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Annekatrin Niebuhr, Jan Cornelius Peters, Duncan Roth

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Dynamic agglomeration effects of foreigners and natives – The role of experience in high-quality sectors, tasks and establishments

Annekatrin Niebuhr (Institute for Employment Research and Kiel University),
Jan Cornelius Peters (Thünen Institute),
Duncan Roth (Institute for Employment Research)

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Abstract

This paper analyzes how dynamic agglomeration effects differ between foreign and native workers using administrative data on individual employment biographies. According to our results, both groups benefit, on average, equally from gathering work experience in large labor markets. The exception are low-skilled foreign workers, who receive a lower premium for big city experience than low-skilled natives. Providing new evidence on the sources of dynamic agglomeration effects, we show that this difference disappears once we consider the sectors, tasks and establishments, in which foreign and native workers gather experience. More generally, our results indicate that, on average, around 50% of the return of an additional year of experience gained in the densest regions can be ascribed to the acquisition of experience in higher-quality jobs in large cities.

Zusammenfassung

In diesem Artikel wird auf Grundlage individueller Erwerbsverläufe untersucht, inwiefern sich dynamische Agglomerationseffekte zwischen deutschen und ausländischen Beschäftigten unterscheiden. Unseren Ergebnissen zufolge profitieren beide Personengruppen im Durchschnitt in vergleichbarem Maß von Arbeitserfahrung, die in großen Arbeitsmärkten gesammelt wurde. Eine Ausnahme bilden dabei geringqualifizierte ausländische Beschäftigte, die für Erfahrung aus großen Städten eine geringer Prämie erzielen als vergleichbare deutsche Beschäftigte. Darüber hinaus liefern wir neue Erkenntnisse über die Faktoren, die dynamischen Agglomerationseffekten zugrunde liegen. Werden die Wirtschaftszweige, Berufe und Betriebe berücksichtigt, in denen Beschäftigte ihre Erfahrung sammeln, findet sich kein Unterschied mehr in der Prämie für Erfahrung aus großen Städten zwischen Deutschen und Ausländern. Insgesamt zeigt sich, dass etwa die Hälfte der Prämie, die für Erfahrung in den größten Städten erzielt wird, darauf zurückzuführen ist, dass in diesen Regionen besonders hochwertige Jobs zur Verfügung stehen.

JEL

J31, J61, R12, R23

Keywords

Dynamic agglomeration effects, ethnic inequality, job quality, learning, work experience

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1 Introduction

There is broad empirical evidence on an urban wage premium and wage growth, which increases with city size (Combes/Gobillon, 2015). According to the literature on agglomeration economies, an important part of the wage differential between urban and rural labor markets is due to agglomeration effects. Glaeser/Maré (2001) and De La Roca/Puga (2017) argue that in particular faster human capital accumulation in cities might explain the urban wage growth premium. These studies suggest that the size of local labor markets in which work experience is accumulated is an important determinant of its value because cities facilitate learning (Glaeser, 1999). Evidence provided by Baum-Snow/Pavan (2012), De La Roca/Puga (2017), and Peters (2020) indicates that a significant fraction of the urban wage premium is indeed caused by higher returns to work experience gained in larger cities.

This paper analyzes the differences in dynamic agglomeration effects between natives and foreigners. We estimate wage equations to investigate whether work experience gained in a large urban labor market influences future wages and whether this effect differs significantly between foreign and native workers in Germany. The analyses use administrative data on individual employment biographies dating back to 1975. This data set not only allows us to differentiate between the types of regions in which experience was gained. Moreover, we are able to classify experience according to the type of sector, task group and establishment in which it was acquired. Based on this information, we assess whether returns to big city experience differ between foreign and native workers. Furthermore, we study to what extent sorting into jobs, that presumably offer different potential to accumulate human capital, explains dynamic agglomeration effects in general and heterogeneous dynamic gains from agglomeration by native and foreign workers in particular. Thereby, this analysis also provides new evidence on the sources of dynamic agglomeration effects. According to our results, the size of dynamic agglomeration effects falls, on average, by about 50 percent once we account for the type of sectors, tasks and establishments in which experience has been acquired.

Dynamic agglomeration effects might matter for the well-documented differences in labor market outcomes between ethnic groups (see, e.g., Algan et al., 2010; Bjerk, 2007) for different reasons. As ethnic minorities are over-represented in large cities, they might benefit more from agglomeration economies than native workers (Longhi, 2020). However, at the same time, their return to density might be lower because they tend to have lower levels of education than natives and may therefore benefit less from the learning advantages of cities. Moreover, there is evidence that foreign workers select into jobs that offer only a small potential for human capital accumulation. Peri/Sparber (2009) show that foreign-born workers specialize in manual tasks in the U.S. while natives often perform work that involves interactive tasks. Most recently, Storm (2022) documented a similar pattern for Germany.

By studying dynamic agglomeration effects of foreign and native workers and by assessing the role of a greater availability of higher-quality sectors, tasks and establishments in denser areas for these effects, this article makes several contributions to the literature. Firstly, it adds to recent research dealing with the significance and nature of agglomeration effects. An important mechanism that contributes to an urban wage (growth) premium is learning (Duranton/Puga, 2004) because dense urban regions promote knowledge spillovers. By investigating whether these effects differ between foreign and native workers, we examine heterogeneous returns to density that have rarely been considered in the urban economics literature so far (see Ananat/Shihe/Ross, 2018 and Longhi, 2020 for rare exceptions). Most studies, instead, analyze whether agglomeration benefits differ between the skill level of workers (see, e.g., Matano/Naticchioni, 2016; Carlsen/Rattsø/Stokke, 2016) or tasks (Bacolod/Blum/Strange, 2009; Koster/Ozgen, 2021).

Secondly, we examine whether the type of the job that foreign and native workers do has an impact on the size of learning effects. Specifically, we evaluate the mechanisms underlying dynamic agglomeration effects by estimating the contribution of experience gained in different sectors, task groups and establishment types. Thereby, we take into account that cities specialize in jobs that offer a high learning potential (see Davis/Dingel, 2019; Koster/Ozgen, 2021) and provide new evidence on the factors behind dynamic agglomeration effects. Eckert/Hejlesen/Walsh (2022) note that most previous studies do not consider how firm characteristics contribute to the urban wage premium. Moreover, existing evidence tends to focus on their relevance for static agglomeration effects (e.g., Combes et al., 2012; Dauth et al., 2022). The study by Eckert/Hejlesen/Walsh (2022) is a notable exception. However, their analysis focuses on a very specific group in the Danish labor market – male refugees arriving between 1986 and 1998 from eight different countries – in order to apply a quasi-experimental research design. Moreover, they do not examine whether foreign and native workers benefit differently from dynamic agglomeration effects. And finally, they do not investigate how experience acquired in different industries, tasks, and establishment types helps to explain the overall return to experience gained in large cities. Rather, they focus on better matching in cities and consider the gradual sorting of refugees into different types of jobs in rural and urban areas over time. Another exception is the study by Peters/Niebuhr (2019), who, however, focus on disentangling the effect of firm and labor market size on the value of work experience. They neither consider individual tasks of a worker nor the knowledge intensity of the sector in which experience was gathered. Furthermore, the authors do not consider potential differences between foreign and native workers with regard to the acquisition of valuable human capital.

Thirdly, our analysis contributes to the literature on ethnic wage gaps and labor market outcomes of minority workers by examining how heterogeneous benefits from dynamic agglomeration effects influence the native-foreign wage gap in Germany. Previous studies that investigate the significance of spatial factors for ethnic inequality either focus on the demographic composition of neighborhoods (Cutler/Glaeser, 1997) and the effects of ethnic social networks (Ananat/Shihe/Ross, 2018) or consider the local availability of jobs (Gobillon/Rupert/Wasmer, 2014) and, more specifically, jobs into which specific ethnic groups are hired (Hellerstein/Neumark/McInerney, 2008; Storm, 2022). In contrast, we investigate whether agglomeration effects matter for wage differences between foreign and native workers. Evidence on this issue is scarce so far and findings are ambiguous. While previous studies examine the role of static agglomeration effects (see Ananat/Shihe/Ross, 2018, Longhi, 2020), this paper focuses on dynamic effects. More precisely, we are interested in the learning opportunities that regions and different types of jobs offer and whether foreign workers benefit less from learning externalities in urban labor markets than natives.[1]

Taken together, our results suggest that, on average, native and foreign workers benefit from dynamic agglomeration effects to a similar extent: compared to experience gained in the least dense regions, the returns to experience from denser areas are similar for both groups. At most, we observe modest differences in the additional premium for work experience gained in dense labor markets between foreigners and natives. However, this result is driven by the middle- and high-skilled workers. Low-skilled foreign workers apparently receive a lower mark-up for past city experience than observationally equivalent natives. As this difference disappears once sector, task group and establishment quality in which experience was gained is controlled for, our results suggest that the initial difference in dynamic agglomeration effects reflects that low-skilled foreigners tend to select into lower-quality jobs in cities than natives. More generally, our results also suggest that the value of work experience depends on task types, the knowledge-intensity of the sector and establishment quality. Together, these mechanisms explain about half of the dynamic agglomeration effect. However, while this applies to the low- and middle-skilled workers, selection into high-quality jobs in big cities appears to be less relevant for dynamic agglomeration effects experienced by high-skilled workers.

In our analyses, we take into account that differences in labor market outcomes between foreign and native workers might be caused by various observable and unobservable worker characteristics. Moreover, workers with specific (un)observed characteristics might sort into dense urban labor markets (Glaeser/Maré, 2001; Combes/Duranton/Gobillon, 2008) and gradual sorting into better jobs over time might play a role

[1] There is likely an overlap of different spatial factors that might be relevant for the size of static and dynamic effects as, for instance, ethnic networks are likely important for static matching advantages as well as dynamic learning effects.

(Eckert/Hejlesen/Walsh, 2022). Detailed data on the employment biographies of the workers along with information on their workplaces and the location of the establishments enables us to control for a large set of worker-level, establishment-level and regional characteristics. Furthermore, making use of the panel structure of the data, we account for unobserved heterogeneity via worker fixed effects and we also control for unobserved factors at the establishment level that affect remuneration.

The paper proceeds as follows. In Section 2, we describe the data and provide descriptive evidence on the heterogeneous distribution of native and foreign workers as well as different types of sectors, tasks and establishments across regions with higher and lower labor market density. In Section 3, we explain our empirical strategy and in Section 4, we present and discuss the results of the regression analysis. Finally, in Section 5, we set out our conclusions.

2 Data and variables

2.1 Construction of an annual worker panel

The empirical analysis of this paper is based on data from the Integrated Employment Biographies (IEB). This data set contains the biographies of the universe of labor market participants in Germany (except for civil servants and the self-employed who account for approximately 12 percent of the labor force). It provides information about spells of employment, unemployment, job search, benefit receipt as well as participation in measures of active labor market policy on a daily basis since 1975. As the IEB is constructed from administrative records, including health, pension and unemployment insurance notifications, the data is highly reliable (Gathmann/Schönberg, 2010). Moreover, each employment record in the IEB contains an establishment identifier which allows linking worker-level with employer-level information (a detailed description of the IEB data is provided by vom Berge/Burghardt/Trenkle, 2013).

We draw a 10 percent random sample of the IEB covering the years 2000 to 2019. Based on this sample, we construct an annual panel of workers who are employed subject to social security contributions. For each worker, we retain the employment spell which contains 30 June of a given year (in case of parallel spells, we retain the one with the higher wage).[2] Our final estimation sample comprises 18,050,610 observations on 1,863,965 individuals.

[2] Like, e.g., Dauth et al. (2021), we exclude observations with wages below the marginal-job threshold.

A central variable of our analysis is a person's work experience (see Section 2.2). As the IEB provides information from 1975 onward (West Germany), we restrict the analysis to individuals born 1960 or later to ensure that we can measure experience from a person's entry into the labor market (cf., Dustmann/Meghir, 2005). For persons born before 1977, we require at least one spell of employment in West Germany before re-unification (as reliable data from East Germany only becomes available from 1993 onward). We exclude individuals for whom information about their place of employment or their sector is missing.

Moreover, the IEB does not contain information about work experience acquired abroad. To ensure that we do not underestimate work experience of foreigners compared to natives, we exclude observations of foreigners who are likely to have acquired work experience outside of Germany. To this end, we drop low-skilled workers (no completed apprenticeship) if they are aged 21 years or older when they first appear in the IEB data. Likewise, we use cut-off ages of 21 years and 27 years, respectively, for middle-skilled (completed apprenticeship) and high-skilled (completed tertiary education) individuals.

2.2 Variables

We provide a summary of the key variables in this section. Descriptive statistics can be found in Table A1 in the Appendix.

Foreign nationality. The employment notifications in the IEB provide information about a person's nationality. Accordingly, we define foreign workers as such based on their nationality (Ozgen et al., 2014; Dustmann et al., 2015). In case a person's nationality changes over time (e.g. due to naturalisation), we categorise a person according to the first recorded nationality. Our definition excludes those migrants (or their children) who acquired German nationality before entering the labor market.[3] In our data set, about 4 percent of observations refer to foreign nationals.

Wages. The IEB data provides information about a person's average daily wage (derived from the total wage earnings from an employment spell divided by the length of that spell). This variable is right-censored at the social security contributions limit. Wages above that limit are top-coded. We adopt the procedure by Dustmann/Ludsteck/Schönberg (2009) and Card/Heining/Kline (2013) to impute these wage observations (detailed information on the imputation procedure can be found in Dauth/Eppelsheimer, 2020). On average, German

[3] Between 1981 and 2019, the average annual naturalization rate was relatively low and amounted to 1.9 percent, i.e., in any of those years on average less than 2 percent of all foreigners who lived in Germany obtained German citizenship (source: "Einbürgerungsstatistik" and "Ausländerstatistik" of the German Federal Statistical Office, accessed on July 16, 2021). Children born in Germany with foreign parents have only since 2000 the right to citizenship in Germany (Ozgen et al., 2014).

nationals earn 106 Euro per day, compared to 98 Euro in the case of foreigners, which provides evidence of an unadjusted wage gap of almost 8 percent.

Employment density. The IEB contains information about a person's place of employment at the level of municipalities (currently, there are approximately 11,000 municipalities in Germany). To account for the attenuation of agglomeration benefits with distance (Di Addario/Patacchini, 2008; Rosenthal/Strange, 2008), we follow Peters/Niebuhr (2019) and compute employment density based on employment in a distance of at most 10 kilometers (≈ 6.2 miles) around the geographic center of the municipality in which a worker is employed in a certain year (see Figure A1 in the Appendix for details). In doing so, we 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/Petrongolo (2017).[4] As workers have discretion over the region that they work in, we use an instrument for current employment density in our analysis. We follow the literature and use historic population density for this purpose (see, e.g., Ciccone/Hall, 1996; Combes et al., 2010). Specifically, we use regional population figures at the level of about 1,000 historic districts for the year 1925 provided by Falter/Hänisch (1990).[5] Foreign and native workers do not appear to be distributed equally across space. The larger mean employment density indicates that foreigners are over-represented in denser areas compared to natives.

Experience. As the IEB data contains records from 1975 onward, we can compute total work experience for each individual in our sample since entry into the labor market (see Section 2.1). On average, German workers have 13.3 years of experience which is slightly more than foreigners (11.5). The information provided by the IEB allows us to construct experience separately by labor market density, sector, task groups and establishment quality (within each of these categories, the sum of experience equals total experience):

- **Labor market density:** We use the information about a worker's place of employment throughout the employment biography to compute experience acquired in differently dense regions (De La Roca/Puga, 2017). Specifically, we divide the distribution of locally weighted employment density (across all years) into quartiles (the thresholds are: 67.6, 190.7 and 532.3 employees per km^2). Reflecting the difference in current employment density, foreign workers also have acquired – proportionally and absolutely – more experience in the two densest categories than natives. Moreover, the average share of experience acquired by foreigners increases with density, while it falls for natives. Experience acquired in denser regions may be more valuable because these regions are

[4] See also Briant/Combes/Lafourcade (2010) for a discussion of the Modifiable Areal Unit Problem (MAUP) in the context of the estimation of agglomeration economies.
[5] We use shape files from the MPIDR Population History GIS Collection (https://censusmosaic.demog.berkeley.edu/data/historical-gis-files), information provided by Rahlf (2020) and the software ArcMap 10.6 to map historic population densities to the 10 km circles around today's municipalities.

more likely to contain higher-quality sectors, task group and establishments (see Section 2.3).

- **Sector:** We map sectors into six sector groups based on Gehrke et al. (2010): knowledge-intensive and non-knowledge-intensive production, knowledge-intensive and non-knowledge-intensive services, agriculture and the public sector.
- **Task groups:** We assign occupations to five task groups based on Dengler/Matthes/Paulus (2014): non-routine abstract, non-routine interactive, routine manual, routine cognitive and non-routine manual. We collect periods of experience for which the occupation is not known in an additional residual category.
- **Establishment quality:** We proxy establishment quality using the estimated establishment fixed effect from an AKM-style wage decomposition (Abowd/Kramarz/Margolis, 1999). In the German context, the former are also referred to as establishment CHK effects (Card/Heining/Kline, 2013). A detailed description is provided by Bellmann et al. (2020). We divide the distribution of the establishment AKM effects into four parts in such a way that approximately one quarter of total experience is assigned to each part. The AKM effects are available only between 1985 and 2017. We collect experience for which the establishment quality is not available in a residual category.

Skill groups. We distinguish between three skill groups based on a person's level of qualification. Low-skilled workers are those without a completed apprenticeship, middle-skilled workers those with a completed apprenticeship and high-skilled workers those with completed tertiary education. We categorize workers according to the highest level of qualification that is obtained until the end of the observation period (in the empirical analysis, we include dummy variables to control for episodes in which a person's current level of qualification does not match her final qualification). On average, 18 percent of observations fall into the high-skill category, 78 percent into the middle-skill category and 4 percent into the low-skilled category. While the share of high-skilled workers is comparatively similar between foreigners and natives, the share of low-skilled among foreign workers is considerably higher (19 percent) than among natives (4 percent).

Additional individual-level variables. In addition, we control for a person's gender, part-time status and tenure. Approximately, 44 percent of observations refer to females, with the share being smaller among foreigners than natives. About 20 percent of workers are recorded to work part-time with comparable shares in the two groups. Moreover, we control for a person's current occupation at a 2-digit level according to the 2010 occupational code (*Klassifikation der Berufe 2010*).

Establishment-level variables. At the establishment level, we account for the sector of economic activity at the 2-digit level according to the 2008 sector classification (*Klassifikation der Wirtschaftszweige, Ausgabe 2008*) as well as for differences in establishment size by defining four categories: small establishments (1-9 employees), medium-sized establishments (10-49 employees), large establishments (50-249 employees) and very large establishments (250 or more employees). Finally, we use the estimated AKM establishment effect (Bellmann et al., 2020), lagged by one period, to control for unobserved differences in establishment quality. Foreigners are, on average, about 10 percentage points more likely to be employed at very large establishments than natives, while the difference in current establishment quality is small.

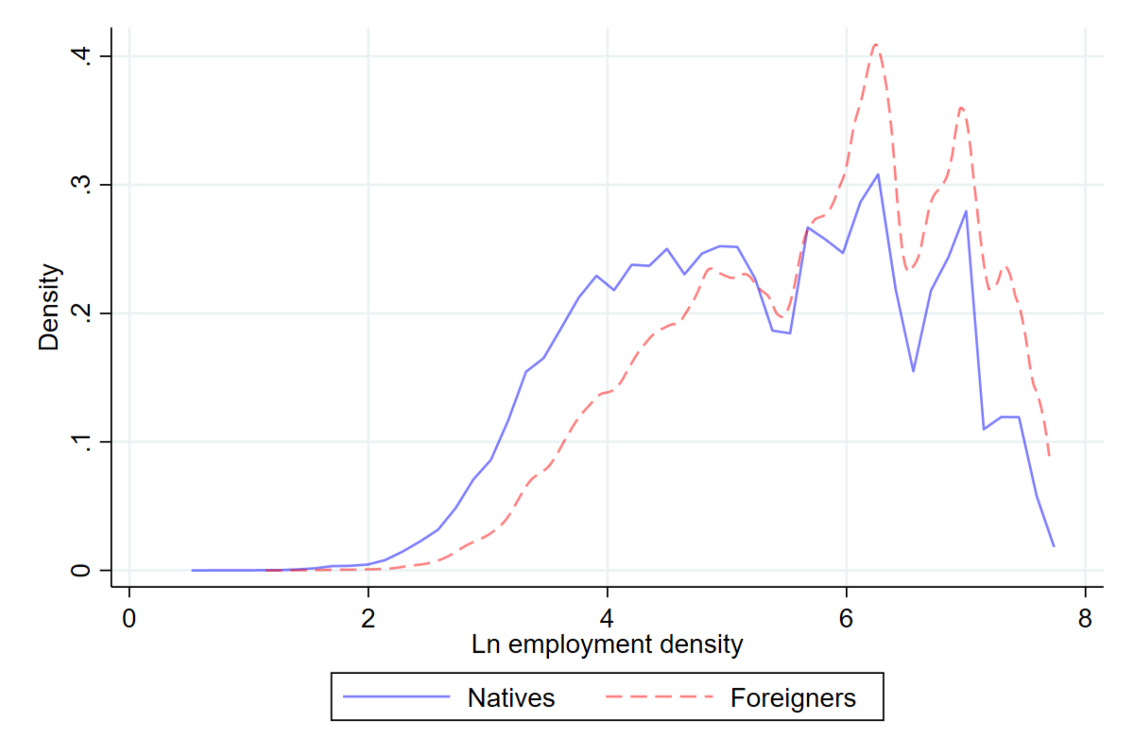
Regional employment share of own nationality. Following Ananat/Shihe/Ross (2018), we include the share of an individual's own nationality in regional employment to control for potential network effects.

2.3 Spatial distribution of workers and types of experience

Table A1 already indicated that the regional distribution of foreigners and natives differs, with foreigners, on average, working in denser regions. Figure 1 shows the kernel density plot of employment density for natives and foreigners. Among foreign workers, the share employed in denser areas is clearly greater than among native workers. According to this evidence, foreign workers may be in a better position to benefit from dynamic agglomeration effects as they more often work in dense areas and as such are able to gather experience in these regions.

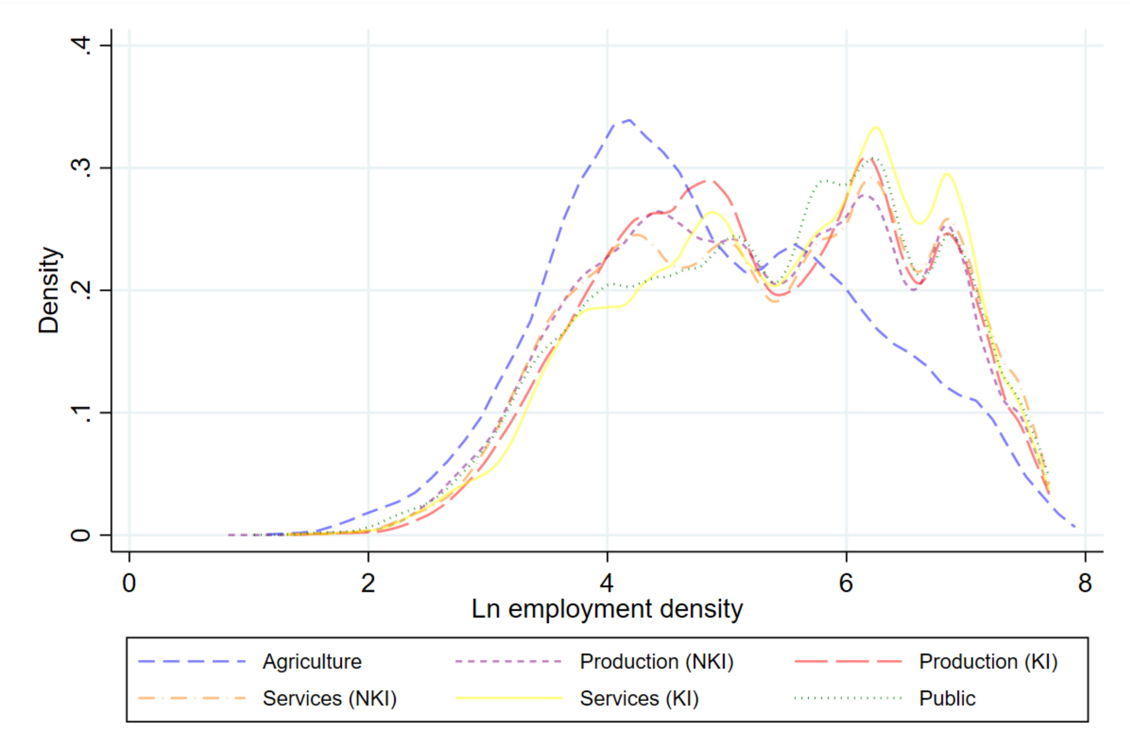
That working in denser regions is potentially associated with acquiring more valuable experience is illustrated in the following figures which show the spatial distribution of employment by sector, task group and establishment quality. As can be seen from Figure 2, knowledge-intensive services, which presumably offer opportunities for acquiring valuable experience (compare discussions by Davis/Dingel, 2019; Peters, 2020; Koster/Ozgen, 2021), are more often located in dense areas than any other sector. By contrast, knowledge-intensive production, where experience may also be highly remunerated, is over-represented in less dense areas. According to Figure 3, regions with a high employment density also display relatively high shares of non-routine analytic and non-routine interactive employment. As shown in Figure 4, denser regions contain proportionately more establishments of high or higher quality, in addition.

Figure 1: Spatial distribution of employment by nationality



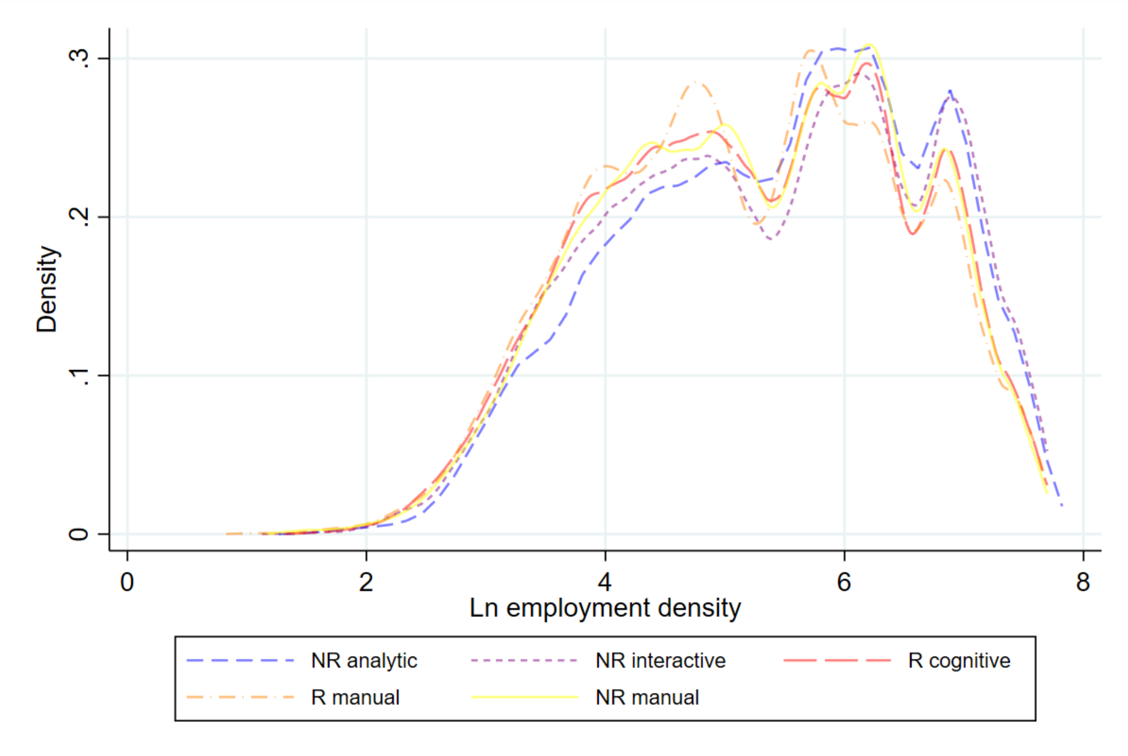
Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,610. Employment density refers to employment in a distance of at most 10 kilometers to the geographic center of the municipality in which a worker is employed in a certain year.
Source: IEB, own calculations. ©IAB

Figure 2: Spatial distribution of employment by sector



Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,610. Employment density refers to employment in a distance of at most 10 kilometers to the geographic center of the municipality in which a worker is employed in a certain year. *KI* indicates *knowledge-intensive sectors* and *NKI* indicates *non-knowledge-intensive sectors*.
Source: IEB and Gehrke et al. (2010), own calculations. ©IAB

Figure 3: Spatial distribution of employment by task group



Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,610. Employment density refers to employment in a distance of at most 10 kilometers to the geographic center of the municipality in which a worker is employed in a certain year. *NR* indicates *non-routine task groups* and *R* indicates *routine task groups*.
Source: IEB and Dengler/Matthes/Paulus (2014), own calculations. ©IAB

Figure 4: Spatial distribution of employment by establishment quality

Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,610. Employment density refers to employment in a distance of at most 10 kilometers to the geographic center of the municipality in which a worker is employed in a certain year. Establishment quality refers to establishment coefficient estimates from AKM regressions by Bellmann et al. (2020), see Section 2.2.
Source: IEB and Bellmann et al. (2020), own calculations. ©IAB

3 Model and identification

3.1 Empirical model

We specify the following model to assess dynamic agglomeration effects and how they differ between natives and foreigners:

$$\begin{aligned}\ln(w_{i,r,t}) = {} & \eta_i + \phi_1^f exp_{i,t} + \phi_2^f exp_{i,t}^2 + \sum_{p=2}^{4} \alpha_p^f exp\_reg_{i,t}^p + \sum_{s=2}^{6} \beta_s^f exp\_sec_{i,t}^s \\ & + \sum_{o=2}^{6} \gamma_o^f exp\_task_{i,t}^o + \sum_{q=2}^{5} \delta_q^f exp\_qual_{i,t}^q + \boldsymbol{\psi^f x_{i,r,t}} + \kappa^f \ln(dens_{r,t}) \\ & + \theta_{l(r),t}^f + \varepsilon_{i,r,t}.\end{aligned} \tag{1}$$

The dependent variable is the log daily wage of worker i who is employed in municipality r in year t. To evaluate how natives and foreigners benefit from dynamic agglomeration effects, we include experience gained in regions from quartile p of the employment density distribution, exp_reg^p. Experience from the first quartile, i.e. acquired in the least dense regions, serves as the reference category. Superscript f on the coefficient indicates that separate effects are estimated for natives and foreigners. Positive coefficient estimates that increase with the employment density of the region in which the experience was acquired would be indicative of dynamic agglomeration effects. We follow De La Roca/Puga (2017) and control for an individual's total work experience, $exp_{i,t}$, using linear and squared terms.

To assess the extent to which access to employment in higher-quality sectors, task groups and establishments in denser areas represent mechanisms behind dynamic agglomeration effects, we separately control for experience acquired in these categories. For experience by sector, exp_sec^s, we choose low-knowledge production as the base category. Likewise, for experience by task group, exp_task^o, and experience by establishment quality, exp_qual^q, we define routine manual tasks and the lowest quartile of the establishment quality distribution as the reference groups.

To account for unobserved worker heterogeneity, we further include individual-level fixed effects, η_i. Vector $x_{i,r,t}$ contains all remaining individual-level, establishment-level and regional control variables that are described in Section 2.2. The log employment density within the 10 km radius around the center of municipality r, $ln(dens_{r,t})$, captures static agglomeration effects and $\theta_{l(r),t}^f$ controls for annual unobserved shocks by labor market region. For this purpose, we assign each municipality r to one of the 141 labor market regions defined by Kosfeld/Werner (2012). These regions combine one or more administrative NUTS-3 regions (counties) based on commuting linkages. Finally, $\varepsilon_{i,r,t}$ denotes a random error term.

3.2 Identification

The sorting of more able workers into local labor markets with a higher density (Combes/Duranton/Gobillon, 2008) is captured by worker fixed effects. The latter also account for different patters of sorting across space between foreign and native workers.

Furthermore, we only use the variation of experience within labor market regions, sectors and occupations to identify dynamic agglomeration effects. The considered region-year fixed effects account for all time-variant and -invariant differences between these regions that affect wages such as general labor market conditions, regional labor supply and demand shocks, the regional monopsony power of firms and the endowment with amenities. The industry and occupation fixed effects may control for a potential sorting of foreign and native workers with certain levels and / or types of experience into specific industries and occupations as discussed by Eckert/Hejlesen/Walsh (2022).

To control for a potential selection of workers into firms, we use establishment coefficient estimates from AKM regression by Bellmann et al. (2020). If workers with certain types of work experience are over-represented in establishments that for any reason pay on average higher or lower wages than other firms, the estimated returns to experience are likely biased. The same applies to corresponding differences between foreign and native workers if the distribution of these two groups of workers across firms differs.

To account for the endogeneity of current employment density, $ln(dens_{r,t})$, in a wage equation, we apply two-stage least squares (2SLS) regression using historic population density in 1925 as an external instrument. Using long lags of population density as instrument, is widely applied in the urban economics literature (see, e.g., Ciccone/Hall, 1996; Combes/Duranton/Gobillon, 2008; Combes et al., 2010; De La Roca/Puga, 2017; Bosquet/Overman, 2019).

A further econometric issue is the computation of standard errors in a model like Equation (1) where individual wages are regressed on characteristics of the regional environment like current employment density. The covariance matrix has a complex structure due to unobserved local shocks, the consideration of density in overlapping circles and the spatial mobility of workers (cf. Combes/Gobillon, 2015). Since the two-stage regression approach proposed by Combes/Duranton/Gobillon (2008) is not feasible in our case as we consider more than 10,000 local employment densities per year, we, in contrast, estimate Equation (1) directly and report standard errors proposed by Driscoll/Kraay (1998), which are robust to very general forms of cross-sectional and temporal dependence.

4 Results

4.1 Differences in agglomeration effects between foreign and native workers

Before discussing the results on dynamic agglomeration effects, we use our regression model to illustrate the foreign-native wage gap in Germany and important explanatory factors. Column (1) of Table 1 shows that the raw wage gap for foreign workers in Germany is 12 percent conditional on region-year fixed effects. This is broadly in line with findings from previous studies. Nanos/Schluter (2014) report raw log wage gaps for Germany that vary between 0.09 and 0.45 depending on the occupation-age segment. Dustmann et al. (2011) note that the majority of second-generation immigrants in large Western European countries (France, Germany, UK) experience on average a wage gap of around 10 percent relative to observationally equivalent native workers controlling for a basic set of characteristics.

Considering static agglomeration benefits and returns to experience reduces the wage gap by 40 percent (see column (2)). The estimated experience profile has the expected concave form. According to our results, the density elasticity of wages is significantly smaller for foreign compared to native workers, ceteris paribus. This is in line with findings concerning racial differences in the returns to density in the U.S. (Ananat/Shihe/Ross, 2018). However, additional results show that the discount that foreign workers face when static agglomeration economies are concerned is not the main cause behind the reduction of the wage gap. This is largely driven by the inclusion of experience. The lower return to density of foreign workers is more or less outweighed by the disproportionately high share of foreigners living in large cities (see density plots in Section 2). Comparing the results from the more parsimonious model in column (2) with the full model in column (7) suggests that the higher return to experience of foreigners in column (2) is due to omitted variable bias.

In column (3), we also include individual characteristics, estimates of establishment fixed effects from an AKM wage decomposition as well as the regional employment worker share of a worker's own nationality as proposed by Ananat/Shihe/Ross (2018).[6] These variables account for a significant part of the static agglomeration effect and the corresponding discount observed for foreign workers. Hence, foreign and native workers differ significantly with respect to attributes that affect wages. Moreover, the results confirm evidence on important sorting effects, i.e. workers with characteristics that are associated with higher wages are more likely to work in large cities (Combes/Duranton/Gobillon, 2008).

Occupational segregation and sorting across sectors are important factors of ethnic wage gaps as well (see e.g., Bjerk, 2007 and Elliott/Lindley, 2008). This is considered in column (4). Including occupation and sector fixed effects also affects the size of static agglomeration effects and the corresponding discount of foreign workers. Cities offer many jobs with an above-average income potential and this specialization on highly productive jobs adds to the urban wage premium. This is in line with recent evidence provided by Eckert/Hejlesen/Walsh (2022). Moreover, our results indicate that natives seem to benefit more than foreign workers from the advantageous economic and occupational structure of cities as the discount experienced by foreign workers with regard to static agglomeration effects decreases once we include occupation and industry fixed effects.

[6] Since all covariates and fixed effects are interacted with an indicator variable for foreign citizenship, the non-interacted foreign dummy is omitted from column (3) onward due to collinearity.

Table 1: Static and dynamic agglomeration effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign (FGN)	-0.1231***	-0.0736***					
	(0.0006)	(0.0050)					
Static agglomeration effects							
Ln employment density		0.0772***	0.0294***	0.0227***	0.0102***	0.0099***	0.0099***
		(0.0020)	(0.0004)	(0.0004)	(0.0011)	(0.0010)	(0.0010)
FGN × ln emp. dens.		-0.0412***	-0.0126***	-0.0099***	-0.0050***	-0.0049***	-0.0049***
		(0.0023)	(0.0014)	(0.0009)	(0.0015)	(0.0015)	(0.0015)
Total experience and tenure							
Total experience		0.0253***	0.0197***	0.0197***	0.0484***	0.0460***	0.0460***
		(0.0034)	(0.0012)	(0.0011)	(0.0024)	(0.0024)	(0.0024)
FGN × total exp.		0.0046***	0.0008	0.0013*	-0.0078***	-0.0084***	-0.0081***
		(0.0007)	(0.0008)	(0.0007)	(0.0011)	(0.0011)	(0.0013)
Total experience^2		-0.0003***	-0.0003***	-0.0003***	-0.0006***	-0.0006***	-0.0006***
		(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FGN × total exp.^{2}		-0.0001***	-0.0001***	-0.0001***	-0.0000***	-0.0000***	-0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure			0.0015***	0.0013***	0.0009***	0.0009***	0.0009***
			(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FGN × tenure			-0.0000***	-0.0000*	-0.0003***	-0.0003***	-0.0003***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure^2			-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign × tenure^2			0.0000	-0.0000	0.0000***	0.0000***	0.0000***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions							
Exp. lower density						0.0018***	0.0018***
						(0.0002)	(0.0002)
FGN × exp. lower dens.							-0.0007***
							(0.0002)
Exp. higher density						0.0031***	0.0031***
						(0.0003)	(0.0003)
FGN × exp. higher dens.							-0.0003
							(0.0004)
Exp. highest density						0.0044***	0.0044***
						(0.0004)	(0.0004)
FGN × exp. highest dens.							0.0001
							(0.0005)
Region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes	Yes
Interaction with foreign	No	No	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes	Yes	Yes
Worker FE	No	No	No	No	Yes	Yes	Yes
R^2 (net of FE)	.066	.092	.593	.481	.232	.233	.233

Note: Unit of observation is person-year. The number of observations is 18,050,610 in each specification. Dependent variable is a worker's log daily wage. Control variables are: sex, level of qualification, part-time status, establishment size, regional worker share of own nationality, establishment coefficient estimate from AKM regression. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. Employment density refers to employment in a radius of 10 km. We use the quartiles of local employment within 10 km as thresholds to consider experience by type of region. Two stage least squares (2SLS) estimation is applied to account for the endogeneity of current labor market density using historic population density as external instrument.
Source: IEB, own calculations. ©IAB

To control for unobserved heterogeneity, we add worker fixed effects in column (5). Unobserved worker heterogeneity reduces both the static agglomeration effects and the corresponding discount for foreign workers considerably. Moreover, the return to work experience of foreign workers is smaller than the return of German employees once we control for observed and unobserved individual characteristics. However, the overall return to experience sharply increases as we include worker fixed effects, indicating that workers with unfavorable unobserved characteristics tend to accumulate more work experience (e.g., due to fewer years of education and, thus, earlier entries into the labor market).

Column (6) summarizes the results of a model, which considers dynamic agglomeration effects in addition to static benefits from local labor market size. In line with previous findings by De La Roca/Puga (2017) and related studies, the estimates indicate that work experience acquired in dense urban labor markets is rewarded higher by employers than work experience gained in less dense regions (see wage-experience profiles in Figure A2 in the Appendix). Including dynamic agglomeration effects in the model, also affects the estimate of the return to experience of foreign workers relative to natives. The gap in the return to experience increases because foreign workers tend to acquire more work experience in cities than German employees do.

In the full model (column (7)), we allow for heterogeneous benefits from dynamic agglomeration effects. However, evidence on important differences in the return between foreign and native workers is weak. Two out of three coefficient estimates of the interaction effects do not differ statistically significantly from zero. Hence, in contrast to static agglomeration effects, from which foreign workers benefit less than native workers, both groups of workers apparently gain (almost) equally from dynamic agglomeration benefits and acquiring work experience in denser regions compared to gathering experience in the least dense regions. However, in labor markets of the second-lowest density category, the earnings experience profile of foreign workers seems to be significantly flatter than the one of native workers. This is indicated by the significantly negative estimate obtained for the interaction of the foreign indicator and work experience acquired in the second density quartile. The benefit of acquiring work experience there rather than in the least dense labor markets is in absolute terms for foreign workers almost 40 percent lower [0.0018-0.0007] than for native workers [-0.0018].

The estimates of dynamic agglomeration effects in columns (6) and (7) refer to dynamic gains from local labor market size net of benefits from a gradual sorting into better jobs in denser regions, which is related to dynamic matching advantages in agglomerated labor markets. Following Eckert/Hejlesen/Walsh (2022), we argue that the latter are captured in our regressions by the fixed effects for occupation and industry as well as a measure for establishment quality. In our case, we use the estimated establishment fixed effect from AKM regression (see Section 2.2). The analyses by Eckert/Hejlesen/Walsh (2022) indicate that about 50 percent of the faster wage growth experienced by refugees in Denmark's capital region of Copenhagen relative to refugees in other parts of the country are related to gradual movements towards higher-quality jobs. However, in our context focusing on a random sample of all labor market participants in Germany, the gradual sorting into better jobs apparently is less relevant for the faster wage growth in urban compared to rural areas. Table A2 in the Appendix summarizes estimates for dynamic agglomeration effects that we obtain when we omit the fixed effects for occupation and industry, as well as the measure of establishment quality. The estimated dynamic agglomeration effects shown there are only roughly 10 percent larger than the ones reported in Table 1. As regards differences between dynamic agglomeration effects for foreign and native workers, the additional results indicate that foreign workers experience a somewhat slower sorting into better jobs in some types of regions compared to the reference category, the least dense regions. However, for the most dense labor markets relative to the most sparsely populated regions, we do not observe such a disadvantage for foreign workers. In the following, we study in more detail the spatial differences in individual wage dynamics of foreign and native workers, hypothesizing that learning benefits are an important determinant of faster wage growth in big cities. In all of these specifications, we again include sector and occupation fixed effects as well as our measure of establishment quality.

4.2 Sources of dynamic agglomerations benefits

The results in column (7) of Table 1 point to the importance of dynamic agglomeration effects for wages. A potential mechanism behind dynamic agglomeration benefits refers to the kind of work experience that is primarily gained in large cities. This likely differs systematically from experience acquired in less dense regions as regards tasks, knowledge-intensity, establishment quality and, thus, learning potential. As the distribution of foreign and native workers across occupations and sectors differs, this might also be relevant for the wage gap and how both groups benefit from work experience and dynamic agglomeration effects. The selection issue may involve an important spatial dimension since sectors, occupations and establishment types are not uniformly distributed across space (see Section 2). In particular, knowledge-intensive sectors, non-routine tasks, and high-quality establishments, which might give rise to more valuable experience, tend to concentrate in large cities (see Davis/Dingel, 2019, Koster/Ozgen, 2021, Eckert/Hejlesen/Walsh, 2022). A significant part of the dynamic agglomeration benefits that we detect may therefore relate to the opportunity to gain work experience in high-quality jobs that primarily large cities offer.[7]

[7] In Germany, there is a noteworthy exception to this pattern: knowledge-intensive manufacturing (e.g., manufacturing of machinery and motor vehicles) is often located outside large cities (see Peters, 2020 and density plots in Section 2).

We apply a simple regression model to investigate the composition of work experience gained in different density categories. The analysis provides information on how experience, which is accumulated in a specific region type translates into task- and sector-specific experience. In addition, we also account for the establishment quality, which is based on AKM establishment fixed effects. We consider five sector and task types and four establishment categories in Table 2. The dependent variable is the work experience that a worker gained in the corresponding type taking into account important individual characteristics such as age, level of education and occupation. We focus on the correlation with experience by density category that is also interacted with an indicator for foreign workers. Thus, we can analyze whether foreign workers take less advantage from working in large cities than observationally equivalent German employees in terms of gaining more valuable knowledge-intensive work experience.

Table 2: Correlation between work experience by labor market density and experience by sector, task group and establishment quality, respectively

	Experience by sector type				
	Production		Services		
	Low knowledge	Knowledge intensive	Low knowledge	Knowledge intensive	Public service
Experience lowest density	0.396***	0.221***	0.145***	0.109***	0.121***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Experience lower density	0.318***	0.283***	0.164***	0.119***	0.115***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Experience higher density	0.246***	0.286***	0.193***	0.150***	0.124***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Experience highest density	0.197***	0.246***	0.228***	0.214***	0.114***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
FGN × exp. lowest density	0.163***	0.087***	-0.075***	-0.070***	-0.101***
	(0.0029)	(0.0026)	(0.0021)	(0.0012)	(0.0011)
FGN × exp. lower density	0.154***	0.097***	-0.075***	-0.079***	-0.097***
	(0.0024)	(0.0023)	(0.0020)	(0.0011)	(0.0010)
FGN × exp. higher density	0.180***	0.089***	-0.081***	-0.092***	-0.095***
	(0.0023)	(0.0023)	(0.0019)	(0.0012)	(0.0011)
FGN × exp. highest density	0.091***	0.117***	-0.015***	-0.117***	-0.076***
	(0.0020)	(0.0021)	(0.0021)	(0.0013)	(0.0011)
Adjusted R^2	0.346	0.261	0.294	0.370	0.268
	Experience by task group				
	Non-routine			Routine	
	Analytic	Interactive	Manual	Cognitive	Manual
Experience lowest density	0.068***	0.073***	0.182***	0.411***	0.259***
	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0003)
Experience lower density	0.081***	0.073***	0.157***	0.432***	0.249***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0003)

Continued on next page

Table 2 continued

Experience higher density	0.098***	0.071***	0.150***	0.455***	0.218***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Experience highest density	0.113***	0.074***	0.144***	0.485***	0.183***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
FGN × exp. lowest density	-0.021***	-0.050***	-0.031***	-0.189***	0.281***
	(0.0011)	(0.0009)	(0.0019)	(0.0020)	(0.0024)
FGN × exp. lower density	-0.033***	-0.050***	-0.008***	-0.185***	0.268***
	(0.0009)	(0.0008)	(0.0017)	(0.0018)	(0.0021)
FGN × exp. higher density	-0.033***	-0.048***	-0.001	-0.192***	0.265***
	(0.0010)	(0.0009)	(0.0016)	(0.0017)	(0.0020)
FGN × exp. highest density	-0.041***	-0.037***	0.046***	-0.199***	0.222***
	(0.0010)	(0.0009)	(0.0017)	(0.0017)	(0.0018)
Adjusted R^2	0.317	0.410	0.425	0.544	0.472

	Experience by establishment quality			
	Lowest	Lower	Higher	Highest
Experience lowest density	0.164***	0.257***	0.273***	0.229***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Experience lower density	0.093***	0.231***	0.291***	0.316***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Experience higher density	0.064***	0.212***	0.291***	0.371***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Experience highest density	0.027***	0.180***	0.285***	0.449***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
FGN × exp. lowest density	-0.141***	-0.068***	0.042***	0.161***
	(0.0017)	(0.0017)	(0.0018)	(0.0022)
FGN × exp. lower density	-0.108***	-0.078***	-0.0058***	0.181***
	(0.0014)	(0.0013)	(0.0015)	(0.0020)
FGN × exp. higher density	-0.089***	-0.077***	-0.007***	0.158***
	(0.0013)	(0.0013)	(0.0015)	(0.0020)
FGN × exp. highest density	-0.053***	-0.056***	-0.004**	0.096***
	(0.0013)	(0.0012)	(0.0015)	(0.0019)
Adjusted R^2	0.199	0.242	0.282	0.346

Note: Unit of observation is person-year. The number of observations is 18,050,610. Dependent variable is a worker's experience in a certain type of industry, task and establishment. Control variables are sex, age, level of qualification, occupation fixed effects and interactions of all controls with the dummy variable that indicates foreign citizenship. ***, ** and * indicate significance at the 1, 5 and 10 percent level. We use the quartiles of local employment within 10 km as thresholds to consider experience by type of region. Establishment quality refers to establishment coefficient estimates from AKM regressions by Bellmann et al. (2020).
Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

The upper panel of Table 2 shows the results for sector types. We differentiate between services, manufacturing and the public sector and also consider knowledge-intensity. The estimates for the service categories indicate that it becomes more likely to accumulate experience in these sectors as the density of the place of work increases. This is in line with an above-average share of services in large cities. The marginal effect of one additional unit of work experience gained in the respective region type to service sector experience increases as we move from low-density locations to the highest density category. This applies in particular to knowledge-intensive services where the coefficient almost doubles as we move from lowest to highest density locations. The opposite applies to low-knowledge manufacturing, while there is no clear gradient for knowledge-intensive manufacturing and the public sector.

Interestingly, foreign workers tend to gain less work experience in knowledge-intensive services through their employment conditional on their occupation, skill level and other controls. This gap increases as we move from low to high density sites. Similar differences arise for experience gained in low-knowledge services and the public sector. However, the gap does not systematically increase with density in these cases. Rather, it tends to be relatively small in the highest density locations. Moreover, foreign workers gain relatively more experience in manufacturing, both in low-knowledge and knowledge-intensive manufacturing.

We find similar evidence for experience in different task types and by establishment quality in the middle and lower panel of Table 2. As regards establishment quality, we observe that the marginal effect of additional experience declines with increasing density for the low-quality categories, while for the highest establishment quality there is a significant increase of the coefficient estimate as we move from low- to high-density experience. Opportunities to gain experience in non-routine analytic and routine cognitive tasks also seem to increase with density of the location, while it is easier to gain experience in manual tasks, both routine and non-routine, in low-density regions. Again, we detect a gap between foreign and German workers, primarily for experience in non-routine tasks. In particular, the size of this gap almost doubles for non-routine analytic tasks as we move from the lowest to the highest density category. Altogether, it seems that foreign workers cannot take full advantage of the opportunities, which large cities offer when valuable work experience is concerned. This pattern prevails for sector- and task-specific experience, while establishment quality represents a noteworthy exception.

We extend the wage model in column (7) of Table 1 and include work experience that is accumulated in different sectors, tasks and firm-types to examine how the different economic structure of rural and urban labor market affects the value of work experience and dynamic agglomeration effects. Specifically, we differentiate work experience by six distinct types of industries, six task groups and five establishment-types.[8] Thereby, we can also

[8] In addition to the experience categories considered in Table 2, we consider three additional experience variables: 'experience agriculture', 'experience unknown task' and 'experience unknown establishment quality'. The two latter variables comprise experience that we cannot assign to one of the other types because some employment spells do not contain information about the occupation and estimates of AKM

consider that native and foreign workers might acquire work experience within the same type of local labor market in different jobs, which might provide very different opportunities to acquire valuable human capital. The results are summarized in Table 3 where we focus on the effects of total experience and experience by density type.[9] As a reference, we include the model without different types of experience (column (7) of Table 1) in column (1).

In column (2) we include experience by sector-type with experience gained in low-knowledge manufacturing in the least dense regions being the reference. Our results indicate that the value of work experience indeed significantly differs between knowledge-intensive sectors, low-knowledge production and the public sector (see Table A3). This apparently explains to some extent as to why the value of work experience increases with the density of the labor market, in which it was acquired. The point estimates obtained for work experience acquired in the second to fourth density quartile are – in absolute terms – 25 percent to 28 percent smaller in column (2) than in column (1). Hence, work experience acquired in the labor markets with the highest density evidently was disproportionately gathered in industries, which provide comparatively large learning opportunities.

Considering that work experience is collected in different tasks and sectors, reduces the estimates of the second and third density category by roughly the same amount (see column (3)). However, differentiating experience by tasks is more important for the highest density locations. The coefficient of experience gained in the latter category declines by almost 39 percent once we include experience by task-type. The changes triggered by controlling for human capital accumulated in different establishment types are, in comparison, smaller, in particular in high density areas (see column (4)).

The comprehensive model in column (5) includes all three types of work experience. Comparing the reductions in the estimates for dynamic agglomeration effects across columns (2)–(5) indicates that different types of experience partly overlap when their contribution to dynamic agglomeration effects is concerned. Altogether, the composition of work experience explains around 50 percent of the dynamic agglomeration effects. This reduction in the size of dynamic agglomeration effects is of a similar magnitude to results by Eckert/Hejlesen/Walsh (2022) after accounting for the above-average job-quality in agglomerations in their analysis of refugees' wage growth in Denmark. However, the authors focus on gradual sorting towards high-wage, service establishments, occupations and industries typically found in cities, which appears to be less relevant for the urban wage growth premium in our context (see the discussion at the end of Section 4.1). In contrast,

establishment fixed effects are not available for all establishments (see data description), respectively.

[9] Table A3 in the Appendix shows the coefficient estimates for all experience categories and, as a robustness check, Table A4 in the Appendix summarizes estimates of dynamic agglomeration effects based on reduced samples focussing on (male) full-time workers that differ only modestly from the estimates reported in Table 3.

our results provide evidence for the significance of learning advantages offered by jobs in cities. These take the form of a more favorable composition in terms of sectors, tasks and establishment quality.

Including experience accumulated in different sectors, tasks and establishment categories also affects the return to experience of foreign worker relative to natives. The point estimate of the corresponding interaction effect declines in absolute terms by 30 percent (-0.0081 versus -0.0057) indicating that foreign workers sort into sectors and tasks that provide relatively low opportunities to acquire valuable work experience conditional on experience by region type and covariates.[10] Moreover, the sorting of foreigners into jobs that offer a rather low learning potential also explains as to why foreign workers experience a lower wage premium than natives for work experience gathered in the regions of the second density category. The corresponding interactions effect declines by more than half if we control for the different types of experience (-0.0007 versus -0.0003).

4.3 Dynamic agglomeration effects for foreign and native workers by skill group

The results so far suggest that sorting of foreign workers into jobs that offer a comparatively low learning potential influences their future wages relative to natives. However, the sorting into specific sectors, tasks and establishments as well as the benefit from gathering experience in large labor markets is likely influenced by a worker's skill level (see, e.g., De La Roca/Puga, 2017 for the latter). Therefore, we examine whether the benefits from dynamic agglomeration effects and the role of experience collected in different jobs varies between skill groups. In Table 4, we present the results from separate estimations for three distinct groups of worker, that we define based on the educational level at the end of the observation period. For each sub-sample of workers, we estimate a model containing experience by density category (as in column (1) in Table 3) as well as an augmented model, in which we control for experience by sector, task group and establishment quality (as in column (5) of Table 3).

For low-skilled workers, the results in column (1) in Table 4 indicate that dynamic agglomeration effects significantly differ between foreign and native workers. Contrasting the results for the entire sample (column (1) in Table 3), all interaction effects of the foreign-indicator and experience by density category are now significantly smaller than zero. Specifically, the estimates imply that foreign low-skilled workers also benefit from acquiring experience in denser labor markets – the premium for one additional year of

[10] Interestingly, the interaction effect between foreign and total experience does change only modestly if we only include experience by establishment type (compare columns (1) and (4)).

experience in the highest density category, for example, is 0.0022 [0.0038-0.0016] – but they gain to a lesser extent from dynamic agglomeration effects than low-skilled natives do. More precisely, the additional mark-up for experience acquired in labor markets of the highest density is, according to the results in column (1), 42 percent [0.0022/0.0038-1] lower for foreign than for native low-skilled.

If we account for the types of occupation, task and establishment, in which foreign and native low-skilled workers gathered experience (column (2)), the interaction effects are in absolute terms substantially smaller and no longer statistically significantly different from zero. In particular, the difference in the wage premium for experience acquired in the most dense labor markets relative to experience in the least dense regions is virtually zero conditional on the other types of experience and covariates. In absolute terms, the interaction effect declines from -0.0016 to 0.0001. Hence, the results indicate that the initial difference in dynamic agglomeration effects reflects that low-skilled foreigners tend to select into lower-quality jobs in cities than natives with a comparable skill level.[11] Figure 5 illustrates that more than 70 percent of the experience acquired by foreign low-skilled workers in the most dense local labor markets is gathered in routine or non-routine manual task, which are the task groups with the lowest return to experience (Table A5). In contrast, among the native low-skilled the share of these task groups amounts to less than 60 percent of the experience gathered in the labor markets with the highest density. Figures A3 and A4 in the Appendix provide additional information on the composition of experience considering different sectors and establishment types, respectively. In line with the results reported in Table 2, low-skilled foreign workers acquire big city experience, on average, in higher-quality establishments than low-skilled natives do. Hence, the lower returns to big city experience compared to experience from less dense labor markets is apparently mainly related to a relatively low quality of sectors and task groups, rather than to a low quality of establishments in which experience has been gathered.

Contrasting the results for the low-skilled, analyses for the middle- and high-skilled do not provide evidence that foreign workers with these skill levels benefit less than similarly educated natives from acquiring experience in agglomerated labor markets. In the case of middle-skilled foreign workers, we even detect an additional wage premium for experience acquired in the labor markets with the highest density if we estimate dynamic agglomeration effects conditional on the other types of experience (column (4)). However,

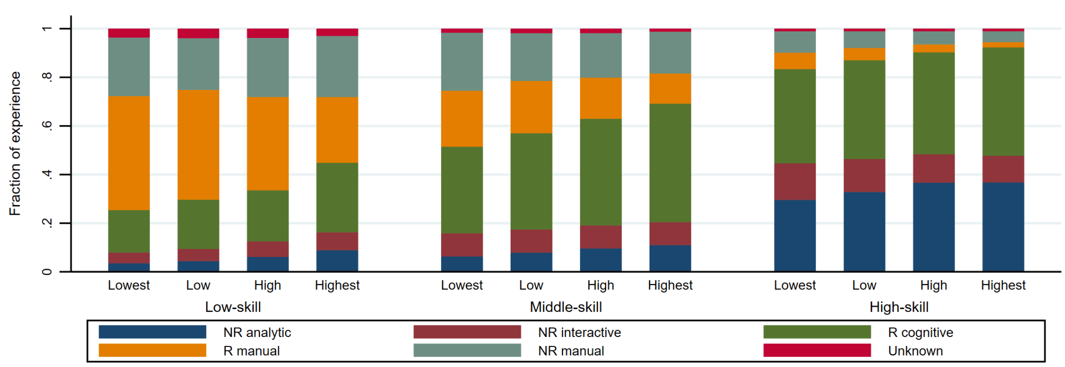
[11] In specifications (2), (4) and (6) of Table 4, we do not only consider additional experience categories, but we also allow that the return to the these types of experience differs between foreign and native workers (see Table A5). Heterogeneous returns to certain types of experience, that are often acquired in dense labor markets, between low-skilled foreigners and natives might be an alternative explanation for the smaller dynamic agglomeration gains experienced by the foreign low-skilled. However, the lower mark-up for big city experience also vanishes if we only consider the additional experience categories and assume that foreign and native low-skilled benefit equally from the different types of experience (Table A6). This points to the significance of sorting for the heterogeneous dynamic agglomeration benefits for the foreign and native low-skilled.

this additional benefit from acquiring experience in highly agglomerated regions is (partly) offset by the sorting of foreign middle-skilled workers into jobs with a rather low potential to accumulate human capital indicated by the smaller and statistically insignificant interaction effect in column (3), see also Figure 5.

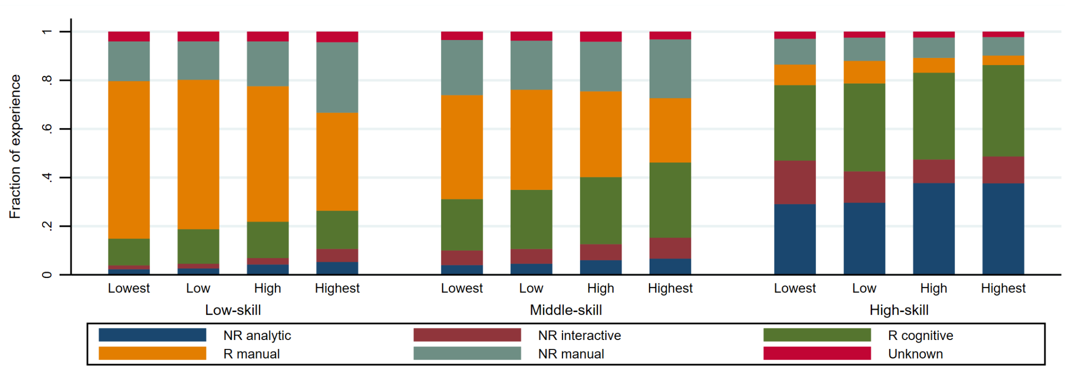
The results in Table 4 also provide new insights on the source of dynamic agglomeration effects in general. Comparing the results for the specification with and without experience by sector, task group and establishment quality indicates that in particular the low- and middle-skilled apparently benefit from the special type of jobs that cities offer with regard to knowledge acquisition. For these two groups, the estimated dynamic agglomeration effects are about 50 percent smaller once we account for the previous sorting into jobs that differ with regard to the learning potential. In contrast, for the high-skilled, the results suggest that the quality of jobs, in which these workers acquired experience, does not systematically differ across labor markets of different sizes. This is in line with the pattern reported in Figure 3, which shows that high-skilled workers acquire in all four types of labor markets more or less the same kind of experience with regard to task groups, while there are larger differences for the low- and medium-skilled, in particular with regard to the share of the routine manual task group.

As regards total experience, which refers to experience in the reference categories (the least dense labor market, low knowledge production, routine manual job task, the lowest establishment quality), the results for the different skill groups in Table 4 point to heterogeneous differences between foreign and native workers. While low-skilled foreign workers receive on average a higher return to work experience than observationally equivalent natives, we observe the reverse for the middle-skilled and for the high-skilled the difference is statistically at most weakly significantly different from zero.

Figure 5: Composition of work experience w.r.t. task groups by labor market density and skill level for foreign and native workers



(a) Native workers



(b) Foreign workers

Note: The figure illustrates the composition of work experience with regard to task groups for low-skilled, middle-skilled and high-skilled workers by the density (lowest, low, high, highest) of the local labor market, in which experience has been acquired. *NR* indicates *non-routine task groups* and *R* indicates *routine task groups*.
Source: IEB and Dengler/Matthes/Paulus (2014), own calculations. ©IAB

Table 3: Sources of dynamic agglomeration effects

	(1)	(2)	(3)	(4)	(5)
			Total experience		
Total experience	0.0460***	0.0434***	0.0414***	0.0441***	0.0403***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0029)
Foreign (FGN) $\times$ total exp.	-0.0081***	-0.0074***	-0.0066***	-0.0083***	-0.0057***
	(0.0013)	(0.0015)	(0.0014)	(0.0012)	(0.0014)
Experience^2	-0.0006***	-0.0006***	-0.0005***	-0.0006***	-0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FGN $\times$ experience^2	-0.0000***	-0.0000***	-0.0000***	-0.0001***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions			
Experience lower density	0.0018***	0.0013***	0.0013***	0.0015***	0.0010***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
FGN $\times$ exp. lower density	-0.0007***	-0.0006**	-0.0004*	-0.0006**	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Experience higher density	0.0031***	0.0022***	0.0020***	0.0026***	0.0016***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
FGN $\times$ exp. higher density	-0.0003	-0.0003	-0.0001	-0.0001	0.0000
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Experience highest density	0.0044***	0.0033***	0.0027***	0.0036***	0.0022***
	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
FGN $\times$ exp. highest density	0.0001	0.0000	0.0005	0.0007*	0.0006*
	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Experience by sector	No	Yes	No	No	Yes
Experience by task group	No	No	Yes	No	Yes
Exp. by establishment quality	No	No	No	Yes	Yes
R^2 (net of FE)	.233	.237	.236	.233	.239

Note: Unit of observation is person-year. The number of observations is 18,050,610 in each specification. Dependent variable is a worker's log daily wage. Each model including fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density", "tenure" and corresponding interactions with "foreign" as with Table 1. Further control variables are: sex, level of qualification, part-time status, establishment size, establishment coefficient estimate from AKM regression, regional worker share of own nationality. All control variables and fixed effects are interacted with a dummy variable that indicates foreign citizenship. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. We use the quartiles of local employment within 10 km as thresholds to consider experience by type of region and establishment coefficient estimates from AKM regression to distinguish experience by establishment quality. The estimates for the value of experience by sector, task group and type of establishment are given in Table A3. Reference categories are experience in low knowledge production (columns (2) and (5)), routine manual tasks (columns (3) and (5)) and establishments with the lowest quality (columns (4) and (5)), resprectively.

Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

Table 4: Dynamic agglomeration effects by skill group

	Low-skilled		Middle-skilled		High-skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
			Total experience			
Total experience	0.0213***	0.0178***	0.0499***	0.0448***	0.0420***	0.0344***
	(0.0012)	(0.0013)	(0.0027)	(0.0031)	(0.0029)	(0.0036)
Foreign (FGN) × total exp.	0.0115***	0.0135***	-0.0126***	-0.0098***	0.0061*	0.0001
	(0.0014)	(0.0013)	(0.0016)	(0.0015)	(0.0035)	(0.0048)
Total experience^2	-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0010***	-0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
FGN × total exp.^{2}	0.0000	0.0000	-0.0001***	-0.0000***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions					
Experience lower density	0.0012***	0.0005***	0.0017***	0.0009***	0.0018***	0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
FGN × exp. lower density	-0.0009***	-0.0004	-0.0001	0.0002	-0.0026	-0.0019
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0019)	(0.0018)
Experience higher density	0.0026***	0.0017***	0.0029***	0.0015***	0.0026***	0.0024***
	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0004)
FGN × exp. higher density	-0.0011***	-0.0005	0.0000	0.0003	-0.0008	-0.0009
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0013)	(0.0013)
Experience highest density	0.0038***	0.0018***	0.0042***	0.0021***	0.0034***	0.0037***
	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0006)	(0.0007)
FGN × exp. highest density	-0.0016***	0.0001	0.0009	0.0012***	-0.0017	-0.0022
	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0018)	(0.0018)
Observations	776118	776118	14061377	14061377	3212561	3212561
Experience by sector	No	Yes	No	Yes	No	Yes
Experience by task group	No	Yes	No	Yes	No	Yes
Exp. by establishment quality	No	Yes	No	Yes	No	Yes
R^2 (net of FE)	.184	.190	.236	.244	.232	.235

Note: Unit of observation is person-year. Dependent variable is a worker's log daily wage. Each model including fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density", "tenure" and corresponding interactions with "foreign" as with Table 1. Further control variables are: sex, level of qualification, part-time status, establishment size, regional worker share of own nationality, establishment coefficient estimate from AKM regression. All control variables and fixed effects are interacted with a dummy variable that indicates foreign citizenship. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. We use the quartiles of local employment within 10 km as thresholds to consider experience by type of region and establishment coefficient estimates from AKM regression to distinguish experience by establishment quality. The estimates for the value of experience by sector, task group and type of establishment are given in Table A5. Reference categories are experience in low knowledge production, routine manual tasks and establishments with the lowest quality, resprectively. Low-skilled workers are those without a completed apprenticeship, middle-skilled workers those with a completed apprenticeship and high-skilled workers those with completed tertiary education.
Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

5 Conclusion

This paper evaluates dynamic agglomeration effects of native and foreign workers and provides evidence on the mechanisms behind these effects. Using administrative data on individual employment biographies that go back until 1975, we provide empirical evidence on how foreign workers benefit differently from work experience accumulated in large urban labor markets compared to native workers. In general, faster individual wage growth in larger cities significantly contributes to regional wage differentials between urban and rural labor markets (Baum-Snow/Pavan, 2012; De La Roca/Puga, 2017) and heterogeneous effects between foreign and native workers might significantly contribute to persistent ethnic inequality with respect to labor market outcomes in big cities.

According to our results, there is a statistically and economically significant wage premium of having acquired work experience in denser areas. Moreover, we find that the extent of these dynamic agglomeration effects are, on average, similar for both groups. Differences exist, however, between natives and foreigners within skill groups. For low-skilled workers, we find that the premium of big city experience is significantly lower than for observationally equivalent natives. We attribute the discount that low-skilled foreigners experience to the fact that when employed in large cities, the former tend to sort into lower-quality tasks and sectors than natives, ceteris paribus, which are likely to offer fewer learning opportunities. By contrast, we find no statistically significant difference in dynamic agglomeration effects between natives and foreigners for middle-skilled and high-skilled workers.

Furthermore, our results suggest that the composition of work experience in terms of sectors, tasks and establishment quality explains about 50 percent of the dynamic agglomeration benefit for low-skilled and middle-skilled workers. This finding emphasizes the importance of the economic structure of cities (in terms of sectors, task groups and establishment quality) for the mechanisms behind the dynamic benefits of cities for these two groups, in line with arguments put forth by Davis/Dingel (2019). By contrast, selection into high-quality jobs appears to be less relevant for high-skilled workers. One reason might be that access to higher-quality sectors, tasks or establishments does not vary over space to the same extent that it does for low- and middle-skilled workers. Our results, altogether, complement resent findings by Eckert/Hejlesen/Walsh (2022), who highlight the significance of industries, occupations and firms for differences between urban and rural labor markets with respect to the gradual sorting into better jobs over time that might result in an urban wage growth premium as well.

Our results also provide evidence for a spatial dimension of native-foreign wage inequality among low-skilled workers as foreign workers appear to gain considerably less from working in denser areas. In light of this discount being associated with selection of foreigners into lower-quality tasks and sectors, policies aimed at reducing ethnic inequality should focus on reducing barriers to entering high-quality jobs that appear to exist for low-skilled foreigners vis-à-vis natives. Such changes would likely increase the learning opportunities for this group in large cities. Against this backdrop, future research should focus on why low-skilled foreign works sort into tasks and sectors such that they cannot take full advantage of the opportunities, which large cities offer when valuable work experience is concerned. Arguments put forth by Ananat/Shihe/Ross (2018) with respect to static agglomeration effects, refer to the role of ethnic social networks for heterogeneous returns to density in the U.S. Furthermore, Dustmann et al. (2015) show that ethnic-based labor market networks matter in the German labor market. Their findings suggest that referral-based job search via ethnic networks results in higher wages and lower turnover.

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Appendix

A1 Data description

Table A1: Summary statistics

	Natives	Foreigners	Total
Worker variables			
Daily wage (imputed)	106.0	98.30	105.7
	(61.53)	(52.14)	(61.19)
Foreign nationality	0.000	1.000	0.042
	(.)	(.)	(0.199)
Female	0.441	0.344	0.437
	(0.496)	(0.475)	(0.496)
Low-skilled	0.0365	0.193	0.0430
	(0.188)	(0.395)	(0.203)
Middle-skilled	0.785	0.639	0.779
	(0.411)	(0.480)	(0.415)
High-skilled	0.178	0.168	0.178
	(0.383)	(0.374)	(0.383)
Part-time indicator	0.200	0.170	0.199
	(0.400)	(0.375)	(0.399)
Tenure (in months)	63.67	56.73	63.38
	(74.81)	(73.91)	(74.79)
Experience variables (in years)			
Total experience	13.25	11.54	13.18
	(9.243)	(9.372)	(9.254)
Experience by labor market density			
lowest density	3.454	1.572	3.376
	(6.652)	(4.661)	(6.592)
lower density	3.382	2.759	3.356
	(6.370)	(5.976)	(6.355)
higher density	3.307	3.366	3.310
	(6.233)	(6.321)	(6.236)
highest density	3.111	3.844	3.141
	(6.304)	(6.792)	(6.327)
Experience by sector			
agriculture	0.0588	0.0292	0.0576
	(0.773)	(0.465)	(0.763)
low knowledge production	3.124	3.628	3.145
	(6.422)	(7.144)	(6.455)
knowledge-intensive production	2.264	2.692	2.282
	(5.822)	(6.369)	(5.846)
low knowledge services	3.534	3.505	3.533
	(6.167)	(5.675)	(6.147)
knowledge-intensive services	2.557	1.090	2.497
	(5.706)	(3.342)	(5.635)
public service	1.715	0.596	1.669
	(4.863)	(2.584)	(4.795)

Continued on next page

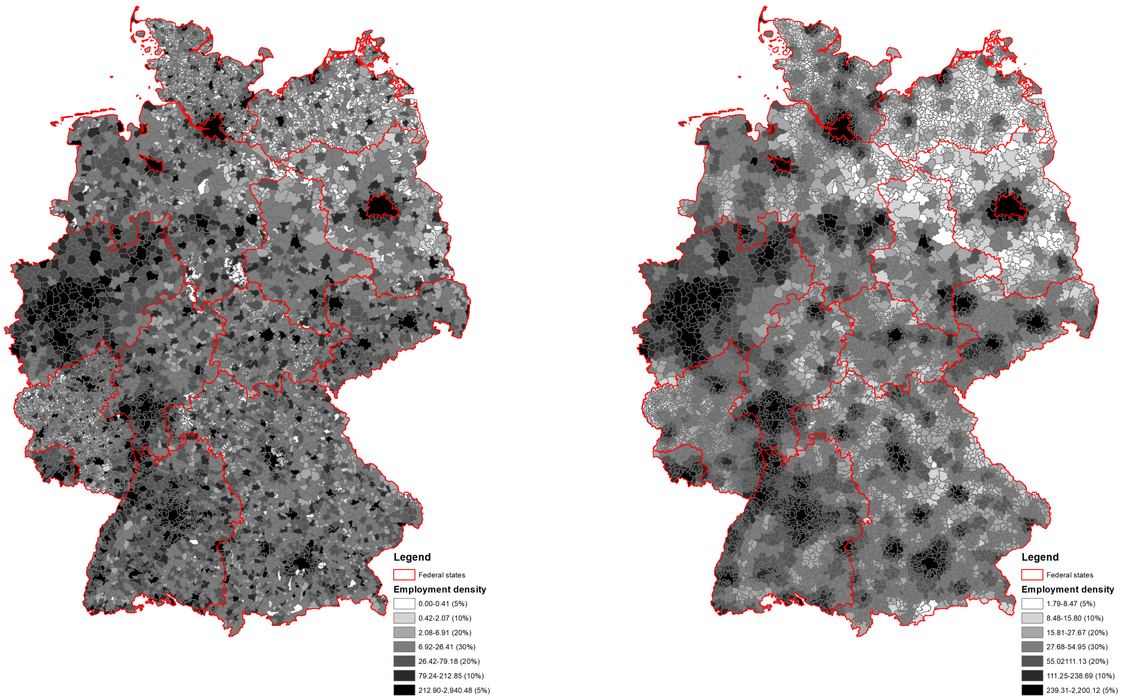
Table 2 continued

	Natives	Foreigners	Total
Experience by task group			
non-routine analytic	1.606	0.903	1.577
	(4.028)	(2.847)	(3.988)
non-routine interactive	1.295	0.754	1.273
	(3.876)	(2.555)	(3.832)
routine cognitive	5.428	2.877	5.322
	(7.806)	(5.610)	(7.744)
routine manual	2.307	4.234	2.387
	(5.557)	(7.437)	(5.660)
non-routine manual	2.402	2.359	2.400
	(5.550)	(5.072)	(5.531)
unknown occupation	0.215	0.413	0.224
	(0.960)	(1.402)	(0.983)
Experience by establishment quality			
lowest quality	3.006	2.182	2.972
	(4.549)	(3.622)	(4.518)
lower quality	2.818	1.880	2.779
	(4.356)	(3.527)	(4.328)
higher quality	3.120	2.624	3.100
	(4.742)	(4.442)	(4.731)
highest quality	3.093	3.737	3.119
	(5.768)	(6.454)	(5.799)
unknown quality	1.217	1.118	1.213
	(1.661)	(1.525)	(1.656)
Establishment variables			
AKM establishment effect (lagged)	-0.0792	-0.0787	-0.0792
	(0.297)	(0.318)	(0.298)
Establishment size: 1-9 employees	0.0994	0.0766	0.0985
	(0.299)	(0.266)	(0.298)
Establishment size: 10-49 employees	0.242	0.193	0.240
	(0.428)	(0.394)	(0.427)
Establishment size: 50-249 employees	0.293	0.285	0.292
	(0.455)	(0.452)	(0.455)
Establishment size: 250+ employees	0.366	0.445	0.369
	(0.482)	(0.497)	(0.483)
Regional variables			
Employment density	379.3	537.4	385.9
	(435.1)	(523.4)	(440.3)
1925 population density	689.8	861.0	696.9
	(910.7)	(936.4)	(912.4)
Share of workers with the same nationality	0.874	0.180	0.845
	(0.136)	(0.334)	(0.203)
Observations	17,301,172	749,438	18,050,610

Note: Means and standard deviations in parentheses. For definitions see Section 2.2
Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

Local employment density. To approximate the annual number of workers per local labor market, we follow Peters/Niebuhr (2019) and sum-up annual employment figures referring to June 30 of the respective year (1975–2019) of all municipalities within the circle of radius 10 km around the center of the considered municipality (see also De La Roca/Puga, 2017). If a municipality encompasses both areas inside and outside a 10 km circle, we assume that employees are evenly distributed across space within the municipality and assign a corresponding fraction of employment to the considered local labor market. As an example, Figure A1 shows for 2019 the original employment density at the level of municipalities and the generated data referring to employment in a distance of at most 10 kilometers. The median size of the municipalities in Germany is 19 km^2, the third quartile is 40 km^2, and the maximum is 894 km^2 (Berlin), which corresponds to a radius of 2.4 km, 3.6 km, and 16.9 km respectively if the municipalities were circular. For local labor markets in East Germany, employment density has only been computed from 1993 onward, the first year for which reliable information on employment in East Germany is available in the IEB.

Figure A1: Employees per km^2 at municipality level and within a 10 km radius around the geographic center of the municipality



(a) Municipality boundary **(b) 10 km radius**

Note: The left panel shows the 2019 employment density at the municipality level (measured per square kilometre). The right panel shows the 2019 employment density within a 10 km radius around the geographic center of the municipality. The values in parentheses show the fraction of municipalities contained in each density class.
Source: IEB, GeoBasis-DE/BKG 2019, own calculations, illustration based on Peters/Niebuhr (2019). ©IAB

A2 Further regression results

Table A2: Estimates of dynamic agglomeration effects omitting fixed effects for occupation and sector as well as establishment coefficient estimates from AKM wage decomposition

	(1)	(2)
Total experience		
Total experience	0.0511***	0.0511***
	(0.0024)	(0.0024)
Foreign (FGN) $\times$ total exp.	-0.0053***	-0.0045**
	(0.0014)	(0.0016)
Experience^2	-0.0006***	-0.0006***
	(0.0000)	(0.0000)
FGN $\times$ experience^2	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions		
Experience lower density	0.0020***	0.0020***
	(0.0002)	(0.0002)
FGN $\times$ exp. lower density		-0.0012***
		(0.0002)
Experience higher density	0.0035***	0.0035***
	(0.0003)	(0.0003)
FGN $\times$ exp. higher density		-0.0010**
		(0.0004)
Experience highest density	0.0048***	0.0048***
	(0.0004)	(0.0004)
FGN $\times$ exp. highest density		-0.0007
		(0.0005)
Region-year FE	Yes	Yes
Controls	Yes, except AKM estab. estimates	
Interaction with foreign	Yes	Yes
Occupation FE	No	No
Sector FE	No	No
Worker FE	Yes	Yes
R^2	.216	.216

Note: Unit of observation is person-year. The number of observations is 18,050,610. Dependent variable is a worker's log daily wage. Unit of observation is person-year. The specifications of the regressions are identical to column (6) and column (7) in Table 1, respectively, except that fixed effects for occupation and sector as well as establishment coefficient estimates from AKM regressions are omitted here. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 1.

Source: IEB, own calculations. ©IAB

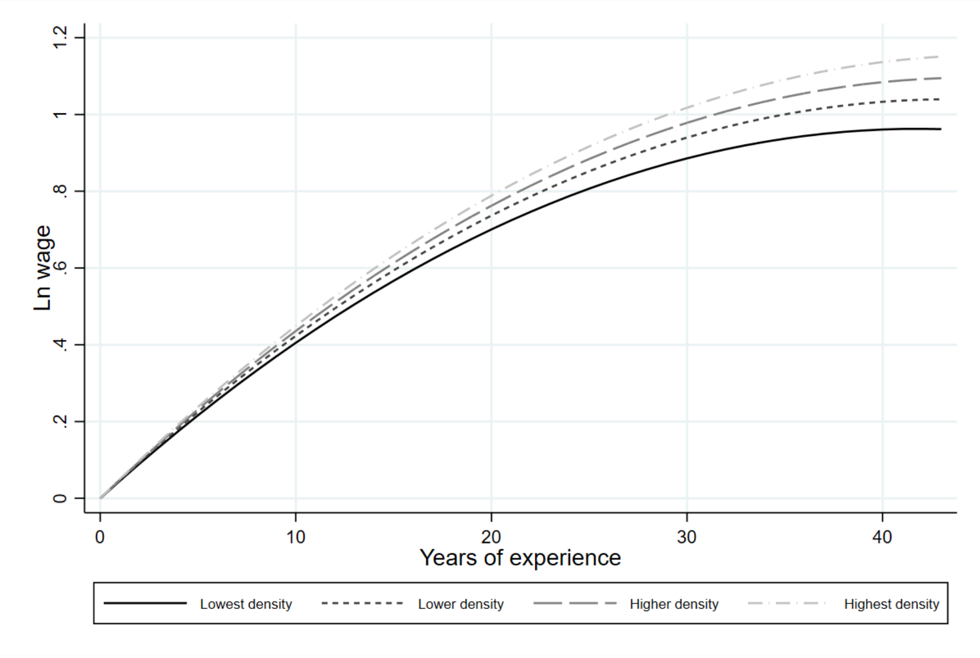
Table A3: Value of experience by type of sector, task and establishment

Experience by sector, reference: low knowledge production								
Experience agriculture	-0.0036***	(0.0003)					-0.0033***	(0.0004)
FGN × exp. agriculture	-0.0024	(0.0021)					-0.0022	(0.0020)
Experience knowledge-intens. production	0.0069***	(0.0006)					0.0049***	(0.0002)
FGN × exp. knowledge-intens. prod.	-0.0017***	(0.0005)					-0.0016**	(0.0005)
Experience low-knowledge services	-0.0004*	(0.0002)					-0.0010***	(0.0002)
FGN × exp. low-knowledge serv.	0.0002	(0.0003)					.0005***	(0.0002)
Experience knowledge-intens. services	0.0040***	(0.0004)					0.0020***	(0.0002)
FGN × exp. knowledge-intens. serv.	0.0008	(0.0005)					0.0006	(0.0004)
Experience public service	0.0075***	(0.0004)					0.0065***	(0.0003)
FGN × exp. public serv.	-0.0020***	(0.0005)					-0.0018***	(0.0003)
Experience by task group, reference: routine manual								
Experience non-routine analytic			0.0086***	(0.0005)			0.0072***	(0.0005)
FGN × exp. non-rout. analytic			0.0014**	(0.0005)			0.0019***	(0.0005)
Experience non-routine interactive			0.0041***	(0.0004)			0.0030***	(0.0002)
FGN × exp. non-rout. interactive			-0.0005	(0.0004)			0.0008**	(0.0003)
Experience routine cognitive			0.0068***	(0.0005)			0.0056***	(0.0004)
FGN × exp. rout. cognitive			-0.0020***	(0.0002)			-0.0022***	(0.0002)
Experience non-routine manual			0.0012*	(0.0006)			0.0008	(0.0005)
FGN × exp. non-rout. manual			-0.0031***	(0.0004)			-0.0026***	(0.0003)
Experience unknown task			0.0004	(0.0012)			0.0015	(0.0011)
FGN × exp. unknown task			-0.0005	(0.0008)			-0.0007	(0.0009)
Experience by establishment quality, reference: lowest quality								
Experience lower establishment quality					0.0009	(0.0006)	-0.0007	(0.0006)
FGN × exp. lower est. quality					-0.0014***	(0.0004)	-0.0018***	(0.0003)
Experience higher establishment quality					0.0031***	(0.0007)	0.0010	(0.0008)
FGN × exp. higher est. quality					-0.0012**	(0.0004)	-0.0014***	(0.0004)
Experience highest establishment quality					0.0042***	(0.0012)	0.0006	(0.0011)
FGN × exp. highest est. quality					0.0001	(0.0002)	-0.0004**	(0.0002)
Experience unknown establishment quality					0.0046***	(0.0014)	0.0032**	(0.0014)
FGN × exp. unknown est. quality					0.0112***	(0.0015)	0.0112***	(0.0015)

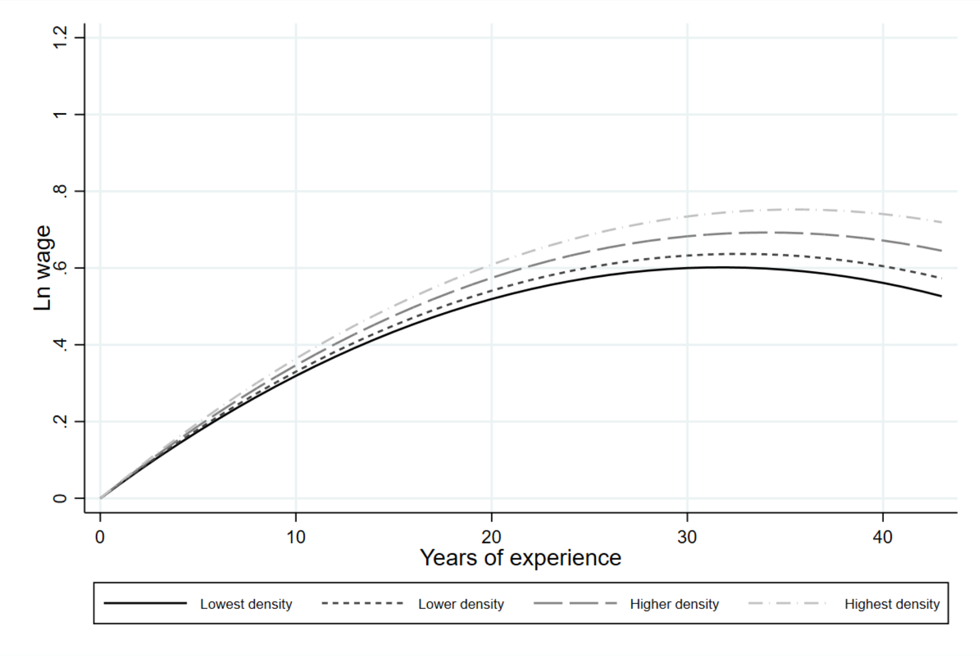
Note: Unit of observation is person-year. Their number is 18,050,610 in each specification. Dependent variable is a worker's log daily wage. Referring to columns (2)–(5) of Table 3, this table summarizes the results for the additionally considered experience categories. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 3.

Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

Figure A2: Wage-experience profile considering differences between native and foreign workers as well as dynamic agglomeration effects



(a) Native workers



(b) Foreign workers

Note: The figure illustrates estimation results reported in Column (7) of Table 1 and refers to the logarithm of wage at different levels of experience relative to the wage at the beginning of individual working life, where experience equals 0. The different density categories refer to the employment density of the labor market in which experience is acquired (see Section 2.2).
Source: IEB, own calculations. ©IAB

Table A4: Dynamic agglomeration effects for full-time and full-time male workers

	Full-time male & female		Full-time male	
	(1)	(2)	(3)	(4)
Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions				
Experience lower density	0.0020***	0.0010***	0.0021***	0.0009***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Foreign × exp. lower density	-0.0009***	-0.0004	-0.0009***	-0.0003
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Experience higher density	0.0035***	0.0017***	0.0036***	0.0016***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Foreign × exp. higher density	-0.0004	0.0001	-0.0003	0.0003
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Experience highest density	0.0053***	0.0028***	0.0053***	0.0025***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Foreign × exp. highest density	-0.0005	0.0000	-0.0006	0.0001
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Experience by sector	No	Yes	No	Yes
Experience by task group	No	Yes	No	Yes
Experience by establishment quality	No	Yes	No	Yes
Observations	14,377,289	14,377,289	9,640,571	9,640,571
R^2	.163	.172	.174	.187

Note: Unit of observation is person-year. Dependent variable is a worker's log daily wage. The specifications of the regressions are identical to column (1) and column (5) in Table 3, respectively. The sample, however, is reduced. While Table 3 refers to part- and full-time male and female workers, the results reported here refer to (male) full-time workers only. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 3.
Source: IEB, Gehrke et al. (2010),Dengler/Matthes/Paulus (2014),Bellmann et al. (2020), own calculations. ©IAB

Table A5: Value of experience by type of sector, task and establishment by skill group

	Low-skilled		Middle-skilled		High-skilled	
Experience by sector, reference: low knowledge production						
Experience agriculture	-0.0003	(0.0008)	-0.0035***	(0.0004)	-0.0025***	(0.0009)
FGN × exp. agriculture	0.0079***	(0.0026)	-0.0059***	(0.0019)	-0.0071	(0.0055)
Exp. knowledge-intens. production	0.0026***	(0.0001)	0.0050***	(0.0002)	0.0035***	(0.0005)
FGN × exp. knowledge-intens. prod.	0.0001	(0.0003)	-0.0015***	(0.0004)	0.0038***	(0.0013)
Experience low-knowledge services	-0.0008***	(0.0002)	-0.0006**	(0.0002)	-0.0039***	(0.0004)
FGN × exp. low-knowledge serv.	0.0008	(0.0006)	0.0013***	(0.0002)	-0.0012	(0.0011)
Exp. knowledge-intens. services	0.0022***	(0.0005)	0.0027***	(0.0003)	-0.0020***	(0.0002)
FGN × exp. knowledge-intens. serv.	-0.0029***	(0.0006)	-0.0003	(0.0002)	0.0038***	(0.0009)
Experience public service	0.0034***	(0.0004)	0.0067***	(0.0003)	0.0037***	(0.0006)
FGN × exp. public service	-0.0013**	(0.0006)	-0.0015***	(0.0005)	-0.00152	(0.0010)
Experience by task group, reference: routine manual						
Experience non-routine analytic	0.0090***	(0.0006)	0.0084***	(0.0005)	0.0064***	(0.0009)
FGN × exp. non-rout. analytic	-0.0028***	(0.0007)	0.0013***	(0.0004)	0.0042*	(0.0019)
Experience non-routine interactive	0.0052***	(0.0005)	0.0033***	(0.0002)	0.0038***	(0.0011)
FGN × exp. non-rout. interactive	0.0007	(0.0008)	-0.0006*	(0.0003)	0.0081**	(0.0029)
Experience routine cognitive	0.0044***	(0.0003)	0.0057***	(0.0004)	0.0069***	(0.0011)
FGN × exp. routine cognitive	-0.0029***	(0.0002)	-0.0016***	(0.0003)	0.0035**	(0.0015)
Experience non-routine manual	-0.0007	(0.0008)	0.0011**	(0.0005)	-0.0000	(0.0010)
FGN × exp. non-routine manual	-0.0011***	(0.0003)	-0.0019***	(0.0003)	-0.0068***	(0.0020)
Experience unknown task	0.0058**	(0.0024)	0.0021	(0.0012)	-0.0018	(0.0022)
FGN × exp. unknown task	-0.0078**	(0.0030)	0.0004	(0.0012)	0.0073	(0.0084)
Experience by establishment quality, reference: lowest quality						
Exp. lower establishment quality	0.0001	(0.0005)	-0.0012*	(0.0006)	0.0014	(0.0009)
FGN × exp. lower est. quality	-0.0013*	(0.0008)	-0.0022***	(0.0003)	-0.0007	(0.0011)
Exp. higher establishment quality	0.0013***	(0.0006)	0.0005	(0.0008)	0.0024**	(0.0010)
FGN × exp. higher est. quality	-0.0002	(0.0008)	-0.0020***	(0.0003)	-0.0006	(0.0015)
Exp. highest establishment quality	0.0029***	(0.0008)	0.0006	(0.0012)	0.0013	(0.0013)
FGN × exp. highest est. quality	-0.0006	(0.0006)	-0.0012***	(0.0003)	-0.0013	(0.0010)
Exp. unknown establishment quality	0.0092***	(0.0017)	0.0013	(0.0011)	0.0151***	(0.0036)
FGN × exp. unknown est. quality	0.0073**	(0.0027)	0.0083***	(0.0012)	0.0291***	(0.0062)
Observations		776118		14061377		3212561

Note: Unit of observation is person-year. Dependent variable is a worker's log daily wage. Referring to columns (2)–(5) of Table 4, this table summarizes the results for the additionally considered experience categories. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 4.

Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

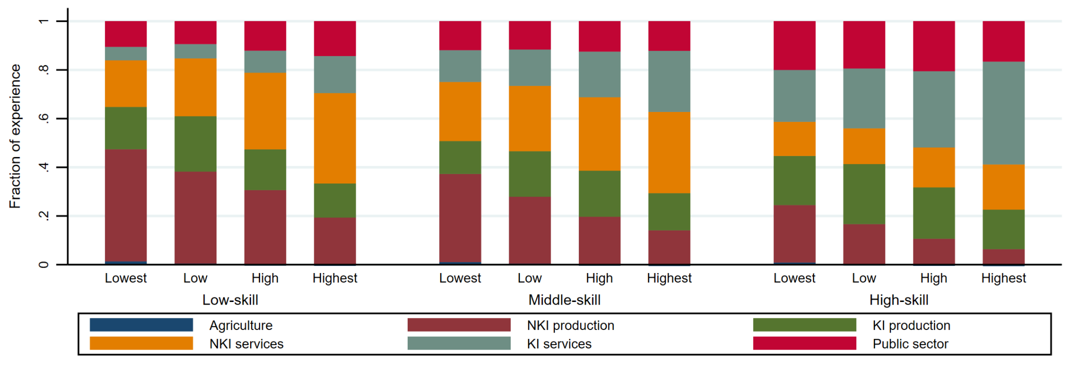
Table A6: Estimates of dynamic agglomeration effects by skill group conditional on further experience categories, but excluding additional interaction effects with foreign-indicator

	Low-skilled		Middle-skilled		High-skilled	
	Total experience					
Total experience	0.0180***	(0.0013)	0.0449***	(0.0031)	0.0342***	(0.0036)
Foreign (FGN) $\times$ total exp.	0.0123***	(0.0014)	-0.0120***	(0.0015)	0.0064*	(0.0033)
Total experience^2	-0.0005***	(0.0000)	-0.0005***	(0.0000)	-0.0010***	(0.0001)
FGN $\times$ total exp.^{2}	-0.0000	(0.0000)	-0.0000***	(0.0000)	-0.0003***	(0.0000)
	Experience by the density of the local labor market in which it was acquired, reference: experience in least dense regions					
Experience lower density	0.0005***	(0.0002)	0.0010***	(0.0001)	0.0015***	(0.0002)
FGN $\times$ exp. lower density	-0.0005	(0.0003)	0.0001	(0.0002)	-0.0022	(0.0019)
Experience higher density	0.0017***	(0.0003)	0.0015***	(0.0001)	0.0024***	(0.0004)
FGN $\times$ exp. higher density	-0.0007*	(0.0004)	0.0001	(0.0003)	-0.0009	(0.0013)
Experience highest density	0.0020***	(0.0003)	0.0021***	(0.0002)	0.0036***	(0.0007)
FGN $\times$ exp. highest density	-0.0005	(0.0005)	0.0010**	(0.0004)	-0.0019	(0.0017)
	Experience by industry, reference: low knowledge production					
Exp. agriculture	0.0004	(0.0009)	-0.0036***	(0.0004)	-0.0026***	(0.0009)
Exp. knowledge-intens. production	0.0026***	(0.0001)	0.0049***	(0.0002)	0.0036***	(0.0004)
Exp. low-knowledge services	-0.0006**	(0.0002)	-0.0006**	(0.0002)	-0.0039***	(0.0004)
Exp. knowledge-intens. services	0.0021***	(0.0005)	0.0028***	(0.0002)	-0.0020***	(0.0002)
Exp. public service	0.0034***	(0.0005)	0.0067***	(0.0003)	0.0037***	(0.0006)
	Experience by task, reference: routine manual					
Exp. non-routine analytic	0.0085***	(0.0006)	0.0084***	(0.0005)	0.0065***	(0.0009)
Exp. non-routine interactive	0.0051***	(0.0005)	0.0032***	(0.0002)	0.0040***	(0.0010)
Exp. routine cognitive	0.0039***	(0.0003)	0.0056***	(0.0004)	0.0070***	(0.0011)
Exp. non-routine manual	-0.0010	(0.0008)	0.0010*	(0.0005)	-0.0002	(0.0010)
Exp. unknown task	0.0041*	(0.0021)	0.0022	(0.0013)	-0.0016	(0.0021)
	Experience by establishment quality, reference: lowest quality					
Exp. lower establ. quality	-0.0001	(0.0006)	-0.0012*	(0.0006)	0.0014	(0.0009)
Exp. higher establ. quality	0.0012*	(0.0006)	0.0004	(0.0008)	0.0024**	(0.0010)
Exp. highest establ. quality	0.0028***	(0.0008)	0.0006	(0.0012)	0.0013	(0.0013)
Exp. unknown establ. quality	0.0102***	(0.0016)	0.0014	(0.0011)	0.0157***	(0.0037)
Observations		776118		14061377		3212561
R^2		.19		.244		.235

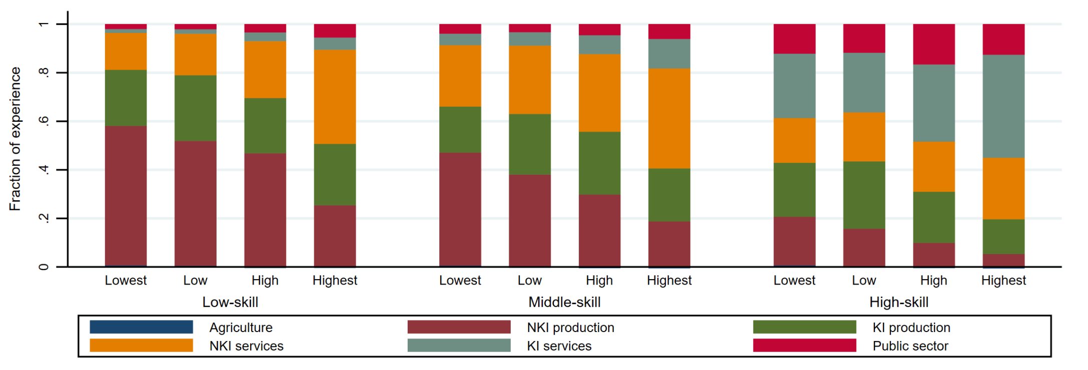
Note: Unit of observation is person-year. Dependent variable is a worker's log daily wage. The specifications are identical to the ones reported in Table 4, except that the models do not contain interaction effects of the indicator for foreign nationality and experience by type of sector, task and establishment quality (cf. Table A5). ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 4.

Source: IEB, Gehrke et al. (2010), Dengler/Matthes/Paulus (2014), Bellmann et al. (2020), own calculations. ©IAB

Figure A3: Composition of work experience w.r.t. sectors by labor market density and skill level for foreign and native workers



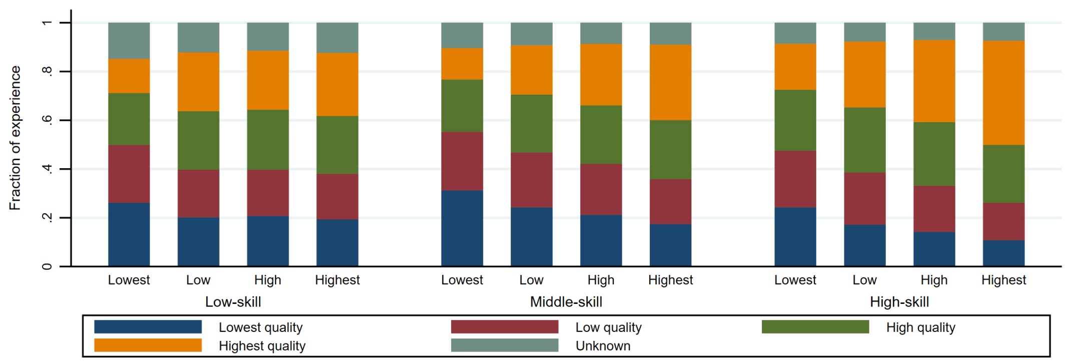
(a) Native workers



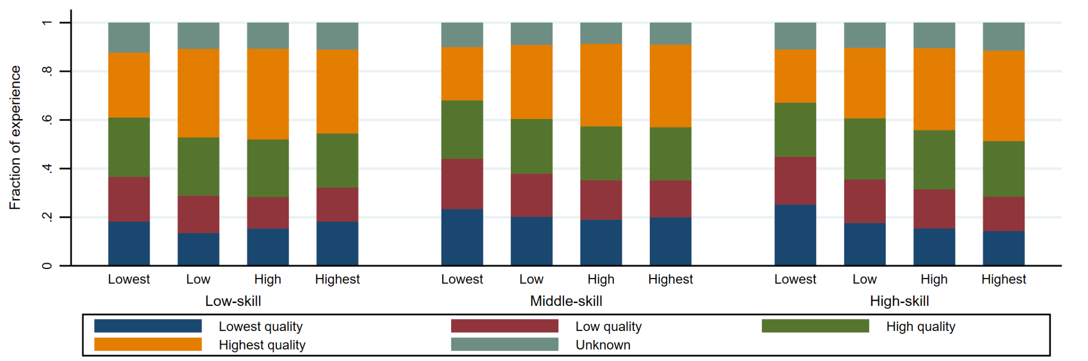
(b) Foreign workers

Note: The figure illustrates the composition of work experience with regard to sectors for low-skilled, middle-skilled and high-skilled workers by the density (lowest, low, high, highest) of the local labor market, in which experience has been acquired. *KI* indicates *knowledge-intensive sectors* and *NKI* indicates *non-knowledge-intensive sectors*.
Source: IEB and Gehrke et al. (2010), own calculations. ©IAB

Figure A4: Composition of work experience w.r.t. establishment quality by labor market density and skill level for foreign and native workers



(a) Native workers



(b) Foreign workers

Note: The figure illustrates the composition of work experience with regard to establishment quality for low-skilled, middle-skilled and high-skilled workers by the density (lowest, low, high, highest at the x-axis) of the local labor market, in which experience has been acquired.
Source: IEB and Bellmann et al. (2020), own calculations. ©IAB

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Corresponding author
Dr. Duncan Roth
Phone: +49 911 179 3552
E-Mail: duncan.roth@iab.de