Final sample (N=147,614)			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
ln(Gross daily wage)	4.113	0.476	3.267	7.192	4.214	0.502	3.267	7.192
Years of work experience	7.373	7.155	0.003	35.066	10.253	7.267	0.003	35.066
Size of workplace in which experience was acquired†:								
ln(Establishment employment)	3.909	1.766	0.000	11.026	3.982	1.656	0.000	10.881
ln(Employment density 0-10km)	5.214	1.204	−0.416	7.514	5.224	1.163	0.664	7.486
Education:								
Secondary / intermediate school leaving certificate								
. . . without completed vocational training	0.098	0.298	0.000	1.000	0.051	0.219	0.000	1.000
. . . with completed vocational training	0.670	0.470	0.000	1.000	0.729	0.444	0.000	1.000
Upper secondary school leaving certificate								
. . . without completed vocational training	0.025	0.156	0.000	1.000	0.009	0.094	0.000	1.000
. . . with completed vocational training	0.097	0.296	0.000	1.000	0.099	0.299	0.000	1.000
University of applied sciences degree	0.040	0.195	0.000	1.000	0.044	0.205	0.000	1.000
College / university degree	0.069	0.254	0.000	1.000	0.068	0.252	0.000	1.000
Female worker	0.362	0.481	0.000	1.000	0.292	0.455	0.000	1.000
Tenure (month)	5.942	3.610	0.033	12.000	5.993	3.618	0.033	12.000
ln(Number of previous employers)	1.321	0.760	0.000	4.575	1.632	0.687	0.000	4.575
Length of non-employment								
0-28 days (job-to-job transition)	0.626	0.484	0.000	1.000	0.622	0.485	0.000	1.000
28-92 days	0.112	0.315	0.000	1.000	0.106	0.308	0.000	1.000
93 days - 1 year	0.131	0.337	0.000	1.000	0.137	0.343	0.000	1.000
$>$ 1 year	0.131	0.338	0.000	1.000	0.135	0.342	0.000	1.000
Pre-employment status								
Not registered as job seeker	0.597	0.490	0.000	1.000	0.581	0.493	0.000	1.000
Unemployed and registered as a job seeker	0.289	0.454	0.000	1.000	0.305	0.460	0.000	1.000
Not unemployed, but registered as a job seeker	0.113	0.317	0.000	1.000	0.115	0.319	0.000	1.000
Participation in measures of active labor market policy	0.066	0.248	0.000	1.000	0.068	0.252	0.000	1.000
Public assistance benefits								
No benefit	0.712	0.453	0.000	1.000	0.689	0.463	0.000	1.000
Unemployment benefit (ALG I)	0.214	0.410	0.000	1.000	0.225	0.418	0.000	1.000
Unemployment assistance (ALG II, ALHI)	0.075	0.263	0.000	1.000	0.085	0.280	0.000	1.000
ln(Number of workers in establishment)	3.916	1.875	0.000	10.875	4.173	1.800	0.000	10.875
Share of high-skilled workers in establishment	0.112	0.201	0.000	1.000	0.106	0.184	0.000	1.000
Share of medium-skilled workers in establishment	0.736	0.249	0.000	1.000	0.736	0.232	0.000	1.000
Share of low-skilled workers in establishment	0.153	0.208	0.000	1.000	0.158	0.200	0.000	1.000
Share of young aged workers in establishment	0.269	0.196	0.000	1.000	0.241	0.167	0.000	1.000
Share of middle aged workers in establishment	0.525	0.176	0.000	1.000	0.542	0.155	0.000	1.000
Share of older workers in establishment	0.206	0.152	0.000	1.000	0.217	0.141	0.000	1.000
ln(Share of industry in local labor market)	−3.538	1.053	−12.732	−0.855	−3.502	1.031	−11.480	−0.855
ln((Herfindahl index based on local industry shares)$^{-1}$)	3.042	0.266	1.444	3.551	2.995	0.249	1.444	3.551
Share of high-skilled workers in local industry	0.106	0.107	0.000	0.855	0.102	0.102	0.000	0.855
Share of medium-skilled workers in local industry	0.703	0.107	0.000	1.000	0.705	0.103	0.000	1.000
Share of low-skilled workers in local industry	0.191	0.087	0.000	1.000	0.193	0.084	0.000	1.000
ln(Local unemployment rate - high-skilled)	1.839	0.419	0.294	2.838	1.881	0.414	0.294	2.838
ln(Local unemployment rate - skilled)	2.242	0.417	0.981	3.484	2.254	0.394	0.981	3.484
ln(Local unemployment rate - low-skilled)	3.406	0.375	2.245	4.293	3.387	0.345	2.245	4.253
ln(Employment density 0-10km)	5.231	1.325	−0.611	7.511	5.232	1.312	−0.391	7.511

† Logarithm of the geometric mean of (i) the size of all previous employers in which a worker acquired work experience and (ii) the size of the local labor markets in which these establishments are located. For the regression analyses firm size and labor market size are centered around their respective mean, i.e., we divide the size of all previous employers by 56.83 employees and the size of the local labor markets in which these establishments were located by 183,83 employees per km^2.

Note: The initial sample also includes observations for which AKM-worker fixed effects and AKM-establishment fixed effects estimated by Bellmann et al. (2020) for the period 1998–2004 are not available. The reduced sample is the one used in the analysis and includes only observations for which these fixed effects are available (see Section A1.1).

Source: IEB, own calculations.

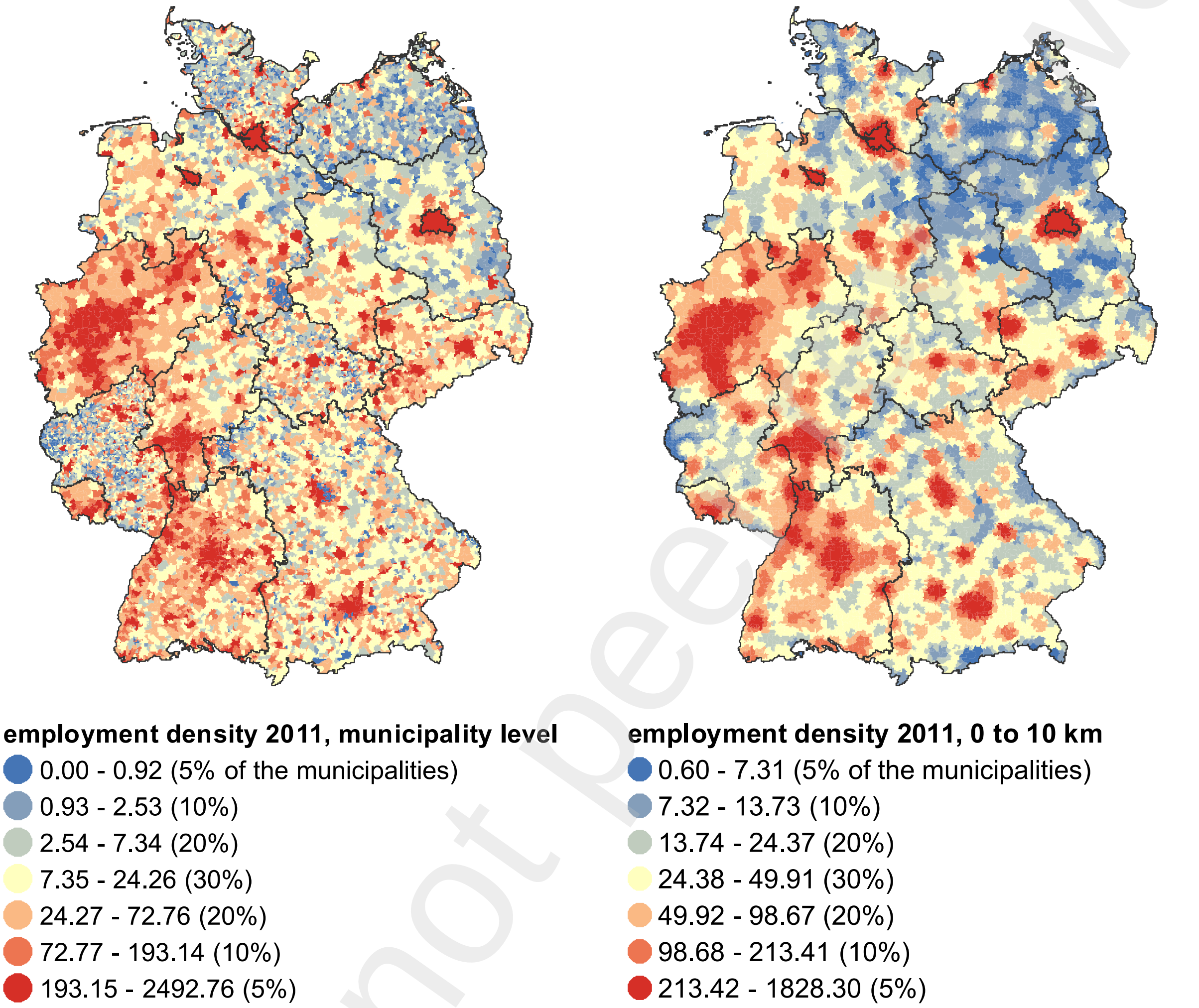


Figure A1: Employees per km^2 at municipality level and 0-10 km (0-6.2 mi) around the geographic center of the municipality

Note: Black lines are borders of NUTS 1-regions (*Federal States*). The maps use the delineation of 11,444 municipalities at December 31, 2012. Their median size is 18 km^2, the third quartile is 38 km^2, and the maximum is 894 km^2 (Berlin) which corresponds to a radius of 2.4 km, 3.5 km, and 16.9 km respectively if the municipalities were circular.
Source: BeH V09.03.00, own calculations.

(a) Share of large establishments

(b) Share of employment in large establishments

Figure A2: Correlation of establishment size and labor market size

Notes: Establishments with at least 250 employees subject to social security contributions are defined as large firms and local labor market size is measured in terms of employees per km^2. The data refers to June 30, 2010. Definition of local labor markets according to Kosfeld and Werner (2012).
Source: FEA, own calculations.

Table A3: New employment relationships by average size of previous employers and of local labor markets in which experience was acquired

	Decile of establishment size										
Decile of labor market size	1	2	3	4	5	6	7	8	9	10	Total
Full sample (N=147,614)											
1	1.7%	1.5%	1.3%	1.2%	1.0%	0.9%	0.8%	0.7%	0.6%	0.3%	10.0%
2	1.3%	1.2%	1.2%	1.2%	1.1%	1.0%	0.9%	0.9%	0.8%	0.4%	10.0%
3	1.2%	1.2%	1.2%	1.1%	1.1%	1.0%	1.0%	0.9%	0.8%	0.5%	10.0%
4	1.0%	1.1%	1.1%	1.1%	1.1%	1.1%	0.9%	1.0%	0.8%	0.7%	10.0%
5	0.9%	1.0%	1.1%	1.1%	1.0%	1.1%	1.0%	1.0%	1.0%	0.9%	10.0%
6	0.9%	0.9%	1.0%	1.0%	1.1%	1.1%	1.1%	1.1%	1.0%	0.9%	10.0%
7	0.8%	0.9%	0.9%	0.9%	1.0%	1.0%	1.1%	1.1%	1.1%	1.2%	10.0%
8	0.8%	0.8%	0.8%	0.9%	1.0%	1.0%	1.1%	1.1%	1.1%	1.3%	10.0%
9	0.6%	0.7%	0.8%	0.8%	0.9%	1.0%	1.2%	1.2%	1.3%	1.5%	10.0%
10	0.7%	0.6%	0.6%	0.7%	0.8%	0.8%	1.0%	1.1%	1.4%	2.3%	10.0%
Total	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	100.0%
Workers with an AKM-worker fixed effect between the 80th and the 90th percentile (N=14,761)											
1	0.8%	0.8%	0.5%	0.6%	0.5%	0.5%	0.4%	0.4%	0.5%	0.4%	5.6%
2	0.7%	0.7%	0.8%	0.8%	0.6%	0.6%	0.5%	0.8%	0.8%	0.5%	6.8%
3	0.7%	0.8%	0.8%	0.7%	0.9%	0.8%	0.7%	0.8%	1.0%	0.6%	7.9%
4	0.6%	0.8%	0.9%	0.9%	0.8%	0.9%	1.0%	1.0%	1.1%	0.8%	8.8%
5	0.7%	0.7%	0.8%	0.8%	0.9%	1.1%	1.1%	1.0%	1.2%	1.0%	9.3%
6	0.8%	0.8%	0.9%	0.9%	1.2%	1.1%	1.2%	1.3%	1.2%	1.2%	10.7%
7	0.5%	0.9%	0.9%	0.9%	1.1%	1.4%	1.3%	1.4%	1.6%	1.7%	11.7%
8	0.7%	0.6%	0.8%	1.0%	1.2%	1.3%	1.2%	1.6%	1.6%	2.1%	12.2%
9	0.6%	0.6%	0.8%	0.9%	1.0%	1.2%	1.7%	1.7%	2.0%	2.4%	12.8%
10	0.7%	0.7%	0.8%	0.8%	0.9%	1.1%	1.4%	1.5%	2.3%	4.0%	14.2%
Total	6.9%	7.5%	7.9%	8.3%	9.2%	10.1%	10.6%	11.6%	13.3%	14.6%	100.0%
Workers with an AKM-worker fixed effect higher than the 90th percentile (N=14,761)											
1	0.5%	0.3%	0.2%	0.3%	0.3%	0.3%	0.4%	0.5%	0.5%	0.4%	3.6%
2	0.4%	0.3%	0.2%	0.3%	0.5%	0.5%	0.5%	0.5%	0.9%	0.7%	4.7%
3	0.4%	0.3%	0.5%	0.4%	0.5%	0.5%	0.5%	0.9%	1.0%	0.9%	5.8%
4	0.4%	0.4%	0.4%	0.6%	0.5%	0.6%	0.6%	0.9%	1.0%	1.4%	6.7%
5	0.3%	0.4%	0.4%	0.6%	0.7%	0.8%	0.9%	1.0%	1.5%	1.7%	8.2%
6	0.4%	0.5%	0.6%	0.7%	1.0%	1.2%	1.0%	1.5%	1.7%	1.9%	10.4%
7	0.4%	0.4%	0.7%	0.8%	0.9%	1.1%	1.4%	1.7%	2.3%	2.8%	12.2%
8	0.5%	0.4%	0.5%	0.7%	0.9%	1.1%	1.6%	1.6%	2.1%	3.1%	12.5%
9	0.4%	0.5%	0.8%	0.9%	1.1%	1.5%	1.8%	2.3%	3.2%	4.1%	16.5%
10	0.7%	0.5%	0.6%	0.9%	1.1%	1.3%	1.6%	2.0%	3.3%	7.4%	19.4%
Total	4.4%	3.8%	4.9%	6.1%	7.4%	8.9%	10.3%	12.8%	17.3%	24.1%	100.0%

Note: Establishment size and local labor market size refer to the average size of establishments and labor markets in which experience was acquired prior to the new employment relationships under investigation measured by the geometric mean of establishment employment and local employment within 10 km (at municipality level, see Table A1 and Figure A1), respectively. Employment figures are weighted by the length of previous employment spells. Deciles of establishment and labor market size are defined based on the full sample. Hence, if establishment and labor market size were independent, the expected share per cell would be 1% in the top panel. The coefficient of correlation between average establishment size and average local labor market size is 0.247 in the full sample.
Source: IEB and Bellmann et al. (2020), own calculations.

A1.5 Spatial (im)mobility prior to new employment relationships

Table A4: New employment relationships by average size of previous and current labor markets

Decile of labor market size previous workplaces	Decile of labor market size - new workplace										
	1	2	3	4	5	6	7	8	9	10	Total
1	4.1%	2.1%	1.0%	0.7%	0.6%	0.4%	0.3%	0.2%	0.3%	0.2%	10.0%
2	1.8%	2.6%	2.0%	1.0%	0.7%	0.6%	0.4%	0.3%	0.3%	0.3%	10.0%
3	1.1%	1.4%	2.3%	1.8%	1.1%	0.7%	0.5%	0.4%	0.4%	0.3%	10.0%
4	0.8%	1.0%	1.3%	2.2%	1.6%	1.0%	0.7%	0.5%	0.5%	0.4%	10.0%
5	0.6%	0.8%	0.9%	1.3%	2.4%	1.4%	0.9%	0.7%	0.5%	0.5%	10.0%
6	0.5%	0.7%	0.8%	0.9%	1.3%	2.2%	1.3%	0.9%	0.8%	0.6%	10.0%
7	0.4%	0.5%	0.6%	0.8%	0.9%	1.6%	2.1%	1.3%	1.0%	0.8%	10.0%
8	0.3%	0.4%	0.4%	0.6%	0.6%	1.0%	1.7%	2.5%	1.4%	1.2%	10.0%
9	0.2%	0.3%	0.3%	0.4%	0.4%	0.7%	1.2%	2.3%	2.7%	1.5%	10.0%
10	0.2%	0.2%	0.2%	0.3%	0.4%	0.5%	0.8%	1.0%	2.5%	4.0%	10.0%
Total	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.2%	9.8%	100.0%

Note: Labor market size at previous workplaces refers to the average size of labor markets in which experience was acquired prior to the considered 147,614 new employment relationships measured by the geometric mean of local employment within 10 km (at municipality level, see Table A1 and Figure A1). If labor market size at previous locations and the new location of employment were independent, the expected share per cell would be 1%. N=147,614.
Source: IEB, own calculations.

Table A5: Distance between the location of the new employer and previous employers

Average distance to all previous employers (km)				
	Percentiles	Smallest		
1%	0.00	0.00		
5%	0.00	0.00		
10%	1.67	0.00	Obs	147,614
25%	11.24	0.00	Sum of Wgt.	147,614
50%	26.58		Mean	76.3
		Largest	Std. Dev.	112.6
75%	86.50	785.32		
90%	238.89	787.36	Variance	12684.8
95%	341.26	814.32	Skewness	2.3
99%	497.52	844.85	Kurtosis	8.0
Distance to the furthest previous employer (km)				
	Percentiles	Smallest		
1%	0.00	0.00		
5%	0.00	0.00		
10%	8.48	0.00	Obs	147,614
25%	20.16	0.00	Sum of Wgt.	147,614
50%	51.74		Mean	133.90
		Largest	Std. Dev.	161.68
75%	206.83	849.97		
90%	402.40	855.59	Variance	26141.68
95%	486.58	872.91	Skewness	1.41
99%	615.60	880.13	Kurtosis	4.05

Note: The statistics refer to the distance between the centers of the municipalities in which the new employer and previous employers are located. When calculating the average distance all previous individual employment relationships are weighted by their length. 10 km approximately are 6.2 miles.
Source: IEB, own calculations.

Table A6: Percentage of work experience acquired within commuting distance (50 km $\approx$ 31 miles) of new employment relationship

	Percentiles	Smallest		
1%	0.00	0.00		
5%	0.00	0.00		
10%	0.00	0.00	Obs	147,614
25%	0.28	0.00	Sum of Wgt.	147,614
50%	0.99		Mean	0.69
		Largest	Std. Dev.	0.41
75%	1.00	1.00		
90%	1.00	1.00	Variance	0.17
95%	1.00	1.00	Skewness	-0.87
99%	1.00	1.00	Kurtosis	1.97

Note: Results refer to the distance between the centers of the municipalities in which the new employer and all previous employers are located.
Source: IEB, own calculations.

A2 Additional regression results

A2.1 Robustness checks and extended regression models

Table A7: Parameter estimates - full sample

	(1)	(2)	(3)	(4)
γ	0.000428***	0.000437***	0.000436***	0.000435***
	(0.0000201)	(0.0000183)	(0.0000183)	(0.0000183)
ρ	0.0000539***		0.0000406***	0.0000407***
	(0.00000465)		(0.00000464)	(0.00000470)
δ		0.0000555***	0.0000507***	0.0000498***
		(0.00000226)	(0.00000213)	(0.00000207)
ω				0.00000334**
				(0.00000155)
κ	0.458***	0.438***	0.437***	0.437***
	(0.0117)	(0.0112)	(0.0112)	(0.0112)
θ	0.000633***	0.000615***	0.000613***	0.000613***
	(0.0000326)	(0.0000244)	(0.0000261)	(0.0000263)
N	147,614	147,614	147,614	147,614
$R^2_{adj.}$	0.705	0.707	0.708	0.708
R^2	0.708	0.710	0.710	0.710
RSS	10866.805	10794.975	10768.821	10767.957

Note: Results for Equation (9). ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. All regressions include control variables (see Table A8), AKM-worker and AKM-establishment fixed effects estimated by Bellmann et al. (2020) as well as industry, occupation, and region-year fixed effects. The parameters reported here are used to compute the parameters reported in Table 2.
Source: IEB, own calculations.

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Table A8: Results for control variables

Education:		
Secondary / intermediate school leaving certificate		
... without completed vocational training	0.207	(0.022)***
... with completed vocational training	0.170	(0.008)***
Upper secondary school leaving certificate		
... without completed vocational training	0.279	(0.035)***
... with completed vocational training	0.166	(0.012)***
University of applied sciences degree	-0.035	(0.016)**
College / university degree	0.071	(0.016)***
Female worker	-0.136	(0.003)***
Tenure (month)	0.008	(0.000) ***
ln(Number of previous employers)	-0.007	(0.002)***
Length of non-employment		
0-28 days (job-to-job transition)	*reference*	
28-92 days	-0.013	(0.003)***
93 days - 1 year	-0.031	(0.003)***
$>$ 1 year	-0.021	(0.004)***
Pre-employment status		
Not registered as job seeker	*reference*	
Unemployed and registered as a job seeker	-0.054	(0.003)***
Not unemployed, but registered as a job seeker	-0.064	(0.003)***
Participation in measures of active labor market policy	-0.016	(0.003)***
Public assistance benefits		
No benefit	*reference*	
Unemployment benefit (ALG I)	-0.010	(0.003)***
Unemployment assistance (ALG II, ALHI)	-0.010	(0.004)***
ln(Number of workers in establishment)	0.014	(0.001)***
Share of high-skilled workers in establishment	0.120	(0.008)***
Share of medium-skilled workers in establishment	*reference*	
Share of low-skilled workers in establishment	-0.027	(0.005)***
Share of young aged workers in establishment	*reference*	
Share of middle aged workers in establishment	0.113	(0.010)***
Share of older workers in establishment	0.082	(0.007)***
ln(Share of industry in local labor market)	0.005	(0.001)***
ln((Herfindahl index based on local industry shares)$^{-1}$)	-0.020	(0.022)
Share of high-skilled workers in local industry	0.098	(0.018)***
Share of medium-skilled workers in local industry	*reference*	
Share of low-skilled workers in local industry	-0.035	(0.018)***
ln(Local unemployment rate - high-skilled)	-0.038	(0.017)**
ln(Local unemployment rate - skilled)	-0.147	(0.015)***
ln(Local unemployment rate - low-skilled)	-0.107	(0.010)***
ln(Employment density 0-10km)	0.006	(0.002)***
AKM worker fixed effect	0.131	(0.003)***
AKM establishment fixed effect	0.097	(0.002)***
Constant	4.556	(0.075)***
N	147,614	

Note: The results refer to specification (4) of Table A7. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. The regression includes work experience (see Table A7) as well as industry, occupation, and region-year fixed effects. See Table A1 for a definition of all control variables.
Source: IEB and Bellmann et al. (2020), own calculations.

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Table A9: Specifications with and without AKM-fixed effects

	(1)	(2)	(3)	(4)	(5)
$\tilde{\gamma}$	0.0430***	0.0433***	0.0466***	0.0442***	0.0455***
	(0.00164)	(0.000927)	(0.00135)	(0.00131)	(0.00165)
$\tilde{\delta}$	0.00493***	0.00442***	0.00425***	0.00384***	0.00550***
	(0.000200)	(0.000134)	(0.000166)	(0.000152)	(0.000207)
$\tilde{\rho}$	0.00403***	0.00395***	0.00380***	0.00373***	0.00414***
	(0.000410)	(0.000220)	(0.000341)	(0.000328)	(0.000436)
$\tilde{\omega}$	0.000330**	0.000341***	0.000289**	0.000262**	0.000361**
	(0.000153)	(0.0000785)	(0.000133)	(0.000122)	(0.000175)
κ	0.437***	0.420***	0.540***	0.529***	0.446***
	(0.0112)	(0.0151)	(0.0196)	(0.0188)	(0.0118)
θ^y	0.201***	0.103***	0.118***	0.118***	0.200***
	(0.00768)	(0.00289)	(0.00399)	(0.00408)	(0.00711)
N	147,614	347,894	147,614	147,614	147,614
$R^2_{adj.}$	0.708	0.644	0.650	0.672	0.688
R^2	0.710	0.645	0.654	0.675	0.691
RSS	10767.957	27974.272	12882.796	12088.330	11479.643
Only obs. for which AKM-FE available	Yes	No	Yes	Yes	Yes
AKM-establishments fixed effects	Yes	No	No	Yes	No
AKM-worker fixed effects	Yes	No	No	No	Yes

Note: $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the results for Equation (9). Depreciation rate θ is expressed in years. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. Specification (1) is identical to Model (4) in Table 2. See Table 2 for additional notes.
Source: IEB and Bellmann et al. (2020), own calculations.

.

Table A10: Results for different sub-samples

	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\gamma}$	0.0430***	0.0553***	0.0417***	0.0196***	0.0344***	0.0335***
	(0.00164)	(0.00239)	(0.00417)	(0.00208)	(0.00158)	(0.00109)
$\tilde{\delta}$	0.00493***	0.00567***	0.00301***	0.00134***	0.00454***	0.00421***
	(0.000200)	(0.000199)	(0.000591)	(0.000397)	(0.000217)	(0.000162)
$\tilde{\rho}$	0.00403***	0.00379***	0.00473***	0.00286***	0.00372***	0.00336***
	(0.000410)	(0.000485)	(0.000812)	(0.000496)	(0.000355)	(0.000337)
$\tilde{\omega}$	0.000330**	0.000160	0.000304	0.000481*	0.000215	0.000224*
	(0.000153)	(0.000167)	(0.000380)	(0.000255)	(0.000169)	(0.000125)
κ	0.437***	0.538***	0.403***	0.239***	0.357***	0.234***
	(0.0112)	(0.0122)	(0.0288)	(0.0239)	(0.0129)	(0.00704)
θ^y	0.200***	0.218***	0.207***	0.154***	0.194***	0.159***
	(0.00768)	(0.00843)	(0.0207)	(0.0167)	(0.00890)	(0.00584)
N	147,614	91,852	15,623	40,139	104,032	182,222
$R^2_{adj.}$	0.708	0.718	0.651	0.593	0.722	0.717
R^2	0.710	0.723	0.682	0.608	0.726	0.719
RSS	10767.957	6677.887	922.313	2742.778	7434.521	13816.337
Reference (cf. Table 2)	x					
Job-to-job-transitions only		x				
Short-term unemployed only			x			
At least 3 month unemployed				x		
Only men					x	
Including older workers						x

Note: $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the results for Equation (9). Depreciation rate θ is expressed in years (θ^y). ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. Specification (1) is identical to Model (4) in Table 2. Workers with a job-to-job transition were at most 28 days and short-term unemployed at most three month out of job before the considered new employment relationship. Workers aged 51 and more in 2011 are considered older workers. Results for sample (6) are also presented in Figure A6. See Table 2 for additional notes.
Source: IEB and Bellmann et al. (2020), own calculations.

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Table A11: Specifications addressing the limited mobility bias of AKM-establishment effects estimates

	(1)	(2)	(3)	(4)	(5)
$\tilde{\gamma}$	0.0430***	0.0408***	0.0375***	0.0347***	0.0440***
	(0.00164)	(0.00157)	(0.00181)	(0.00204)	(0.00167)
$\tilde{\delta}$	0.00493***	0.00484***	0.00490***	0.00500***	0.00511***
	(0.000200)	(0.000191)	(0.000208)	(0.000235)	(0.000197)
$\tilde{\rho}$	0.00403***	0.00385***	0.00373***	0.00386***	0.00412***
	(0.000410)	(0.000428)	(0.000430)	(0.000400)	(0.000475)
$\tilde{\omega}$	0.000330**	0.000138	-0.0000274	-0.000109	0.000315*
	(0.000153)	(0.000161)	(0.000167)	(0.000174)	(0.000169)
κ	0.437***	0.428***	0.425***	0.430***	0.448***
	(0.0112)	(0.0117)	(0.0144)	(0.0183)	(0.0108)
θ^y	0.201***	0.197***	0.191***	0.185***	0.202***
	(0.00768)	(0.00754)	(0.00863)	(0.0101)	(0.00824)
N	147,614	126,624	100,678	78,412	128,468
$R^2_{adj.}$	0.708	0.716	0.723	0.728	0.700
R^2	0.710	0.719	0.727	0.733	0.703
RSS	10767.957	9237.808	7496.838	5977.956	9755.868
Reference (cf. Table 2)	x				
Hiring establishments $\geq$ 10 workers only		x			
Hiring establishments $\geq$ 25 workers only			x		
Hiring establishments $\geq$ 50 workers only				x	
Grouped-FE instead of establishment-FE					x

Note: $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the results for Equation (9). Depreciation rate θ is expressed in years. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. See Table 2 for additional notes. Specification (1) is the reference and identical to Model (4) in Table 2. In specifications (2)-(4), we exclude small establishments based on different thresholds and in specification (5), we use fixed effects estimates for 100 clusters of establishments with similar wage structure as controll variable instead of estimates of AKM-establishment effects to address the limited mobilit bias in AKM models (see Section A1.3 in this Appendix).
Source: IEB and Bellmann et al. (2020), own calculations.

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Table A12: Specification considering the square of establishment size and city size

	(1) all workers	(2) AKM09	(3) AKM10
$\tilde{\gamma}$	0.0361***	0.0927***	0.0916***
	(0.00194)	(0.00870)	(0.0108)
$\tilde{\delta}_{lin}$	0.000361***	0.000293***	0.000155***
	(0.0000363)	(0.000102)	(0.0000482)
$\tilde{\delta}_{sq}$	-0.000000687***	-0.000000365	-0.000000296**
	(0.000000103)	(0.000000332)	(0.000000117)
$\tilde{\rho}_{lin}$	0.00298***	0.00356***	0.00368***
	(0.000764)	(0.000956)	(0.000899)
$\tilde{\rho}_{sq}$	-0.0000983	-0.000146**	-0.000142***
	(0.0000626)	(0.0000710)	(0.0000540)
κ	0.456***	0.681***	0.883***
	(0.0110)	(0.0446)	(0.0489)
θ^y	0.212***	0.247***	0.207***
	(0.00860)	(0.0176)	(0.0205)
N	147,614	14,761	14,761
$R^2_{adj.}$	0.706	0.536	0.482
R^2	0.709	0.576	0.526
RSS	10837.810	1369.841	2103.871

Note: The table contains results for an alternative specification of Equation (9). Specifically, the regression is based on an alternative learning function which includes – instead of the *logarithm* of establishment and labor market size – establishment and labor market size as well as the respective square: $v_{i,\tau} = \gamma + \delta_{lin} emp_{f(i,\tau),\tau} + \delta_{sq} emp^2_{f(i,\tau),\tau} + \rho_{lin} emp_{r(i,\tau)-f(i,\tau),\tau} + \rho_{sq} emp^2_{r(i,\tau)-f(i,\tau),\tau}$. Establishment and labor market size are measured in terms of 100 workers in this specification. $\tilde{\gamma}$, $\tilde{\delta}_{lin}$, $\tilde{\delta}_{sq}$, $\tilde{\rho}_{lin}$, $\tilde{\rho}_{sq}$, $\tilde{\phi}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the regression results. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets. AKM09 and AKM10 refer to the two groups at the top of the ability distribution as indicated by the AKM-worker fixed effects estimated by Bellmann et al. (2020). To define the sub-samples we consider the deciles of AKM-worker fixed effects as thresholds. The reported negative association between wage and squared size supports our assumption that the value of work experience increases with the size of establishments and labor markets in which it was aquired, but at a decreasing rate (see Section 3). The explanatory power of this specification is sligthly lower than the one of our main specification considering size in logarithmic form (cf. Table 2).
Source: IEB and Bellmann et al. (2020), own calculations.

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Table A13: Specification including average establishment size of local labor market in which experience was acquired

	(1)	
$\tilde{\gamma}$	0.0394***	(0.00581)
$\tilde{\delta}$	0.00492***	(0.000210)
$\tilde{\rho}$	0.00420***	(0.000751)
$\tilde{\phi}$	0.00305	(0.00373)
κ	0.434***	(0.0112)
θ^y	0.195***	(0.00821)
N	147,614	
$R^2_{adj.}$	0.708	
R^2	0.710	
RSS	10768.793	

Note: The table contains results for an augmented version of Equation (9). Specifically, the regression is based on an alternative learning function which includes average establishment size of local labor markets as an additional characteristics. The alternative learning function is given by $v_{i,\tau} = \gamma + \delta \ln\left(\frac{emp_{f(i,\tau),\tau}}{\frac{emp_{r(i,\tau)-f(i,\tau),\tau}}{firms_{r(i,\tau)}-1}}\right) + \phi \ln\left(\frac{emp_{r(i,\tau)-f(i,\tau),\tau}}{firms_{r(i,\tau)}-1}\right) + \rho \ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right)$ where $\frac{emp_{r(i,\tau)-f(i,\tau),\tau}}{firms_{r(i,\tau)}-1}$ denotes the average establishment size in the local labor market in which individual i acquired work experience at day τ, excluding the firm in which worker i is employed. $\tilde{\gamma}$, $\tilde{\delta}$, $\tilde{\rho}$, $\tilde{\phi}$ and $\tilde{\omega}$ have been computed according to Equations (10) to (13) based on the results for an augmented version of Equation (9). ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 local labor markets.
Source: IEB and Bellmann et al. (2020), own calculations.

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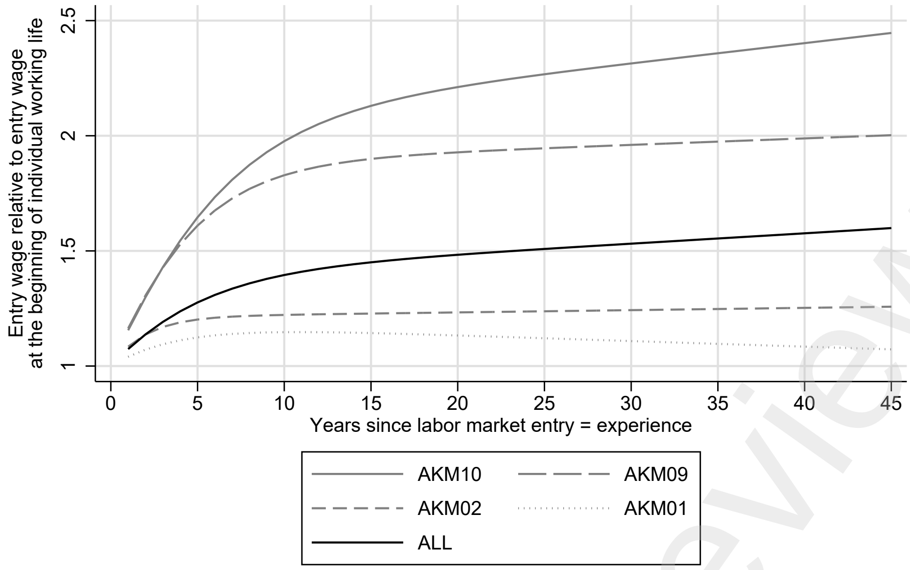
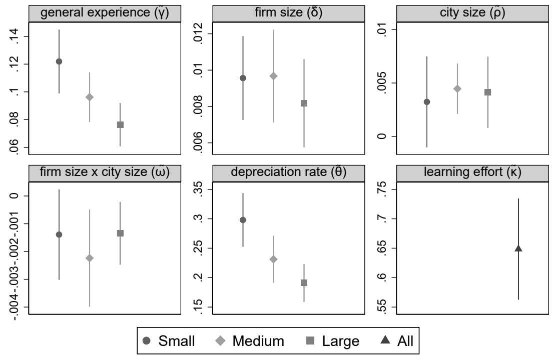
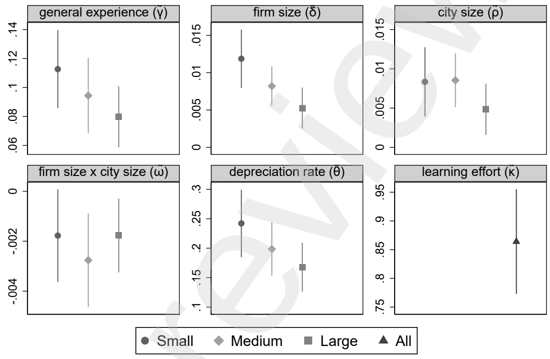


Figure A3: Entry wage-experience profile

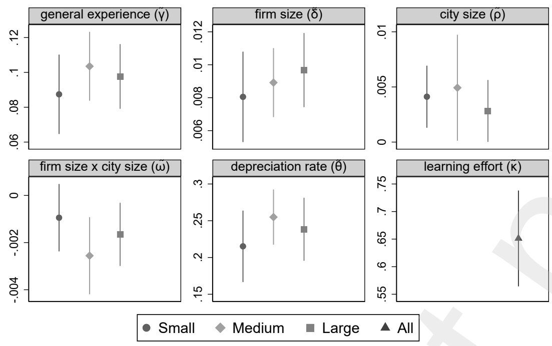
Notes: Based on the estimation results for Equation (9) given in Table A7 and Figure 3, the figure illustrates entry wages over the course of individual working lifes for workers who were never unemployed since labor market entry and who acquired all of their work experience in firms with an average size located in a labor market with an average employment density. The length of individual working life (T) is assumed the be almost 45 years (16,266 days = sample mean). Entry wages are only observed up to 36 years after labor market entry (p99: 29 years, p95: 24 years). ALL refers to the full sample (cf. Table 2) while AKM01 and AKM02 denote the two groups of workers with the lowest AKM-fixed effects estimated by Bellmann et al. (2020). AKM09 and AKM10 refer to the two groups of workers with the highest AKM-fixed effects. Thresholds of the sub-samples are the deciles of AKM-worker fixed effects.
Source: IEB, own calculations.



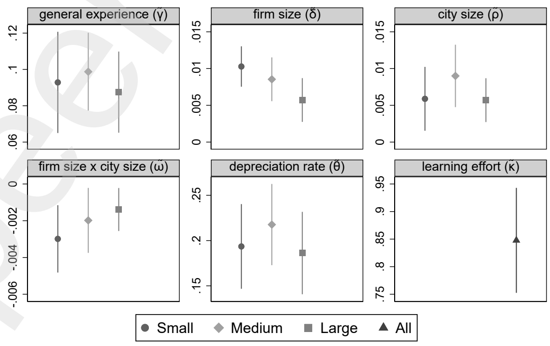
(a) By the size of the hiring establishment, AKM09



(b) By the size of the hiring establishment, AKM10



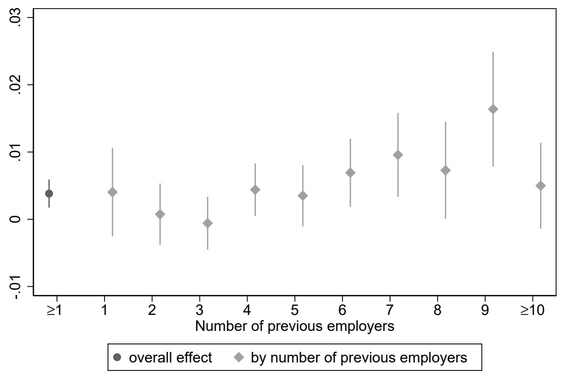
(c) By size of the labor market in which the hiring establishment is located, AKM09



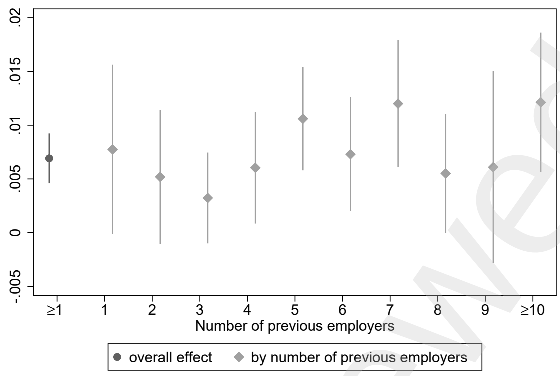
(d) By size of the labor market in which the hiring establishment is located, AKM10

Figure A4: Heterogeneous effects across different types of hiring establishments

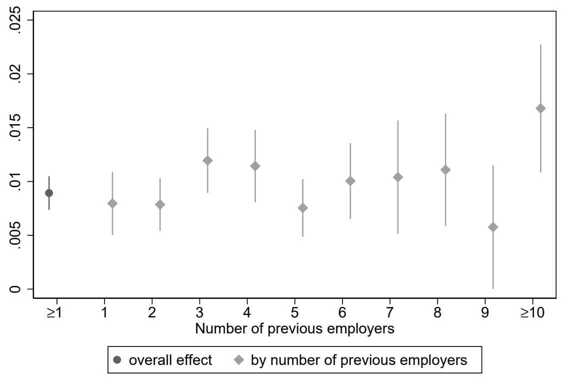
Notes: The figure summarizes results of four estimations of an augmented version of Equation (9): in each regression θ, γ, δ, ρ and ω are allowed to vary depending on the size of the hiring establishment and the labor market in which employment is taken-up, respectively. The thresholds as regards firm size are 50 employees and 250 employees. Regarding labor market size we use the 33th and 66th percentile of local employment density. Figures (a) and (c) refer to workers with an AKM-worker fixed effect between the 80th and the 90th percentile while figures (b) and (d) refer to workers with an AKM-worker fixed effect higher than the 90th percentile.
Source: IEB and Bellmann et al. (2020), own calculations.



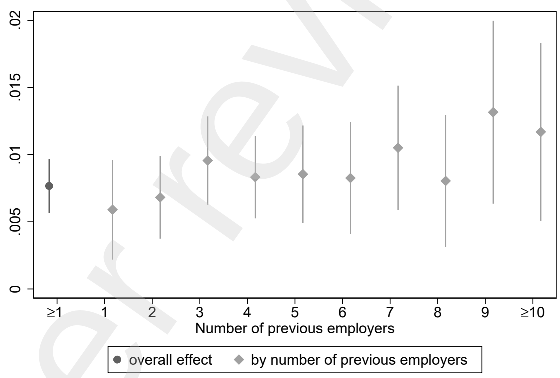
(a) City size effect ($\tilde{\rho}$), AKM09



(b) City size effect ($\tilde{\rho}$), AKM10



(c) Firm size effect ($\tilde{\delta}$), AKM09



(d) Firm size effect ($\tilde{\delta}$), AKM10

Figure A5: Effect of previous city and firm size on the return on experience along the job ladder

Notes: The figure summarizes results of an augmented version of Equation (9) that we estimate separately for workers with an AKM-worker fixed effect between the 80th and the 90th percentile (figures (a) and (c)) and for workers with an AKM-worker fixed effect higher than the 90th percentile (figures (b) and (d)): in the regressions, we interact all experience variables with indicator variables that refer to the number of previous employers as a proxy for the individual position on the job ladder (cf. Dauth et al., 2022) so that the parameters of the learing function γ, δ, ρ and ω are allowed to vary accordingly. Identification is only based on the variation between workers with the same number of previous employers. The "overall effect" is the benchmark. It refers to our baseline specification without interaction effects of experience and the number of previous employers. These effects are identical to the estimates reported in Figure 1 for the respective sub-sample.
Source: IEB and Bellmann et al. (2020), own calculations.

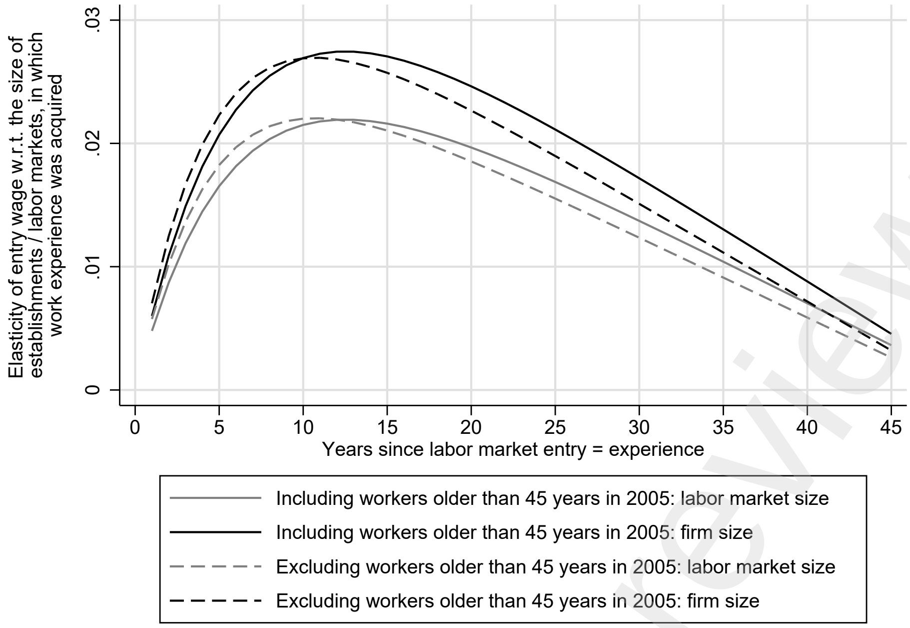


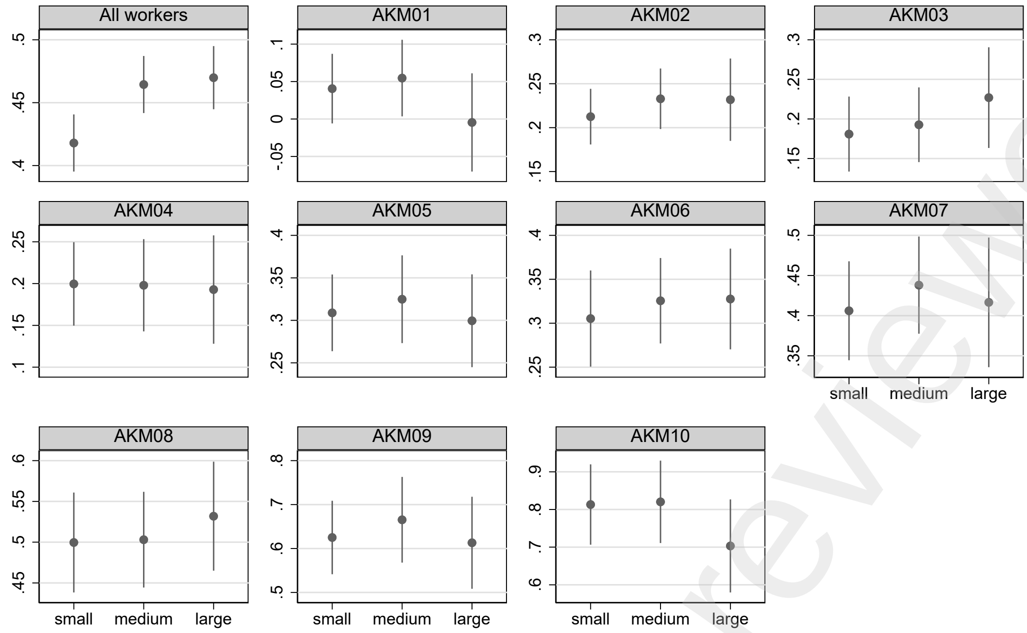
Figure A6: Elasticity of entry wage w.r.t. the size of establishments and labor markets in which experience was acquired with / without workers aged 45 years or more in 2005

Notes: In our main analysis, we exclude workers who were older than 45 years in 2005 to avoid left-censored employment biographies (see Section A1.1). Here we compare our main results (Figure 4a) with estimates that are based on a sample that also includes older workers (Table A10, Column (6)).
Source: IEB and Bellmann et al. (2020), own calculations, illustration based on Peters (2020).

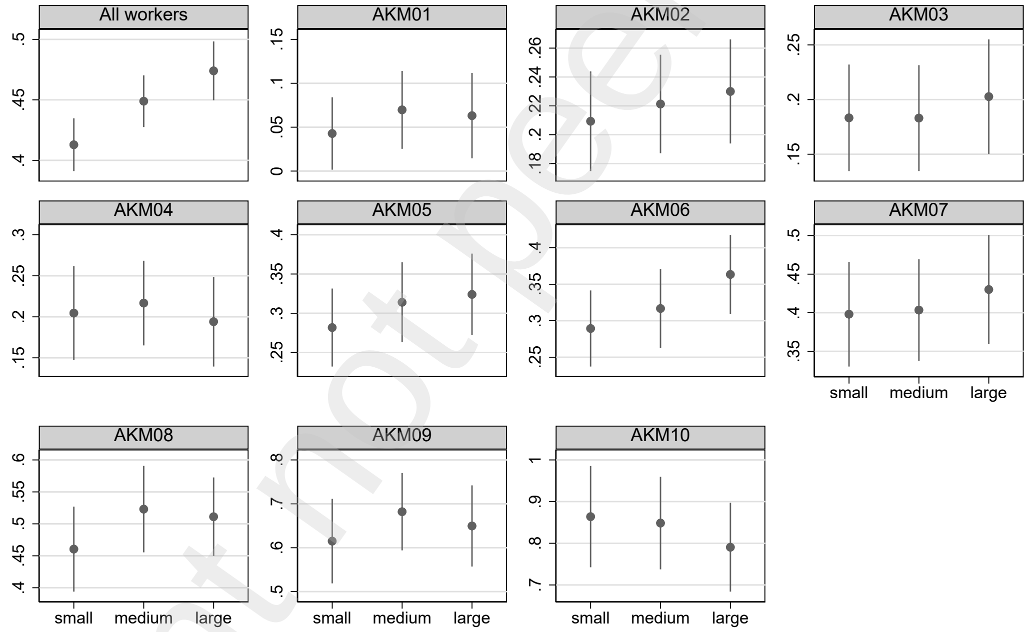
Table A14: Share of workers with establishment change by labor market size

	Share of workers with a change of establishment	
Category of labor market size	all workers	high-skilled
1 (lowest)	8.4%	9.4%
2	7.9%	8.9%
3	8.0%	8.8%
4	8.2%	9.0%
5	8.2%	9.4%
6	8.6%	9.2%
7	9.2%	10.0%
8	9.1%	9.5%
9	10.1%	11.0%
10 (highest)	10.6%	11.1%
Total	8.8%	9.9%

Notes: The table is based on information about 5,881,362 worker-year-observations referring to the period 2005 to 2011 (reference date: June 30). In 518,873 cases (8.8%) we observe a change of the establishment identifier from one to another year. Workers with a university degree / degree in applied sciences are considered high-skilled (763,518 worker-year-observations). Labor market size is measured in terms of number of employees per km^2 10 km around the center of the municipality of an establishment's location. The ten categories are defined such that the 5,881,414 worker-year-observations are uniformly distributed across them.
Source: IEB, own calculations.



(a) Estimates by average firm size



(b) Estimates by average labor market size

Figure A7: Estimates for learning effort κ depending on the average size of the firms and the labor markets in which experience was acquired

Notes: Figure (a) and (b) summarize the results of in total 22 estimations of an augmented version of Equation (9): two regression for the full sample of workers and two for each sub-sample defined based on the AKM-worker fixed effects (cf. Figure 1). In each regression the parameters κ, θ, γ, δ, ρ and ω are allowed to vary depending on (a) the geometric mean of the size of the firms and (b) the geometric mean of the size of the labor markets in which a worker acquired work experience. The thresholds as regards average firm size are 50 employees and 250 employees and the threshold regarding average labor market size are 104 employees/km^2 (p33) and 355 employees/km^2 (p66).
Source: IEB and Bellmann et al. (2020), own calculations.

A2.2 Alternative specifications using city size categories and establishment size categories

Our regression model described in Section 4 assumes a specific functional form with establishment size and labor market size entering as continuous variables as specified in the learning function (Equation (3) in Section 3). To check the robustness of our results to this specification, we follow De La Roca and Puga (2017) more closely and consider different types of experiences based on labor market size categories and establishment size categories. Specifically, we estimate the following wage equation (cf., Equation (9) in Section 4):

$$\begin{aligned} \ln w_{i,t} \quad = \quad & \alpha + \eta_{edu(i)} + \gamma_1 exp_{i,t} + \gamma_2 exp_{i,t}^2 \\ & + \sum_{f=2}^{4} \delta_{1f} exp_{i,t,f} + \sum_{f=2}^{4} \delta_{2f} exp_{i,t,f} \times exp_{i,t} + \sum_{r=2}^{4} \rho_{1r} exp_{i,t,r} + \sum_{r=2}^{4} \rho_{2r} exp_{i,t,r} \times exp_{i,t} \\ & + \text{FE}_i \pi + \text{FE}_{f(i,t)} \phi + \mu_{r(i,t),y(t)} + \mathbf{x}'_{i,t} \beta + \varepsilon_{i,t} \end{aligned} \tag{A2}$$

where $exp_{i,t}$ denotes total work experience of worker i at time t measured on a daily basis but expressed in years. $exp_{i,t,f}$ and $exp_{i,t,r}$ are experience acquired in a certain type of establishment and labor market, respectively. The categories have been defined such that roughly the same amount of experience has been acquired in each considered type of establishment and labor market (see Table A15). We consider experience acquired in establishments with less than 10 workers, 10-49 workers, 50-249 workers and at least 250 workers. As regards labor market size, we differentiate between experience gathered in cities with an employment density of less than 75 workers/km^2, 75-199 workers/km^2, 200-499 workers/km^2 and at least 500 workers/km^2. Experience acquired in the smallest establishments and labor markets serve as reference categories. To capture the non-linear relationship between logarithmic wages and experience, we follow De La Roca and Puga (2017) and interact all experience terms with total experience.

Table A15: Summary statistics for experience by categories of labor market size and categories of establishment size

	Mean	SD	Min.	Max.
Total experience	10.253	7.267	0.003	35.066
Experience by establishment size categories				
$<$ 10 workers	2.062	3.500	0.000	32.140
10-49 workers	2.817	3.991	0.000	32.068
50-249 workers	2.723	4.041	0.000	31.190
$\geq$250 workers	2.652	4.894	0.000	34.251
Experience by labor market size categories				
$<$ 75 workers/km^2	2.720	4.958	0.000	33.561
75-199 workers/km^2	2.322	4.434	0.000	35.066
200-499 workers/km^2	2.235	4.272	0.000	33.227
$\geq$ 500 workers/km^2	2.976	5.242	0.000	32.747
N	147,614			

Source: IEB, own calculations.

Table A16 summarizes the results for different specifications of Equation A2. In the first three columns, the interaction with total experience is omitted. Furthermore, we omit experience by establishment size (Columns (1) and (4)) and experience by labor market size (Columns (2) and (5)) analogously to Table 2.

The results in Table A16 are in line with the findings of our main model. Firstly, they confirm that the value of experience increases with the size of the establishments and labor markets in which it was acquired. Secondly, the additional wage premium for experience acquired in those labor markets, that are larger than the reference category, are smaller if we consider experience by establishment size in addition. If we compare the estimates in Columns (1) and (3), the drop in the benefit from acquiring experience in the largest local labor markets amounts to 27 percent and is, thus, consistent with the decline in the wage elasticity with respect to previous city size of about 26 percent discussed in Section 6.4. Thirdly, the benefit from acquiring experience in the largest firms appears to be larger than the gain from gathering experience in the largest labor markets (recall that each category accounts for about a quarter of total experience). Fourthly, the accumulated benefits from acquiring experience in the largest establishments and cities significantly increase in the first half of working lives. However, the premium for big city or large establishment experience is lower for workers close to retirement age (cf. Figure 4 in Section 6). In the model given by Equation (A2), this is captured by significant negative interaction effects of big city experience and large establishment experience with total experience in Columns (4)-(6) (cf. De La Roca and Puga, 2017).

Throughout our analyses, we estimate the wage effect of acquiring work experience in big cities and in large firms conditional on characteristics of the establishment where the experience is used, i.e., the current employer that pays the wage analyzed. By doing so, we take into account that workers who gained experience in small or large labor markets and in small or large establishments for any reason might select in firms with certain properties that also affect wages. Recently, Porcher et al. (2023) studied for Spain to which extent the consideration of current firm size, i.e. the size of the firm in which a worker uses (big city) experience, affects the estimates of static and dynamic agglomeration effects. While they find a significant decrease in the static agglomeration benefit of about 29 percent, the estimated gains from acquiring experience in big cities decline by less than 5 percent. To compare the role of *current* and *past* firm size – the latter is the focus of our analysis and has not been considered by Porcher et al. (2023) – for the return on work experience acquired in large labor markets, we estimate additional specifications where we omit different covariates included in our full specification. The results are summarized in Table A17.

Table A16: Regression results for Equation (A2)

	(1)	(2)	(3)	(4)	(5)	(6)
Total experience	0.0161***	0.0141***	0.0133***	0.0148***	0.0108***	0.00938***
	(0.000655)	(0.000623)	(0.000620)	(0.000678)	(0.000702)	(0.000788)
Total experience^2	-0.000356***	-0.000398***	-0.000401***	-0.000290***	-0.000224***	-0.000199***
	(0.0000220)	(0.0000235)	(0.0000228)	(0.0000261)	(0.0000334)	(0.0000386)
Experience by labor market size categories, reference: experience acquired in small labor markets (<75 workers/km^2)						
75-199 workers/km^2	0.00110***		0.000615**	0.00134*		0.000548
	(0.000276)		(0.000268)	(0.000709)		(0.000684)
200-499 workers/km^2	0.00150***		0.000818**	0.00273***		0.00145*
	(0.000325)		(0.000318)	(0.000906)		(0.000860)
$\geq$ 500 workers/km^2	0.00436***		0.00317***	0.00765***		0.00550***
	(0.000444)		(0.000428)	(0.000930)		(0.000917)
Experience by establishment size categories, reference: experience acquired in small establishments (<10 workers)						
10-49 workers		0.00318***	0.00313***		0.00468***	0.00445***
		(0.000310)	(0.000311)		(0.000886)	(0.000877)
50-249 workers		0.00529***	0.00509***		0.00767***	0.00719***
		(0.000266)	(0.000271)		(0.000836)	(0.000829)
$\geq$ 250 workers		0.00821***	0.00759***		0.0155***	0.0145***
		(0.000387)	(0.000378)		(0.00102)	(0.000989)
Experience by labor market size categories $\times$ total experience						
75-199 workers/km^2				-0.0000121		0.00000572
				(0.0000350)		(0.0000336)
200-499 workers/km^2				-0.0000619		-0.0000288
				(0.0000431)		(0.0000403)
$\geq$ 500 workers/km^2				-0.000169***		-0.000117***
				(0.0000354)		(0.0000334)
Experience by establishment size categories $\times$ total experience						
10-49 workers					-0.0000880*	-0.0000787*
					(0.0000452)	(0.0000446)
50-249 workers					-0.000133***	-0.000119***
					(0.0000446)	(0.0000442)
$\geq$ 250 workers					-0.000383***	-0.000363***
					(0.0000506)	(0.0000483)
N	147614	147614	147614	147614	147614	147614
$R^2_{adj.}$	0.703	0.704	0.705	0.703	0.704	0.705
R^2	0.706	0.707	0.708	0.706	0.707	0.708
RSS	10945.528	10892.951	10874.005	10942.973	10884.059	10863.332

Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 labor market regions. All regressions include control variables (see Table A8), AKM-worker and AKM-establishment fixed effects estimated by Bellmann et al. (2020) as well as industry, occupation, and region-year fixed effects.
Source: IEB, own calculations.

In Column (1) of Table A17, we neither consider characteristics of the current employer, that is the establishment at which the experience is used, nor the size of the establishments at which work experience previously was acquired. Based on the simplified model where we estimate the average linear wage effect of experience, the premium for one additional year of experience acquired in the largest labor markets in Germany is about 0.00499 log points. This effect declines to 0.00471 log points (Column (2)) if we control for the logarithmic size of the establishment in which the experience is used, following Porcher et al. (2023). In relative terms, the decrease amounts to 5.7 percent and thus corresponds with the decline observed by Porcher et al. (2023). If we, in addition, control for the composition of the firm's workforce and unobserved establishment characteristics by means of pre-determined AKM-establishment fixed effect of the current employer, the premium for experience acquired in the largest Germany cities is 0.00436 (Column (3)). If we finally also take into account the size of the establishments in which work experience was acquired (by experience categories), the effect is 0.00317 (Column (4)). The last extension leads to a decline in the premium for big city experience by another 28 percent ($= (0.00317/0.00436 - 1) \times 100\%$). Hence, the size of the firms in which experience was gained explains a significantly larger fraction of the benefits from acquiring work experience in big cities than observable and unobservable characteristics of the establishment in which the experience is used, in particular in comparison to the size of the *current* employer considered by Porcher et al. (2023).

Table A17: Estimates for the benefits from acquiring work experience in large labor markets conditional on different firm characteristics

	(1)	(2)	(3)	(4)
Total experience	0.0170***	0.0172***	0.0161***	0.0133***
	(0.000685)	(0.000694)	(0.000655)	(0.000620)
Total experience^2	-0.000373***	-0.000379***	-0.000356***	-0.000401***
	(0.0000222)	(0.0000235)	(0.0000220)	(0.0000228)
Experience by labor market size categories, reference: experience acquired in small labor markets (<75 workers/km^2)				
75-199 workers/km^2	0.00103***	0.00107***	0.00110***	0.000615**
	(0.000308)	(0.000293)	(0.000276)	(0.000268)
200-499 workers/km^2	0.00139***	0.00135***	0.00150***	0.000818**
	(0.000373)	(0.000344)	(0.000325)	(0.000318)
$\geq$ 500 workers/km^2	0.00499***	0.00471***	0.00436***	0.00317***
	(0.000514)	(0.000489)	(0.000444)	(0.000428)
Experience by establishment size categories, reference: experience acquired in small establishments (<10 workers)				
10-49 workers				0.00313***
				(0.000311)
50-249 workers				0.00509***
				(0.000271)
$\geq$ 250 workers				0.00759***
				(0.000378)
N	147614	147614	147614	147614
$R^2_{adj.}$	0.669	0.677	0.703	0.705
R^2	0.672	0.680	0.706	0.708
RSS	12191.109	11907.928	10945.528	10874.005
Considered firm characteristics				
Size of current employer	No	Yes	Yes	Yes
Workforce composition of current employer	No	No	Yes	Yes
AKM-establishment fixed effect of current employer	No	No	Yes	Yes
Size of previous employers (by experience categories)	No	No	No	Yes

Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent level. Robust standard errors given in parentheses are clustered at the level of 141 labor market regions. All regressions include control variables referring to the individual worker, the local labor market and the local industry (see Table A8) as well as establishment characteristics as indicated in the Table. Furthermore, all models comprize pre-determined AKM-worker fixed effects estimated by Bellmann et al. (2020) as well as industry, occupation, and region-year fixed effects.
Source: IEB, own calculations.

A3 How to compute work experience based on spell data

The Integrated Employment Biographies provide information on work experience in the form of employment spells. Therefore, the terms capturing experience in Equation (9) have to be re-written. How to compute $\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right)$ based on spell data:

$$
\begin{aligned}
&\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\ln\left(emp_{f(i,\tau),\tau}\right)\\
=\;&\sum_{s=1}^{S_{it}}\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{t-(x_{is}+\tau_s)-1}\left(1-\frac{(x_{is}+\tau_s)}{T_i}\right)\ln\left(emp_{f(i,s),s}\right)\quad\text{, with } \tau=x_{is}+\tau_s\\
=\;&\sum_{s=1}^{S_{it}}\ln\left(emp_{f(i,s),s}\right)\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{t-x_{is}-1}(1-\theta)^{-\tau_s}\left(1-\frac{x_{is}}{T_i}-\frac{\tau_s}{T_i}\right)\\
=\;&\sum_{s=1}^{S_{it}}(1-\theta)^{t-x_{is}-1}\ln\left(emp_{f(i,s),s}\right)\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\left(1-\frac{x_{is}}{T_i}\right)-(1-\theta)^{-\tau_s}\frac{\tau_s}{T_i}\\
=\;&\sum_{s=1}^{S_{it}}(1-\theta)^{t-x_{is}-1}\ln\left(emp_{f(i,s),s}\right)\left[\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\left(1-\frac{x_{is}}{T_i}\right)-\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\frac{\tau_s}{T_i}\right]\\
=\;&\sum_{s=1}^{S_{it}}(1-\theta)^{t-x_{is}-1}\ln\left(emp_{f(i,s),s}\right)\left[\left(1-\frac{x_{is}}{T_i}\right)\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}}_{A}-\frac{1}{T_i}\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s}_{B}\right]
\end{aligned}
\tag{A3}
$$

where s refers to the employment spells of a person, S_{it} is the total number of employment spells of worker i since labor market entry prior to day t and x_{is} is the number of days that has passed between individual labor market entry and the beginning of spell s. Since we only consider spells of employment, the indicator function $I(O_{i,\tau}=1)$ can be omitted. $\tau_s=1$ indicates the first day of spell s and T_i^s is the length of spell s in terms of days. A and B depend on the length of the considered spell only and, thus, can be computed separately and then merged to the spells according to their length.

To apply the Gauß-Newton-Algorithm the derivative of $w_{i,t}$ as given by Equation (8) w.r.t. θ is needed (again, we need to take into account that the data at hand is spell data):

$$
\begin{aligned}
&w_{i,t}=\dots\\
+\;&\alpha(1-\theta)^t edu_i\\
+\;&\sum_{\tau=1}^{t-1}\left[(1-\theta)^{t-\tau-1}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\right]\underbrace{\left[\gamma\kappa+\delta\kappa\ln\left(emp_{f(i,\tau),\tau}\right)+\rho\kappa\ln\left(emp_{r(i,\tau)-f(i,\tau),\tau}\right)\right]}_{\Omega_{i,\tau}}\\
+\;&\dots
\end{aligned}
$$

$$
\frac{\partial w_{i,t}}{\partial\theta}=(-1)\alpha t(1-\theta)^{t-1}edu_i+\sum_{\tau=1}^{t-1}\left[(-1)(t-\tau-1)(1-\theta)^{t-\tau-2}\left(1-\frac{\tau}{T_i}\right)I(O_{i,\tau}=1)\right]\Omega_{i,\tau}
$$

$$
\begin{aligned}
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\sum_{\tau_s=1}^{T_i^s}\left[(-1)(t-(x_{is}+\tau_s)-1)(1-\theta)^{t-(x_{is}+\tau_s)-2}\left(1-\frac{(x_{is}+\tau_s)}{T_i}\right)\right]\Omega_{i,s} \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}(-1)\left(1-\frac{x_{is}}{T_i}-\frac{\tau_s}{T_i}\right) \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}(-1)\left(1-\frac{x_{is}}{T_i}\right) \\
& +(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}(-1)\left(-\frac{\tau_s}{T_i}\right) \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}[\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}\left(\frac{x_{is}}{T_i}-1\right) \\
& +\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}\left(\frac{\tau_s}{T_i}\right)] \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}[\left(\frac{x_{is}}{T_i}-1\right)\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-1)(1-\theta)^{-\tau_s}-\tau_s(1-\theta)^{-\tau_s} \\
& +\frac{1}{T_i}\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-\tau_s-1)(1-\theta)^{-\tau_s}\tau_s] \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}[\left(\frac{x_{is}}{T_i}-1\right)\left((t-x_{is}-1)\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}-\sum_{\tau_s=1}^{T_i^s}\tau_s(1-\theta)^{-\tau_s}\right) \\
& +\frac{1}{T_i}\left(\sum_{\tau_s=1}^{T_i^s}(t-x_{is}-1)(1-\theta)^{-\tau_s}\tau_s-\sum_{\tau_s=1}^{T_i^s}\tau_s(1-\theta)^{-\tau_s}\tau_s\right)] \\
= \;& (-1)\alpha t(1-\theta)^{t-1}edu_i \\
& +\sum_{s=1}^{S_{it}}\Omega_{i,s}(1-\theta)^{t-x_{is}-2}[\left(\frac{x_{is}}{T_i}-1\right)\left((t-x_{is}-1)\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}}_{A}-\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s}_{B}\right) \\
& +\frac{1}{T_i}\left((t-x_{is}-1)\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s}_{B}-\underbrace{\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s^2}_{C}\right)] \qquad \text{(A4)}
\end{aligned}
$$

Test: derivative of equation (A3) w.r.t. θ (with Ω instead of $\ln(emp_{f(i,s),s})$):

$$
\begin{aligned}
& \sum_{s=1}^{S_{it}}(-1)(t-x_s-1)(1-\theta)^{t-x_{is}-2}\Omega_{is}\left((1-\frac{x_{is}}{T_i})\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}-\frac{1}{T_i}\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s\right) \\
+ \quad & (1-\theta)^{t-x_{is}-2}\Omega_{is}\left((1-\frac{x_{is}}{T_i})\sum_{\tau_s=1}^{T_i^s}(-1)(-\tau_s)(1-\theta)^{-\tau_s-1}-\frac{1}{T_i}\sum_{\tau_s=1}^{T_i^s}(-1)(-\tau_s)(1-\theta)^{-\tau_s-1}\tau_s\right) \\
= \quad & \sum_{s=1}^{S_{it}}(1-\theta)^{t-x_{is}-2}\Omega_{is}[(t-x_s-1)(\frac{x_{is}}{T_i}-1)\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}+(t-x_s-1)\frac{1}{T_i}\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s \\
- \quad & (\frac{x_{is}}{T_i}-1)\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s-\frac{1}{T_i}\sum_{\tau_s=1}^{T_i^s}(1-\theta)^{-\tau_s}\tau_s^2]
\end{aligned} \tag{A5}
$$

After computing A, B, and C for all values of T_i^s, A, B, and C can be merged to the employment spells.

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