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

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Abstract

Using administrative data on individual employment biographies, this paper analyzes whether dynamic agglomeration effects are primarily due to the quality of jobs in large cities and associated advantages for acquiring valuable work experience. Our results indicate that around 50% of the return of an additional year of work experience gained in the densest local labor markets in Germany can be ascribed to the sectors, tasks and types of establishments in which experience was acquired. We further show that native and foreign workers, on average, benefit to a similar extent from dynamic agglomeration effects and from better access to higher-quality jobs in big cities. However, low-skilled foreign workers receive a lower return to big city experience than observationally identical natives. This difference can be explained by the fact that the former gain work experience in lower-quality jobs.

Keywords: Dynamic agglomeration effects, ethnic inequality, job quality, learning, work experience
JEL: J31, J61, R12, R23

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1 Introduction

There is broad empirical evidence that wages in big cities are higher and grow faster than in less dense labor markets (Combes and Gobillon, 2015). According to the literature on agglomeration economies, a considerable part of this urban wage (growth) premium is due to agglomeration effects. An important mechanism considered to be behind dynamic agglomeration effects is the faster accumulation of human capital in cities (Glaeser, 1999; Duranton and Puga, 2004). Thus, the size of local labor markets in which work experience is accumulated likely constitutes a relevant determinant of the value of experience. Evidence provided by Baum-Snow and Pavan (2012), De La Roca and Puga (2017), and Peters (2020) suggests 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 whether dynamic agglomeration effects are primarily due to the quality of jobs in large cities. Thereby we provide novel evidence on a mechanism underlying dynamic agglomeration benefits: better access to high-quality jobs that are likely to promote the acquisition of human capital. Administrative data on individual employment biographies dating back to 1975 allows us to precisely measure the amount of experience that workers acquired in regions of different size as well as in sectors, task groups and establishment types. Based on this information, we show that, on average, about 50% of the wage premium for big city experience can be traced back to the quality of jobs in which experience has been acquired.

When a substantial part of the benefits associated with big city experience is due to easier access to higher-quality jobs, the question naturally arises whether certain groups of workers benefit less from dynamic agglomeration effects because they lack access to these types of jobs. This might apply in particular to foreign workers. Evidence suggests that they select into jobs that might provide less potential for human capital accumulation: Peri and Sparber (2009) show that foreign-born workers specialize in manual tasks in the U.S., while natives often perform work that involves interactive tasks. Findings by D'Amuri and Peri (2014) indicate that immigrants in Western European countries seem to push natives towards more complex occupations and tasks by performing primarily manual-routine type jobs in the host country. Storm (2022) documents a similar pattern for Germany. Our results suggest that, on average, native and foreign workers benefit to a similar extent from dynamic agglomeration effects. However, low-skilled foreign workers receive a lower return to work experience acquired in big cities than equally skilled natives. This discount can indeed be attributed to the fact that low-skilled foreigners tend to work in lower-quality jobs compared to similarly skilled natives.

In assessing the role of a greater availability of higher-quality jobs in large cities for dynamic agglomeration effects and studying differences in the benefits between foreign and native workers, this article makes several contributions to the literature. First, 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 and Puga, 2004) because dense urban regions promote knowledge spillovers. We examine whether the type of jobs that workers perform 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 and Dingel, 2019; Koster and Ozgen, 2021) and provide new evidence on the factors behind dynamic agglomeration effects.

Eckert et al. (2022) note that most previous research does 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). Studies by Eckert et al. (2022) and Peters and Niebuhr (2019) are notable exceptions. However, the former analysis focuses on a very specific group in the Danish labor market – male refugees from eight different countries – and on better matching in large cities rather than learning. Peters and Niebuhr (2019) in turn investigate the effect of firm size on the value of work experience. They neither consider the role of occupational tasks nor the knowledge intensity of the sector in which experience was gathered.

Second, by investigating whether the size of dynamic agglomeration effects differs between foreign and native workers, we also examine heterogeneous returns to density that have so far only seldomly been considered in the urban economics literature (see Ananat et al., 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 and Naticchioni, 2016; Carlsen et al., 2016) or tasks (Bacolod et al., 2009; Koster and Ozgen, 2021).

Third, our analysis contributes to the literature on ethnic wage gaps and labor market outcomes of minority workers. Dynamic agglomeration effects might matter for the well-documented differences in labor market outcomes between ethnic groups (see, e.g., Bjerk, 2007; Algan et al., 2010) because work experience that is accumulated in the host country is an important factor of wage growth of immigrants (Eckstein and Weiss, 2004). 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 often select into lower-quality jobs. They may therefore benefit less from the learning advantages that cities offer.

Previous studies that investigate the significance of spatial factors for ethnic inequality either focus on the demographic composition of neighborhoods (Cutler and Glaeser, 1997) and the effects of ethnic social networks (Ananat et al., 2018) or consider the local availability of jobs (Gobillon et al., 2014) and, more specifically, jobs into which specific ethnic groups are primarily hired (Hellerstein et al., 2008). 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 analyse the role of static agglomeration effects (see Ananat et al., 2018, Longhi, 2020), this paper focuses on dynamic effects and examines whether foreign workers take less advantage of learning benefits in urban labor markets than natives.

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 and Maré, 2001; Combes et al., 2008) and gradual sorting into better jobs over time might play a role (Eckert et al., 2022). Detailed data on workers' employment biographies 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 local 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 distribution of employment in different types of sectors, tasks and establishments across locations with higher and lower labor market density. We also examine differences in the distribution of foreign and native workers across space. 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% 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 and 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 et al., 2013).

We draw a 10% 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).[1] Our final estimation sample comprises 18,050,610 observations on 1,863,965 individuals.

A central variable of our analysis is a person's work experience (see Section 2.2). As

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

the IEB provides information from 1975 onward (initially, the data only refers to 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 and 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.[2] In our data set, about 4% 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 used by Dustmann et al. (2009) and Card et al. (2013) to impute these wage observations (detailed information on the imputation procedure can be found in Dauth and Eppelsheimer, 2020). On average, German nationals earn 106 € per day, compared to 98 € in the case of foreigners, which provides evidence of an unadjusted wage gap of almost 8%.

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 and Patacchini, 2008; Rosenthal and Strange, 2008), we follow Peters

[2]Between 1981 and 2019, the average annual naturalization rate was relatively low and amounted to 1.9%, i.e., in any of those years, on average, less than 2% 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). Only since the year 2000 do children born in Germany to foreign parents have the right to apply for German citizenship (Ozgen et al., 2014).

and 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 based on the level of non-overlapping areas as discussed by Manning and Petrongolo (2017).[3] 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 and 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 and Hänisch (1990).[4] 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 and 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 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 et al. (2014): non-routine abstract, non-routine interactive, routine manual, routine cog-

[3] See also Briant et al. (2010) for a discussion of the Modifiable Areal Unit Problem (MAUP) in the context of the estimation of agglomeration economies.

[4] 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.

nitive 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 et al., 1999). In the German context, the former are also referred to as establishment CHK effects (Card et al., 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% of observations fall into the high-skill category, 78% into the middle-skill category and 4% into the low-skilled category. While the share of high-skilled workers is comparatively similar between foreigners and natives, the share of low-skilled is considerably higher among foreign (19%) than native workers (4%).

Additional individual-level variables. In addition, we control for a person's gender, part-time status and tenure. Approximately, 44% of observations refer to females, with the share being smaller among foreigners than natives. About 20% 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 et al. (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 types of jobs and workers

In line with discussions by Michaels et al. (2018); Davis and Dingel (2019); Peters (2020); Koster and Ozgen (2021), the following figures illustrate that working in denser regions is potentially associated with acquiring more valuable experience. They show the spatial distribution of employment by sector, task group and establishment quality. As can be seen from Figure 1, knowledge-intensive services, which presumably offer opportunities for acquiring valuable work experience, 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 2, regions with a high employment density also display relatively high shares of non-routine analytic and non-routine interactive employment. As shown in Figure 3, denser regions also contain proportionately more establishments of high or higher quality.

Table A1 already indicated that also the regional distribution of foreigners and natives differs, with foreigners, on average, more often working in denser regions. Figure 4 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.

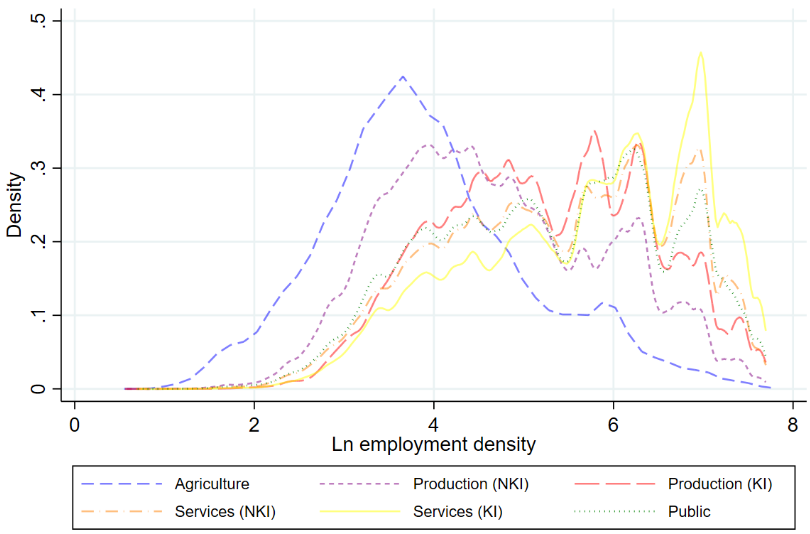


Figure 1: Spatial distribution of employment by sector

Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613. 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, Gehrke et al. (2010), own calculations.

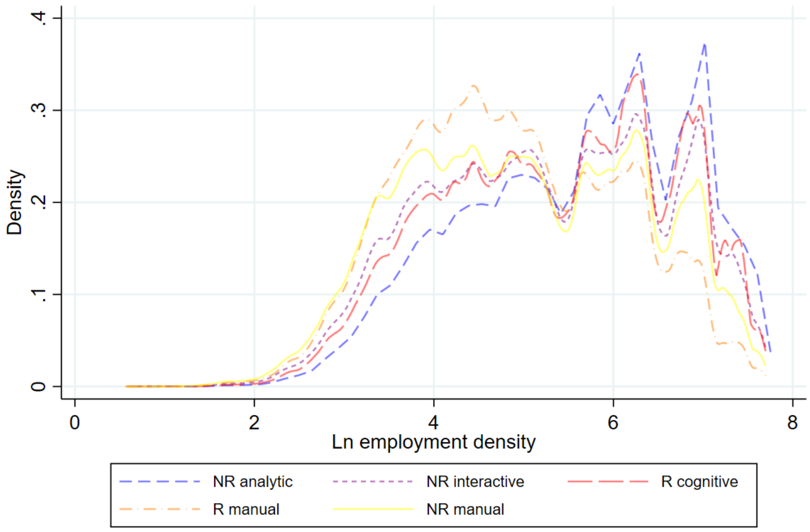


Figure 2: Spatial distribution of employment by task group

Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613. 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, Dengler et al. (2014), own calculations.

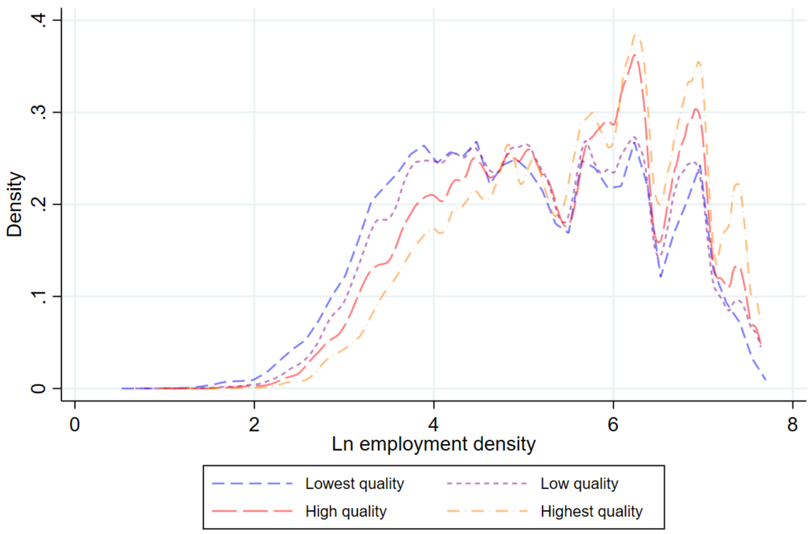


Figure 3: Spatial distribution of employment by establishment quality

Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613. 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, Bellmann et al. (2020), own calculations.

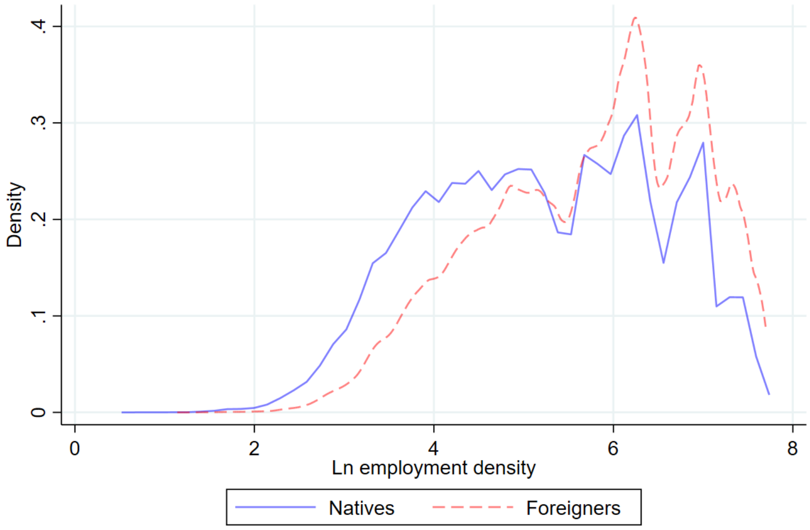


Figure 4: Spatial distribution of employment by nationality

Note: Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613. 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.

3 Model and identification

3.1 Empirical model

We specify the following model to assess dynamic agglomeration effects, the role of experience by sectors, task groups and types of establishments as well as heterogeneous effects between natives and foreigners. Thereby, we build on findings of De La Roca and Puga (2017), confirmed for Germany by Peters (2020), which indicate that the value of experience is significantly influenced by the size of the labor markets in which the experience is acquired. These studies also indicate that the benefits of labor market size are highly portable across regions, suggesting that the mechanism underlying the higher returns to experience acquired in large cities is learning (De La Roca and Puga, 2017).

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

The dependent variable is the log daily wage of worker i who is employed in municipality r in year t. To evaluate benefits 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. 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 and Puga (2017) and control for an individual's total work experience, $exp_{i,t}$, using linear and squared terms. Superscript f on the coefficient indicates that separate effects are estimated for natives and foreigners to allow for heterogeneous returns to the different types of experience.

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 $\theta^f_{l(r),t}$ 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 and 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 et al., 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 control for potential sorting of foreign and native workers with certain levels or types of experience into specific industries and occupations as discussed by Eckert et al. (2022).

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

To account for the endogeneity of current employment density, $ln(dens_{r,t})$, we apply a two-stage least squares (2SLS) regression using historic population density in 1925 as an external instrument. Use of a long lag of population density as an instrument is widely applied in the urban economics literature (see, e.g., Ciccone and Hall, 1996; Combes et al., 2008, 2010; De La Roca and Puga, 2017; Bosquet and 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 such as 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 and Gobillon, 2015). Since the two-stage regression approach proposed by Combes et al. (2008) is not feasible in our case as we consider more than 10,000 local employment densities per year, we instead estimate Equation (1) directly and report standard errors proposed by Driscoll and Kraay (1998), which are robust to very general forms of cross-sectional and temporal dependence.

4 Results

4.1 Baseline estimates of dynamic agglomeration effects

Before examining the role of sectors, tasks and types of establishments for dynamic agglomeration benefits, we estimate baseline models where we omit experience by sectors, tasks and types of establishments to evaluate the magnitude of the benefits from acquiring experience in large labor markets unconditional of these factors. However, we allow for differences between natives and foreigners in order to obtain baseline results for both groups which then allow us to study the impact of sorting into jobs of different quality on the return to big city experience for foreign and native workers.

Column (1) of Table 1 shows the association between an individual's wage and different types of experience, conditional on region-year fixed effects and the local employment density within 10 km of the current workplace which captures static agglomeration effects. The estimated experience profile has the expected concave form for foreigners and natives. Moreover, the results illustrate the existence of dynamic as well as static agglomeration benefits, confirming previous findings by De La Roca and Puga (2017) and related studies: work experience acquired in dense urban labor markets is associated with a higher wage premium than work experience gained in less dense regions and wages also tend to increase with the contemporaneous employment density. The model allows for heterogeneous agglomeration effects for foreigners and natives. The results in column (1) suggest that foreign workers benefit less from dynamic agglomeration effects than natives as foreigners receive a significantly lower wage premium for experience gained in each density category. They also receive a significantly lower static wage premium from working in denser areas, which is in line with evidence by Ananat et al. (2018) on racial differences in the U.S..

Table 1: Dynamic agglomeration effects of foreigners and natives

	(1)	(2)	(3)	(4)
Total experience				
Total experience	0.0216***	0.0194***	0.0513***	0.0463***
	(0.0034)	(0.0022)	(0.0024)	(0.0024)
FGN × total exp.	0.0129***	-0.0013	-0.0067***	-0.0098***
	(0.0014)	(0.0015)	(0.0011)	(0.0010)
Total experience^2	-0.0003***	-0.0004***	-0.0006***	-0.0005***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
FGN × total exp.^{2}	-0.0002***	-0.0000	-0.0001***	-0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Experience by density category reference: experience in least dense regions				
Experience lower density	0.0023***	0.0019***	0.0020***	0.0018***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
FGN × exp. lower dens.	-0.0020***	0.0008***	-0.0007***	-0.0004**
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Experience higher density	0.0037***	0.0036***	0.0035***	0.0031***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
FGN × exp. higher dens.	-0.0037***	-0.0002	-0.0004	0.0001
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Experience highest density	0.0079***	0.0072***	0.0048***	0.0044***
	(0.0004)	(0.0003)	(0.0004)	(0.0004)
FGN × exp. highest dens.	-0.0071***	-0.0026***	-0.0000	0.0008
	(0.0002)	(0.0003)	(0.0005)	(0.0005)
Static agglomeration effects				
Ln employment density	0.0572***	0.0245***	0.0057***	0.0099***
	(0.0024)	(0.0028)	(0.0017)	(0.0010)
FGN × ln emp. dens.	-0.0323***	-0.0140***	-0.0141***	-0.0051***
	(0.0035)	(0.0019)	(0.0013)	(0.0012)
Region-year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Controls (full interaction)	No	Yes	Yes	Yes
Worker FE	No	No	Yes	Yes
Occupation FE	No	No	No	Yes
Sector FE	No	No	No	Yes
Lagged establishment AKM effect	No	No	No	Yes
R^2	.094	.406	.216	.233

Notes: Unit of observation is person-year. There number is 18,050,613 in each specification. Dependent variable is a worker's log daily wage. Control variables are: sex, level of qualification, part-time status, tenure and its square, establishment size, regional worker share of own nationality. ***, ** 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.
Source: IEB, own calculations.

We extend the model in column (2) by including worker characteristics, the size of the establishments at which workers are employed as well as the regional employment share of a worker's own nationality to capture social network effects as proposed by Ananat et al. (2018). Inclusion of these variables accounts for a considerable part of the gap in the dynamic and static agglomeration effects between foreigners and natives. Compared to the results in column (1), the wage penalties that foreign workers face for experience in lower and higher density regions disappear, while the penalty on experience from highest density regions falls by more than half. Likewise, the difference in the static agglomeration effect declines by more than 50%. These results suggest that foreign and native workers differ significantly with respect to attributes that correlate with experience acquired in regions of different size and that also affect wages. Moreover, the decrease in the contemporaneous elasticity with respect to density points to sorting into large cities based on observable characteristics (Combes et al., 2008).

However, sorting of workers may also take place based on unobservable characteristics. This can be seen in column (3) where worker fixed effects are added to the model. Compared to the previous specifications, the overall return to experience sharply increases when worker fixed effects are included which indicates that, altogether, 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). Moreover, the return to experience is significantly smaller for foreign than for native workers once we control for observed and unobserved characteristics.

Regarding dynamic agglomeration effects, we continue to observe that the return to experience increases with density in column (3). The lower return to experience acquired in the densest regions for natives in column (3) relative to column (2) suggests, however, that workers with high levels of big-city experience tend to be those with favorable unobserved characteristics. By contrast, the return to big-city experience for foreigners [$0.0048 = 0.0048 - 0.0000$] remains virtually unchanged compared to column (2) [$0.0046 = 0.0072 - 0.0026$], revealing a weaker association between work experience in the largest cities and unobservable characteristics than for natives. Overall, foreigners no longer appear to benefit significantly less from experience in regions in the higher or highest density category than natives once worker fixed effects and observable characteristics are included in the model.

Occupational segregation and sorting across sectors are important factors of ethnic wage gaps (see e.g., Bjerk, 2007 and Elliott and Lindley, 2008). Moreover, gradual sorting into better jobs might contribute to faster wage growth in agglomerated labor markets since cities offer more jobs with an above-average income potential (Eckert et al., 2022). To take these influences into account, column (4) includes occupation and sector fixed effects as well as the estimated establishment fixed estimates from an AKM wage decomposition.[5] The return to total experience and the premium on experience acquired in big

[5]See Section 2.2 for a description of the variables.

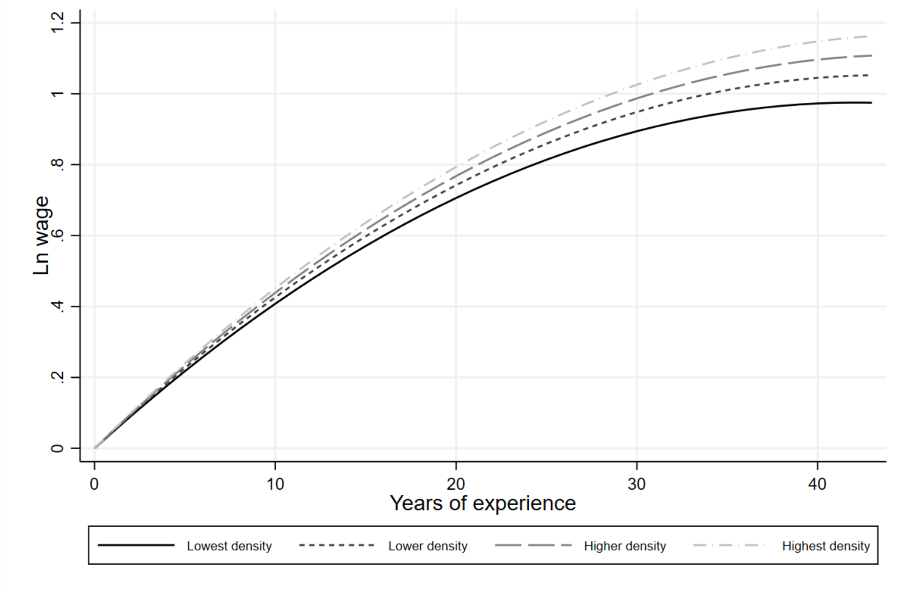
labor markets declines slightly. This reduction suggests that gradual sorting matters also in our context. Foreign workers apparently benefit somewhat more from improvements of matching over time than native workers (the negative interaction effect of total experience and the foreign indicator becomes larger in absolute terms). Furthermore, dynamic agglomeration advantages of foreign and native workers are also related to sorting. However, the corresponding coefficients decline only by about 10%, indicating that faster wage growth in large labor markets is not primarily due to this mechanism. Gradual sorting is apparently less important in our context than in the case studied by Eckert et al. (2022), who find that about 50% of the faster wage growth is related to gradual moves towards higher-paying jobs. One reason for this difference may be that Eckert et al. (2022) focus on the specific group of refugees.

To illustrate how dynamic agglomeration effects influence the development of wages over the career and to examine their economic significance in more detail, Figure 5 plots wage-experience profiles by region type for native (top panel) and foreign workers (bottom panel) based on the results from column (4), i.e. conditional on (un)observed characteristics and gradual sorting into better jobs. Foreigners and natives both benefit from dynamic agglomeration effects, as evidenced by the fact that experience from denser regions leads to steeper wage profiles. Moreover, Figure 5 illustrates that dynamic agglomeration effects are economically important. Ceteris paribus, the expected wage of a native person with 20 years of work experience is about 8.2% $[= (\exp(0.80 - 0.72) - 1)100\%]$ higher if experience was entirely gained in the densest as opposed to the least dense labor markets. This difference increases to 13.3% $[= (\exp(1.025 - 0.9) - 1)100\%]$ after 30 years. While wage growth is slower for foreign workers, the composition of experience in terms of region-specific experience is more relevant in relative terms. Ceteris paribus, wages are about 10.5% $[= (\exp(0.6 - 0.5) - 1)100\%]$ higher after 20 years if experience was acquired entirely in the densest regions as opposed to the least dense regions. The corresponding premium for foreign workers with 30 years of experience is 26.5% $[= (\exp(0.71 - 0.475) - 1)100\%]$. Having controlled for sorting into higher-quality occupations, tasks and establishments, we argue that our results are in line with the assumption that learning constitutes the predominant mechanism underlying dynamic agglomeration effects (De La Roca and Puga, 2017).

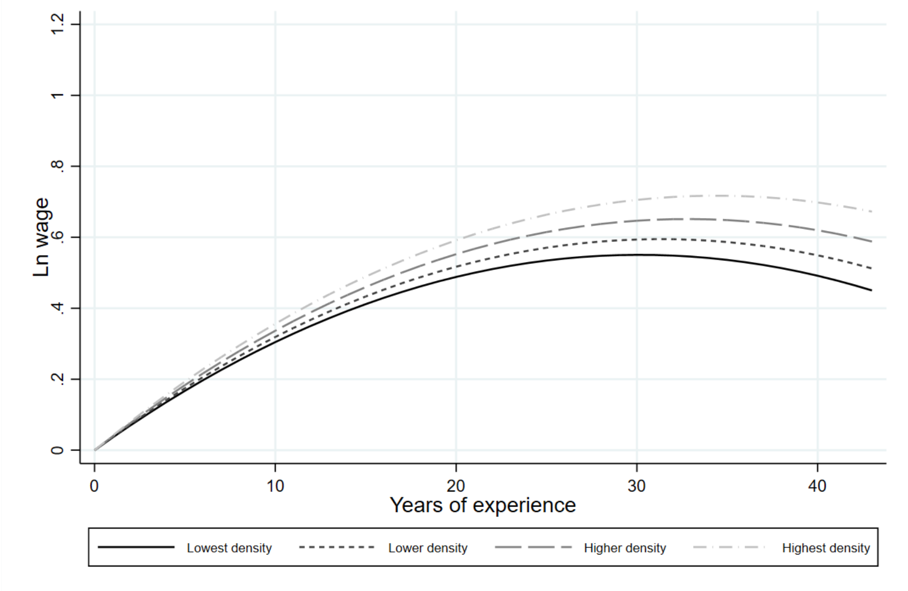
4.2 Experience in sectors, occupations and establishments

The results in column (4) of Table 1 as well as Figure 5 show 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. Big-city experience is likely to differ systematically from experience acquired in less dense regions because the former regions differ in terms of tasks, knowledge-intensity, establishment quality (as shown in Figures 1, 2, 3) and, thus, learning potential. In particular, knowledge-intensive sectors, non-routine tasks, and high-quality establishments, which

Figure 5: 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 (4) 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.

might give rise to more valuable experience, tend to be concentrated in large cities (see also Davis and Dingel, 2019, Koster and Ozgen, 2021, Eckert et al., 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 are primarily available in large cities.[6]

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 that is accumulated in a specific region type is associated with work experience acquired in different sectors, tasks and establishments. We consider five sector and task types and four establishment categories in Table 2. The dependent variable is the number of years of work experience that a worker gained in the corresponding sector, task and establishment type. We control for important individual characteristics such as age, level of education and occupation. We focus on the association between experience by density category that is also interacted with an indicator for foreign workers. Thus, we can analyze whether work experience gained in different density groups translates into different types of experience for foreign and observationally identical native workers. Based on these results, we can also assess whether experience is associated with less favorable types of work experience for foreigners.

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

	Experience by sector type				
	manufacturing		services		
	low knowledge	knowledge intensive	low knowledge	knowledge intensive	public service
Experience lowest density	0.396***	0.221***	0.146***	0.109***	0.122***
	(0.000438)	(0.000365)	(0.000397)	(0.000328)	(0.000339)
Experience lower density	0.317***	0.282***	0.164***	0.119***	0.115***
	(0.000434)	(0.000410)	(0.000410)	(0.000341)	(0.000343)
Experience higher density	0.245***	0.285***	0.193***	0.151***	0.125***
	(0.000407)	(0.000423)	(0.000426)	(0.000368)	(0.000358)
Experience highest density	0.197***	0.245***	0.228***	0.216***	0.115***
	(0.000374)	(0.000400)	(0.000439)	(0.000400)	(0.000357)
FGN × exp. lowest density	0.146***	0.0954***	-0.0721***	-0.0630***	-0.102***
	(0.00256)	(0.00230)	(0.00188)	(0.00120)	(0.000978)
FGN × exp. lower density	0.150***	0.0897***	-0.0706***	-0.0766***	-0.0922***
	(0.00219)	(0.00208)	(0.00177)	(0.00102)	(0.000953)
FGN × exp. higher density	0.165***	0.0889***	-0.0767***	-0.0847***	-0.0916***
	(0.00203)	(0.00201)	(0.00174)	(0.00111)	(0.00102)
FGN × exp. highest density	0.0874***	0.117***	-0.0153***	-0.116***	-0.0739***
	(0.00173)	(0.00186)	(0.00184)	(0.00120)	(0.00102)
Adjusted R^2	0.346	0.261	0.294	0.371	0.268
	Experience by task group				
	non-routine			routine	

Continued on next page

[6]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).

Table 2 continued

	analytic	interactive	manual	cognitive	manual
Experience lowest density	0.0679***	0.0735***	0.412***	0.258***	0.182***
	(0.000226)	(0.000250)	(0.000406)	(0.000341)	(0.000345)
Experience lower density	0.0808***	0.0735***	0.433***	0.248***	0.158***
	(0.000242)	(0.000253)	(0.000418)	(0.000341)	(0.000341)
Experience higher density	0.0977***	0.0717***	0.456***	0.216***	0.150***
	(0.000259)	(0.000257)	(0.000426)	(0.000327)	(0.000341)
Experience highest density	0.113***	0.0740***	0.486***	0.182***	0.144***
	(0.000271)	(0.000260)	(0.000427)	(0.000305)	(0.000336)
FGN × exp. lowest density	-0.0172***	-0.0531***	-0.181***	0.270***	-0.0298***
	(0.000960)	(0.000828)	(0.00178)	(0.00213)	(0.00171)
FGN × exp. lower density	-0.0299***	-0.0473***	-0.179***	0.263***	-0.0150***
	(0.000852)	(0.000795)	(0.00163)	(0.00185)	(0.00151)
FGN × exp. higher density	-0.0250***	-0.0479***	-0.182***	0.249***	-0.00484***
	(0.000938)	(0.000787)	(0.00159)	(0.00176)	(0.00146)
FGN × exp. highest density	-0.0337***	-0.0377***	-0.185***	0.211***	0.0368***
	(0.000935)	(0.000844)	(0.00155)	(0.00162)	(0.00149)
Adjusted R^2	0.317	0.411	0.544	0.473	0.425

	Experience by establishment quality			
	lowest	lower	higher	highest
Experience lowest density	0.165***	0.257***	0.272***	0.228***
	(0.000335)	(0.000289)	(0.000295)	(0.000308)
Experience lower density	0.0941***	0.232***	0.291***	0.315***
	(0.000318)	(0.000295)	(0.000303)	(0.000361)
Experience higher density	0.0643***	0.213***	0.291***	0.370***
	(0.000309)	(0.000297)	(0.000314)	(0.000389)
Experience highest density	0.0272***	0.180***	0.284***	0.448***
	(0.000293)	(0.000292)	(0.000320)	(0.000399)
FGN × exp. lowest density	-0.139***	-0.0632***	0.0409***	0.152***
	(0.00153)	(0.00150)	(0.00161)	(0.00194)
FGN × exp. lower density	-0.101***	-0.0754***	-0.00255*	0.162***
	(0.00125)	(0.00123)	(0.00137)	(0.00183)
FGN × exp. higher density	-0.0837***	-0.0769***	-0.00433***	0.149***
	(0.00117)	(0.00114)	(0.00131)	(0.00176)
FGN × exp. highest density	-0.0514***	-0.0550***	0.00121	0.0908***
	(0.00114)	(0.00107)	(0.00131)	(0.00168)
Adjusted R^2	0.199	0.242	0.282	0.346

Notes: Unit of observation is person-year. Their number is 18,050,613. Dependent variable is a worker's experience in a certain type of industry, task and establishment, respectively. 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 density within 10 km as thresholds to determine experience by type of region. Establishment quality refers to estimates of establishment fixed effects from AKM regressions by Bellmann et al. (2020).
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.

The upper panel of Table 2 shows the results for experience by sector types. We differentiate between services and manufacturing (knowledge-intensive and non-knowledge-intensive) as well as the public sector. The results in the first two columns in the top panel show that the fraction of an additional year of work experience that can be ascribed to the service categories increases with the density of the region. This is in line with an above-average share of service employment in large cities. The marginal effect of one additional year of work experience gained in the respective region type on 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 estimate almost doubles from the lowest to the highest density regions. 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 acquire less work experience in knowledge-intensive services in every density category, conditional on their occupation, skill level and other controls. This gap increases with the density of regions. Similar differences arise for experience gained in low-knowledge services and the public sector. However, in the latter cases, the gap does not systematically increase with regional density. 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 find that the marginal effect of an additional year of experience declines with increasing density for the low-quality categories, while for the highest establishment quality there is a significant increase in the coefficient estimate as we move from low- to high-density regions. Opportunities to gain experience in non-routine analytic and non-routine manual tasks also seem to increase with the density of the location, while it is easier to gain experience in routine tasks, both cognitive and manual, in low-density regions. Again, we find significant differences between foreign and German workers. Foreign workers accumulate less non-routine experience in dense regions than natives. In particular, the size of the 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.[7] This pattern prevails for sector- and task-specific experience, while establishment quality represents a noteworthy exception.

4.3 Sources of dynamic agglomeration effects

To evaluate the sources of dynamic agglomeration effects and examine the role of different types of experience, we extend the model underlying the results in column (4) of Table 1. To this end, we successively control for experience that was acquired in different sector, task and establishment quality classes. Specifically, we differentiate work experience by six distinct types of sectors, six task groups and five establishment-types.[8]

As shown in Table 2, work experience that was acquired in denser regions more often

[7] This is in line with evidence provided by D'Amuri and Peri (2014) who show that immigrants in Western European countries seem to push natives towards more complex occupations and tasks by performing primarily manual-routine type jobs in the host country. They argue that immigration has promoted a specialization of native workers in abstract-complex occupations and away from manual-routine tasks.

[8] In addition to the experience categories in Table 2, we consider three additional experience variables: 'agriculture', 'unknown task' and 'unknown establishment quality'. The two latter variables comprise experience that we cannot assign to one of the other task and establishment types because some employment spells do not contain information about the occupation and estimates of AKM establishment fixed effects are not available for all establishments (see data description), respectively.

Table 3: Sources of dynamic agglomeration effects

	(1)	(2)	(3)	(4)	(5)
	Total experience				
Total experience	0.0463***	0.0437***	0.0416***	0.0443***	0.0405***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0029)
Foreign (FGN) × total exp.	-0.0098***	-0.0090***	-0.0083***	-0.0099***	-0.0074***
	(0.0010)	(0.0011)	(0.0010)	(0.0009)	(0.0010)
Experience^2	-0.0005***	-0.0006***	-0.0005***	-0.0006***	-0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FGN × experience^2	-0.0001***	-0.0001***	-0.0000***	-0.0001***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Experience by density category, 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 × exp. lower density	-0.0004**	-0.0002	-0.0001	-0.0003*	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Experience higher density	0.0031***	0.0022***	0.0020***	0.0026***	0.0015***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
FGN × exp. higher density	0.0001	0.0002	0.0002	0.0003	0.0004
	(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 × exp. highest density	0.0008	0.0008**	0.0011**	0.0013***	0.0012***
	(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

Notes: Unit of observation is person-year. Their number is 18,050,613 in each specification. Dependent variable is a worker's log daily wage. Each model includes fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density". Further control variables are: sex, level of qualification, part-time status, tenure and its square, 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 A2. 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)), respectively.
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.

coincides with work experience that was gained in knowledge-intensive services, analytical tasks or high-quality establishments than is the case for work experience from low density regions. Likewise, experience from less dense areas more often takes the form of experience acquired in low-knowledge services or manufacturing as well as routine manual or routine cognitive tasks. If experience from the first group is associated with a higher return – potentially due to better learning opportunities –, one would expect that part of the dynamic agglomeration effects in column (4) of Table 1 reflect easier access to better types of jobs in denser regions. In that case, inclusion of separate variables for these types of experience should reduce the estimated returns to experience gained in denser regions.

While column (1) of Table 3 contains the estimated returns to experience by density group from the final column of Table 1, column (2) shows the results when sector-specific experience is included. Inclusion of experience by sector category reduces the marginal return to total experience, which reflects the fact that the variable now captures the effect of an additional year of experience that was acquired in low-knowledge manufacturing in the least dense regions.

In terms of the dynamic agglomeration effects, we find that controlling for experience by sector reduces the return to experience for each density group. For natives, this reduction varies between 25% (highest density) and 29% (higher density). This finding suggests that a considerable part of dynamic agglomeration effects are due to the fact that denser regions provide better access to employment in higher-quality sectors. Further evidence for this explanation can be found in Table A2 which shows that experience from sectors that can more often be found in denser areas display higher returns: experience in knowledge-intensive services has a significantly higher return than experience gained in low-knowledge manufacturing (the reference category). Significantly higher returns are also found for experience in public services. Thus, a considerable part of dynamic agglomeration effects seem to be due to the fact that denser regions provide better access to employment in higher-quality sectors. While the returns to experience by density category of foreign workers are very similar to those of German workers, inclusion of sector-specific experience leads to two minor changes in the interaction terms between experience by density category and the foreign indicator. First, in the case of experience from the highest density regions, the interaction term becomes statistically significant (though the point estimate remains unchanged). Second, the interaction effect of the foreign indicator and experience from the lower density regions is smaller in absolute terms and no longer statistically significant.

We repeat the same exercise by adding experience by task groups (column (3)) and establishment quality (column (4)). The results are similar to those described above. The types of work experience that are associated with denser areas – experience in non-routine analytical tasks and in higher-quality establishments – are estimated to have significantly larger returns than the respective reference categories.[9] Controlling for experience by

[9] In both cases, the reduction in the return to overall experience reflects that the reference category no longer refers to experience in the least dense regions, but to experience in the least dense areas *and* routine manual tasks as well as to experience in the least dense areas *and* lowest-quality establishments.

task groups has a larger impact on the return to regional experience than in the case of experience by sector: while the return to experience in lower density areas falls by about 28%, the reduction to the return from experience in regions with the highest density amounts to 39%. As in the case of sectors, these changes reflect that experience in denser areas more often consists of experience in task groups that are associated with a higher return. The impact of controlling for experience by establishment type is smaller. The estimated return to experience by density type falls by between 17% and 18%.

Column (5) shows the results from the most comprehensive model in which all types of experience are controlled for. The reduction in the estimated returns to experience by regional density are most pronounced. The estimate for experience from highest density regions falls by 50% (the decrease for the returns to the two other types of experience amount to 44% and 52%, respectively). According to these results, approximately half of the dynamic agglomeration effects can be ascribed to the availability of higher-quality employment in cities in terms of sectors, task groups and establishments.

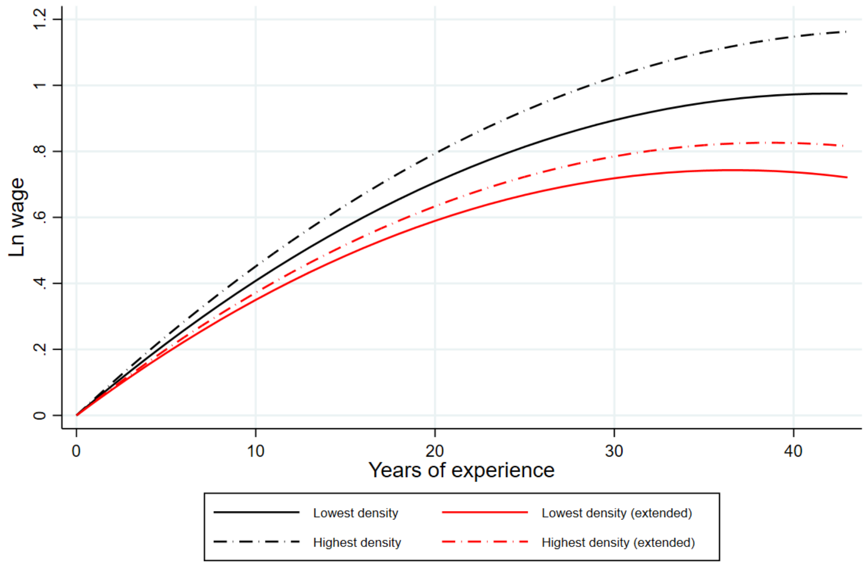
While the returns to experience for foreigners are overall very similar to those of natives, inclusion of the additional experience variables leads to two changes. First, the baseline specification in column (1) shows a small, but statistically significant reduction in the return to experience acquired in lower density regions for foreigners compared to natives. This difference becomes smaller in magnitude and is no longer statistically significant in columns (2), (3) and (5). In these regions, the lower return to experience appears to be due to the sorting of foreigners into less valuable types of employment. Second, the results in columns (3), (4) and (5) show that controlling for the additional types of experience increases the excess returns to experience from highest density regions for foreigners compared to natives. This suggests that dynamic agglomeration effects of natives are to a larger extent due to access to higher-quality types of employment that are available in denser regions than is the case for foreigners.

Figure 6 plots the experience-wage profiles for experience that was either gained in regions with the lowest or the highest density for native workers (top panel) and foreigners (bottom panel). In both cases, the profiles are shown with and without controlling for experience by sectors, task groups and establishments. As discussed above, parts of the dynamic agglomeration effects shown in column (4) of Table 1 are due to the composition of jobs in denser regions. The profiles – for foreign as well as for native workers – therefore become less steep. While the reduction in the gradient can be found for experience gained in regions with the highest as well as with the lowest density, it is considerably more pronounced for big-city experience.[10] This result provides evidence that an important part of dynamic agglomeration effects is due to the favorable composition of denser regions (rather than an unfavorable composition of less dense regions). As a result, the wage gap

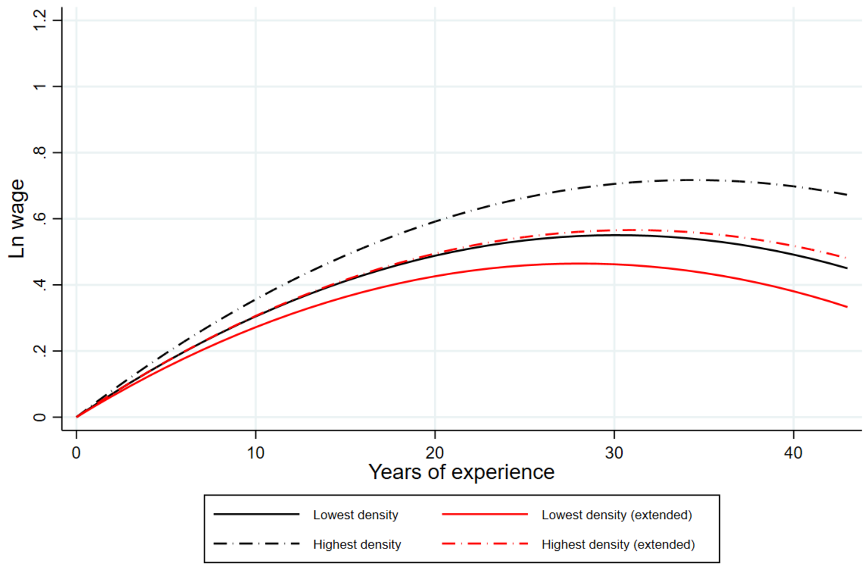
[10]The reduction in the return to experience gained in regions with the lowest density also reflects that, after controlling for experience by type of job, the former captures the return to experience gained in regions with the lowest density *and* the reference categories of experience by sector, task group and establishment quality.

for experience gained in the densest as opposed to the least dense regions also becomes smaller. After 20 years (30 years) the gap reduces to 2.5% (8.3%) for natives and to 7.8% (10.5%) for foreigners.

Figure 6: 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 columns (1) and (4) of Table 3 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.

4.4 Dynamic agglomeration effects by skill group

The results so far suggest that sorting into jobs that offer different learning potentials contributes to dynamic agglomeration benefits and to differences in future wages of foreigners 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 to depend on a worker's skill level (see, e.g., De La Roca and Puga, 2017). We therefore examine whether the benefits from dynamic agglomeration effects and the role of experience collected in different types of jobs varies between skill groups. In Table 4, we present the results from separate estimations for low-skilled, middle-skilled and high-skilled workers 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).

Comparing the results for the specifications with and without these different experience variables indicates that in particular low- and middle-skilled workers benefit from the types of jobs that cities offer. For these two groups, the estimated dynamic agglomeration effects are about 50% smaller once we account for the previous sorting into jobs that differ with regard to learning potential. In contrast, for the high-skilled, the results suggest that the quality of jobs, in which these workers acquired experience, does not differ systematically across labor markets of different size. This is in line with the pattern reported in Figure 2, which shows that high-skilled workers acquire more or less the same kind of experience with regard to task groups in all types of regional labor markets. By contrast, there are larger differences for the low- and medium-skilled. Specifically, the share of experience in routine manual occupations shrinks considerably in denser regions.

As regards dynamic agglomeration effects for foreigners and natives, the results in column (1) in Table 4 reveal significant differences in the case of low-skilled workers. Compared to the results for the entire sample (column (1) in Table 3), the interaction effect of the foreign-indicator and experience in the highest density category is now negative. Specifically, the estimates imply that low-skilled foreign workers also benefit from acquiring experience in the densest labor markets – the premium for one additional year of experience acquired there is 0.0027 [= 0.0038 - 0.0011] – but this gain is significantly smaller than for low-skilled natives. According to the results in column (1), the discount amounts to 29%.

If we account for the types of sectors, task groups and establishments, in which foreign and native low-skilled workers gather experience (column (2)), the difference in the wage premium for experience acquired in the densest labor markets relative to experience gained in the least dense regions is, however, virtually zero and no longer statistically significant. In absolute terms, the interaction effect declines from -0.0011 to 0.0003. The results therefore suggest that the initial difference in dynamic agglomeration effects between foreign and native low-skilled workers reflects that foreigners in the biggest cities tend to work in

Table 4: Dynamic agglomeration effects by skill group

	Low-skilled		Middle-skilled		High-skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
			Total experience			
Total experience	0.0215***	0.0177***	0.0501***	0.0450***	0.0424***	0.0349***
	(0.0012)	(0.0013)	(0.0027)	(0.0031)	(0.0029)	(0.0036)
Foreign (FGN) × total exp.	0.0087***	0.0115***	-0.0123***	-0.0096***	-0.0034**	-0.0099***
	(0.0013)	(0.0014)	(0.0013)	(0.0011)	(0.0016)	(0.0023)
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***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Experience by density category, reference: experience in least dense regions			
Experience lower density	0.0011***	0.0003	0.0017***	0.0009***	0.0018***	0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
FGN × exp. lower density	-0.0003	0.0001	-0.0002	0.0001	0.0003	0.0008
	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0011)	(0.0010)
Experience higher density	0.0025***	0.0016***	0.0029***	0.0014***	0.0026***	0.0023***
	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0004)
FGN × exp. higher density	-0.0004	0.0000	0.0003	0.0005*	0.0023**	0.0024**
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0009)	(0.0009)
Experience highest density	0.0038***	0.0018***	0.0042***	0.0021***	0.0034***	0.0036***
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0006)	(0.0007)
FGN × exp. highest density	-0.0011**	0.0003	0.0013***	0.0017***	0.0016	0.0013
	(0.0004)	(0.0006)	(0.0004)	(0.0003)	(0.0010)	(0.0010)
Observations	776,135	776,135	14,061,421	14,061,421	3,212,590	3,212,590
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	.19	.236	.244	.231	.234

Notes: 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, tenure and its square, 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 A4. 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 et al. (2014), Bellmann et al. (2020), own calculations.

lower-quality jobs than natives with a comparable skill level.[11] Figure 7 illustrates that about 70% of the experience acquired by foreign low-skilled workers in the densest regions is gathered in routine or non-routine manual tasks, which are the task groups with the lowest return to experience (Table A4). In contrast, among the native low-skilled the share of these task groups amounts to less than 60% of the experience gathered in the labor markets with the highest density. Figures A2 and A3 in the Appendix provide additional information on the composition of experience by sector and establishment type, respectively. In line with the results reported in Table 2, low-skilled foreign workers acquire big-city experience, on average, in establishments of higher quality than low-skilled natives. Hence, the lower returns to big-city experience compared to experience from less dense labor markets appears to be mainly related to a relatively low quality of sectors and task groups, rather than to a low quality of establishments.

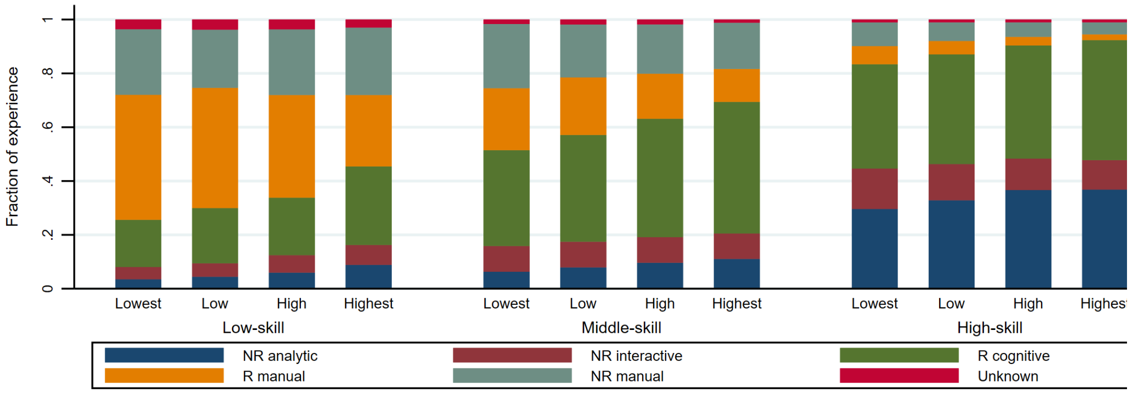
Compared to the results for the low-skilled, analyses for the middle- and high-skilled do not provide evidence that foreign workers in these skill groups benefit less than similarly skilled natives from acquiring experience in denser labor markets. In the case of middle-skilled foreign workers, we find an additional wage premium for experience acquired in the labor markets of higher and highest density compared to natives (column (4)). This additional benefit from acquiring experience in agglomerated regions is to some extent offset by the sorting of foreign middle-skilled workers into jobs with a low potential to accumulate human capital, as indicated by the smaller and partly statistically insignificant interaction effects in column (3), see also Figure 7. Among foreign high-skilled workers, we observe a larger wage premium for experience gained in higher density labor markets relative to natives, but we find no such difference with respect to experience acquired in the highest density regions.

Concerning total experience, which refers to experience in the reference categories (the least dense labor market, low-knowledge production, routine manual occupations, the lowest establishment quality), the results for the different skill groups in Table 4 point to heterogeneous effects for foreign and native workers. While low-skilled foreign workers, on average, receive a higher return to work experience than observationally identical natives, we find the opposite for middle- and high-skilled workers.

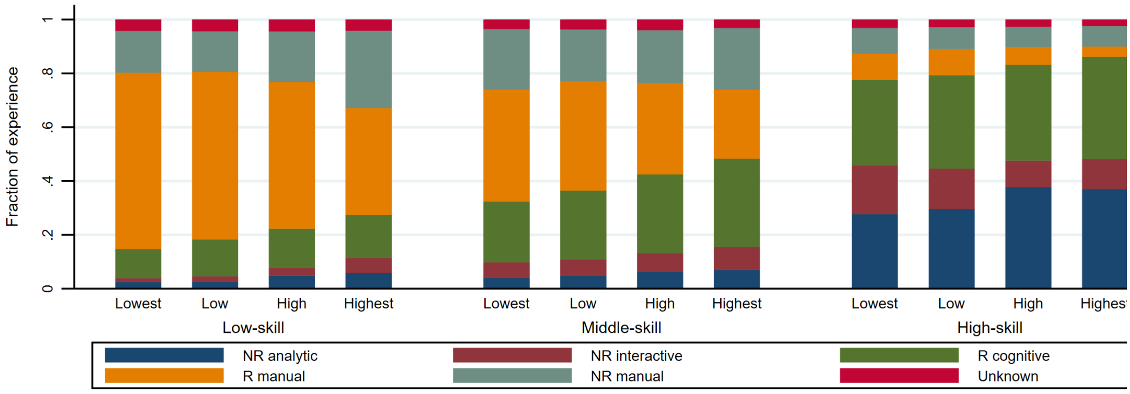
4.5 Results for low-skilled foreign workers by nationality

The results in columns (1) and (2) of Table 4 indicate that only low-skilled foreign workers benefit less from the favorable composition of employment that the highest-density loca-

[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 A4). 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 benefits experienced by low-skilled foreign workers. However, the lower return from big-city experience also disappears if we only account for the additional experience categories and assume that foreign and native low-skilled workers benefit equally from the different types of experience (Table A5). This points to the significance of sorting for the heterogeneous dynamic agglomeration benefits for foreign and native low-skilled workers.



(a) Native workers



(b) Foreign workers

Figure 7: Composition of work experience w.r.t. task groups by labor market density and skill level for foreign and native 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*. Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613.
Source: IEB, Dengler et al. (2014), own calculations.

tions offer. In this subsection, we examine whether this is a general result or whether it only holds for specific groups of foreign workers. The most important groups among low-skilled foreign workers in Germany belong to the nationalities of those immigrants who came to West Germany as so-called guest workers between the late 1950s and the early 1970s and their descendants.[12] In our sample, we differentiate between Turks, who represent a particularly large group in Germany, on the one hand and workers from European guest worker countries, namely Greece, Italy, Portugal, Spain as well as the former Yugoslavia, on the other hand. Together, these nationalities account for 77% of the low-skilled foreign workers.

Table 5: Dynamic agglomeration effects for low-skilled foreign workers

	All		European guest worker nationalities		Turks	
	(1)	(2)	(3)	(4)	(5)	(6)
Total experience						
Total experience	0.0302***	0.0292***	0.0269***	0.0277***	0.0316***	0.0307***
	(0.0017)	(0.0017)	(0.0030)	(0.0031)	(0.0017)	(0.0020)
Total experience^2	-0.0005***	-0.0005***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience by density category, reference: experience in least dense regions						
Experience lower density	0.0008**	0.0004	0.0023***	0.0019***	0.0013***	0.0012***
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Experience higher density	0.0021***	0.0016***	0.0016**	0.0007	0.0032***	0.0030***
	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0004)	(0.0004)
Experience highest density	0.0027***	0.0021***	0.0038***	0.0020**	0.0031***	0.0031***
	(0.0004)	(0.0004)	(0.0007)	(0.0008)	(0.0005)	(0.0005)
Observations	165,984	165,984	36,254	36,254	91,770	91,770
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)	0.212	0.217	0.208	0.215	0.218	0.222

Notes: Unit of observation is person-year. Dependent variable is a worker's log daily wage. Each model includes fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density". Further control variables are: sex, level of qualification, part-time status, tenure and its square, 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. 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. Low-skilled workers are those who have neither completed an apprenticeship nor completed tertiary education. European guest workers refer to nationals from Greece, Italy, Portugal, Spain and the former Yugoslavia.
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.

For these two groups, we replicate the analysis described in Section 4.4 and estimate models containing experience by density category as well as the augmented model in which we control for experience by sector, task groups and establishment quality. Table 5 shows the results for all foreigners, the Turks and other European guest worker nationalities. The results for all foreigners in column (1) and (2) are identical to the estimates for low-skilled foreign workers in Table 4. They illustrate the lower returns to experience gained in the

[12] West Germany signed contracts with Italy, Greece, Spain, Turkey, Portugal, Morocco, Tunisia and the former Yugoslavia to recruit labor migrants, with the Turks being by far the largest group.

densest regions [0.0027 = 0.0038 - 0.0011] which suggests that low-skilled foreign workers, on average, benefit less from the availability of higher-quality jobs in large cities than comparable natives. However, low-skilled foreign workers also tend to take advantage of the jobs that the highest density category offers. Controlling for experience by sector, task group and establishment quality reduces the return to experience gained in the densest regions from a value of 0.0027 to 0.0021: 22% of the dynamic agglomeration effects can therefore be ascribed to the type of jobs in which experience was acquired.

The findings for the European guest worker nationalities (columns (3) and (4)) indicate that low-skilled workers from this group benefit from dynamic agglomeration advantages in the largest cities to the same extent as low-skilled German workers (compare columns (1) and (2) in Table 4). For both groups, the return to big-city experience is 0.0038. Moreover, the estimated return falls once experience by type of job is included, which suggests that parts of the benefits to experience in the densest regions are due to access to higher-quality jobs. This is not the case for low-skilled Turkish workers (columns (5) and (6) in Table 5). While the return to experience gained in high-density regions is slightly larger than for low-skilled foreign workers (0.0031 compared to 0.0027), low-skilled Turks do not seem to benefit from the type of jobs that urban labor markets offer. Including work experience by sector, task and establishment quality leaves the estimated return to big-city experience virtually unchanged (column (6)). These results are consistent with evidence by Kogan (2004) who shows that all immigrant groups in Germany, with the exception of EU immigrants, have a significantly lower chance of entering white-collar employment. More importantly, she reports no transitions from unemployment into skilled employment for Turkish guest workers.

The lower benefits from big-city experience that we observe for low-skilled foreign workers are therefore not purely a skill effect. The fact that the finding applies to a specific nationality points to a potential role of lacking integration of certain ethnic groups into the host country. There is broad evidence for an unfavorable labor market performance of Turks in Germany (see Kogan, 2004; Algan et al., 2010). In fact, Algan et al. (2010) show that male Turkish workers experience no wage assimilation in Germany, but rather a worsening of their relative wage position from the first to the second generation. By contrast, other guest worker groups experience partly pronounced improvements. Kogan (2004) notes that Turkish workers might experience a particularly large penalty in the German labor market because they are perceived as the most non-integrated immigrant group (see also Becker, 2011).

Table A6 and Table A7 in the Online Appendix show the corresponding findings for middle-skilled and high-skilled Turks and guest workers, respectively. One insight from these results is that, after controlling for experience by job categories, the return to experience in the densest regions increases with skill for both groups of foreigners. This is in line with the results from Table 4, which showed the increase in returns to experience from denser regions for foreign workers in general. Moreover, these estimates suggest that middle- and high-skilled Turkish workers can take advantage of high quality jobs in the largest cities - in contrast to low-skilled Turks. This implies that the specific disadvantage of this group is not caused by low level of integration of this ethnic group per se.

We do not provide direct evidence on the factors behind this specific disadvantage of low-skilled Turks. However, there are some likely candidates. Lacking language skills might exclude them from jobs of better quality that offer more learning opportunities.[13] There is evidence that Turks lag behind other migrants groups in terms of their language skills in Germany (e.g. Becker, 2011. Diehl and Schnell (2006) shows that even among second generation Turks less than half state that they have very good German-language skills.

There is also evidence that Turks have fewer contacts with Germans (Diehl and Schnell, 2006). This points to another factor that might influence the selection into jobs with poor learning potential. Findings by Dustmann et al. (2015) indicate that referral-based job search via social networks is an important feature of recruiting in the German labor market and referral-based matches tend to be of higher quality. However, referrals might not provide access to good jobs if friends and relatives themselves work in low-knowledge sectors and low-quality firms. Differences between low-skilled Turks and low-skilled individuals from guest worker countries might be caused by a lower share of middle-skilled and high-skilled workers among the Turks, i.e. ethnic networks that do not primarily offer access to high quality jobs.[14]

5 Conclusion

This paper evaluates dynamic agglomeration effects and provides evidence on the mechanisms behind these effects. Using administrative data on individual employment biographies that go back until 1975, we also 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 wage differentials between urban and rural labor markets (Baum-Snow and Pavan, 2012; De La Roca and 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 work experience that was acquired in denser areas. The composition of work experience in terms of sectors, tasks and establishment quality explains about 50% 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

[13] Unfortunately, there is no data that allows us to directly estimate the effect of language skills on the probability to acquire work experience in specific sectors, tasks and firms. We lack information on German-language proficiency in the IEB.

[14] Dustmann et al. (2015) provide evidence that social contacts of foreign workers in Germany are primarily ethnicity based. This also applies to migrants who reside in Germany for a long time or those born in Germany.

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 and Dingel (2019). By contrast, selection into high-quality jobs appears to be less relevant for high-skilled workers. One reason might be that while accessing high-quality jobs becomes easier in denser areas for low- and middle-skilled workers, access to these types of jobs does not vary as much over space for the high-skilled.

Moreover, we find that, on average, the size of the dynamic agglomeration effects is similar for foreigners and natives. Differences exist, however, between native and foreign workers within skill groups. For low-skilled workers, we find that the premium of big-city experience is significantly lower than for observationally identical natives. We attribute this discount to the fact that when employed in large cities, low-skilled foreigners tend to work in lower-quality tasks and sectors than natives which are likely to offer fewer learning opportunities. This disadvantage is primarily due to low-skilled Turks, who constitute the largest single nationality among low-skilled foreigners in Germany. By contrast, we find no statistically significant difference in dynamic agglomeration effects between natives and foreigners for middle-skilled and high-skilled workers.

Our results 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 workers sort into tasks and sectors that do not provide the opportunities that large cities offer with respect to valuable work experience. In light of our finding that failure to benefit from the favorable job structure in cities appears to be more relevant for some nationalities than others, particular attention should be paid to the reasons for this heterogeneity among foreigners. Arguments for heterogeneous returns to density put forth by Ananat et al. (2018) with respect to static agglomeration effects, refer to the role of ethnic social networks. 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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Online Appendix

A Data description

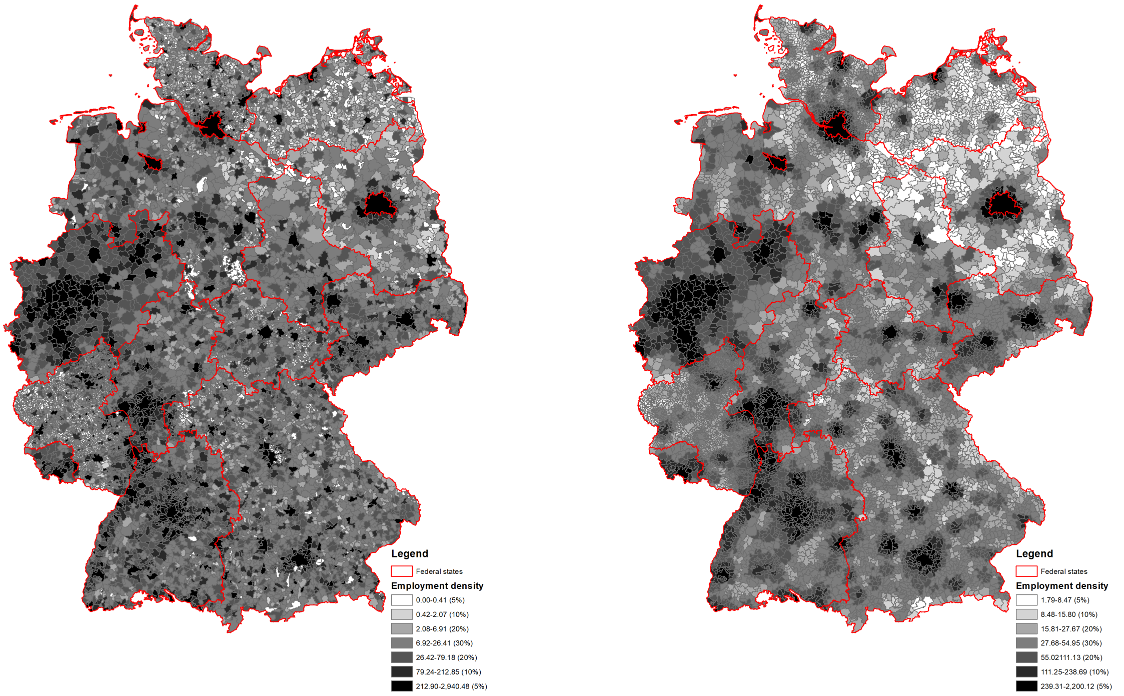
Table A1: Summary statistics

	Natives	Foreigners	Total
Worker variables			
Daily wage (imputed)	106.1	99.14	105.7
	(61.63)	(52.42)	(61.19)
Foreign nationality	0.000	1.000	0.054
	(.)	(.)	(0.225)
Female	0.442	0.351	0.437
	(0.497)	(0.477)	(0.496)
Low-skilled	0.0357	0.171	0.0430
	(0.186)	(0.377)	(0.203)
Middle-skilled	0.786	0.656	0.779
	(0.410)	(0.475)	(0.415)
High-skilled	0.178	0.172	0.178
	(0.383)	(0.378)	(0.383)
Part-time	0.201	0.171	0.199
	(0.400)	(0.377)	(0.399)
Tenure (in months)	63.84	55.34	63.38
	(74.92)	(71.90)	(74.79)
Experience variables (in years)			
Total experience	13.28	11.45	13.18
	(9.249)	(9.179)	(9.254)
Experience by labor market density			
lowest density	3.480	1.540	3.376
	(6.673)	(4.570)	(6.592)
lower density	3.399	2.614	3.356
	(6.387)	(5.728)	(6.355)
higher density	3.306	3.376	3.310
	(6.237)	(6.228)	(6.236)
highest density	3.097	3.918	3.141
	(6.298)	(6.765)	(6.327)
Experience by sector			
agriculture	0.0594	0.0263	0.0576
	(0.778)	(0.433)	(0.763)
low knowledge production	3.128	3.445	3.145
	(6.429)	(6.893)	(6.455)
knowledge-intensive production	2.263	2.623	2.282
	(5.824)	(6.213)	(5.846)
low knowledge services	3.536	3.491	3.533
	(6.176)	(5.606)	(6.147)
knowledge-intensive services	2.570	1.205	2.497
	(5.724)	(3.499)	(5.635)
public service	1.726	0.659	1.669

	(4.881)	(2.709)	(4.795)
Experience by task group			
non-routine analytic	1.612	0.949	1.577
	(4.039)	(2.889)	(3.988)
non-routine interactive	1.301	0.779	1.273
	(3.889)	(2.575)	(3.832)
routine cognitive	5.452	3.034	5.322
	(7.826)	(5.666)	(7.744)
routine manual	2.295	4.014	2.387
	(5.546)	(7.196)	(5.660)
non-routine manual	2.408	2.259	2.400
	(5.563)	(4.928)	(5.531)
unknown occupation	0.213	0.413	0.224
	(0.954)	(1.381)	(0.983)
Experience by establishment quality			
lowest quality	3.016	2.197	2.972
	(4.561)	(3.591)	(4.518)
lower quality	2.829	1.906	2.779
	(4.365)	(3.505)	(4.328)
higher quality	3.126	2.638	3.100
	(4.748)	(4.395)	(4.731)
highest quality	3.092	3.604	3.119
	(5.771)	(6.261)	(5.799)
unknown quality	1.219	1.103	1.213
	(1.663)	(1.521)	(1.656)
Establishment variables			
AKM establishment effect (lagged)	-0.0793	-0.0762	-0.0792
	(0.297)	(0.315)	(0.298)
Establishment size: 1-9 employees	0.0996	0.0780	0.0985
	(0.300)	(0.268)	(0.298)
Establishment size: 10-49 employees	0.242	0.196	0.240
	(0.428)	(0.397)	(0.427)
Establishment size: 50-249 employees	0.293	0.285	0.292
	(0.455)	(0.451)	(0.455)
Establishment size: 250+ employees	0.365	0.441	0.369
	(0.482)	(0.496)	(0.483)
Regional variables			
Employment density	377.2	538.4	385.9
	(434.1)	(513.9)	(440.3)
1925 population density	686.4	881.8	696.9
	(909.6)	(941.9)	(912.4)
Share of workers with the same nationality	0.892	0.0187	0.845
	(0.0521)	(0.0170)	(0.203)
Observations	17,080,833	969,780	18,050,613

Notes: Means and standard deviations in parentheses. For definitions see Section 2.2.

Figure A1: Employees per km^2 at municipality level and 0–10 km around the geographic center of the municipality



(a) Municipality boundary

(b) 10km 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 10km 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 and Niebuhr (2019). ©IAB

Local employment density. To approximate the annual number of workers per local labor market, we follow Peters and 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 and 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. The left panel of Figure A1 shows for the original employment density at the level of municipalities in 2019, while the right panel shows employment density within a concentric ring with 10km radius around each municipality's centroid. 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.

B Further regression results

Table A2: 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	0.0002	(0.0015)					0.0001	(0.0016)
Experience knowledge-intens. production	0.0070***	(0.0006)					0.0049***	(0.0003)
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.	-0.0003	(0.0003)					-0.0001	(0.0002)
Experience knowledge-intens. services	0.0039***	(0.0004)					0.0020***	(0.0002)
FGN × exp. knowledge-intens. serv.	0.0010*	(0.0005)					0.0007*	(0.0004)
Experience public service	0.0075***	(0.0004)					0.0065***	(0.0003)
FGN × exp. public serv.	-0.0020***	(0.0004)					-0.0021***	(0.0003)
Experience by task group, reference: routine manual								
Experience non-routine analytic			0.0086***	(0.0005)			0.0071***	(0.0005)
FGN × exp. non-rout. analytic			0.0022***	(0.0004)			0.0027***	(0.0004)
Experience non-routine interactive			0.0041***	(0.0004)			0.0030***	(0.0002)
FGN × exp. non-rout. interactive			-0.0009	(0.0006)			0.0005	(0.0005)
Experience routine cognitive			0.0069***	(0.0005)			0.0056***	(0.0004)
FGN × exp. rout. cognitive			-0.0021***	(0.0001)			-0.0021***	(0.0002)
Experience non-routine manual			0.0012*	(0.0006)			0.0008	(0.0005)
FGN × exp. non-rout. manual			-0.0030***	(0.0002)			-0.0024***	(0.0002)
Experience unknown task			0.0000	(0.0012)			0.0010	(0.0011)
FGN × exp. unknown task			0.0033***	(0.0007)			0.0034***	(0.0008)
Experience by establishment quality, reference: lowest quality								
Experience lower establishment quality					0.0009	(0.0006)	-0.0007	(0.0006)
FGN × exp. lower est. quality					-0.0010***	(0.0003)	-0.0013***	(0.0002)
Experience higher establishment quality					0.0032***	(0.0007)	0.0010	(0.0008)
FGN × exp. higher est. quality					-0.0011***	(0.0003)	-0.0014***	(0.0002)
Experience highest establishment quality					0.0042***	(0.0012)	0.0007	(0.0011)
FGN × exp. highest est. quality					0.0001	(0.0003)	-0.0005**	(0.0002)
Experience unknown establishment quality					0.0046***	(0.0014)	0.0032**	(0.0014)
FGN × exp. unknown est. quality					0.0080***	(0.0013)	0.0081***	(0.0013)

Notes: 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 et al. (2014), Bellmann et al. (2020), own calculations.

Table A3: 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 category, reference: experience in least dense regions			
Experience	0.0363***	0.0297***	0.0302***	0.0229***
	(0.0019)	(0.0023)	(0.0019)	(0.0016)
Foreign × Experience	-0.0055***	-0.0037***	-0.0031**	-0.0006
	(0.0010)	(0.0011)	(0.0012)	(0.0014)
Experience^2	-0.0006***	-0.0006***	-0.0007***	-0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign × Experience^2	0.0000	0.0000***	0.0000***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience lower density	0.0020***	0.0009***	0.0021***	0.0009***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Foreign × exp. lower density	-0.0003	0.0003	-0.0001	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Experience higher density	0.0035***	0.0017***	0.0036***	0.0015***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Foreign × exp. higher density	-0.0001	0.0003	0.0003	0.0008***
	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Experience highest density	0.0053***	0.0028***	0.0053***	0.0024***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Foreign × exp. highest density	0.0001	0.0006**	0.0002	0.0009***
	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Experience by sector	No	Yes	No	Yes
Experience by task group	No	Yes	No	Yes
Experience by establishment quality	No	Yes	No	Yes
Observations	14,377,282	14,377,282	9,640,579	9,640,579
R^2	.163	.172	.174	.187

Notes: 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 et al. (2014),Bellmann et al. (2020), own calculations.

Table A4: 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	0.0000	(0.0008)	-0.0035***	(0.0004)	-0.0024***	(0.0008)
FGN × exp. agriculture	0.0074**	(0.0028)	-0.0010	(0.0015)	-0.0061	(0.0052)
Exp. knowledge-intens. production	0.0030***	(0.0001)	0.0050***	(0.0002)	0.0035***	(0.0005)
FGN × exp. knowledge-intens. prod.	-0.0013***	(0.0002)	-0.0011**	(0.0005)	0.0014	(0.0009)
Experience low-knowledge services	-0.0005***	(0.0002)	-0.0006**	(0.0002)	-0.0038***	(0.0004)
FGN × exp. low-knowledge serv.	-0.0002	(0.0005)	0.0011***	(0.0002)	-0.0037***	(0.0010)
Exp. knowledge-intens. services	0.0023***	(0.0005)	0.0027***	(0.0003)	-0.0020***	(0.0002)
FGN × exp. knowledge-intens. serv.	-0.0016***	(0.0005)	-0.0002	(0.0002)	0.0015	(0.0010)
Experience public service	0.0036***	(0.0005)	0.0067***	(0.0003)	0.0038***	(0.0006)
FGN × exp. public service	-0.0015*	(0.0007)	-0.0019***	(0.0005)	-0.0045***	(0.0009)
Experience by task group, reference: routine manual						
Experience non-routine analytic	0.0089***	(0.0006)	0.0084***	(0.0005)	0.0061***	(0.0009)
FGN × exp. non-rout. analytic	-0.0014**	(0.0006)	0.0012***	(0.0004)	0.0110***	(0.0015)
Experience non-routine interactive	0.0052***	(0.0005)	0.0033***	(0.0003)	0.0035***	(0.0011)
FGN × exp. non-rout. interactive	0.0007	(0.0007)	-0.0009	(0.0006)	0.0119***	(0.0024)
Experience routine cognitive	0.0042***	(0.0003)	0.0057***	(0.0004)	0.0067***	(0.0011)
FGN × exp. routine cognitive	-0.0012***	(0.0003)	-0.0018***	(0.0003)	0.0079***	(0.0015)
Experience non-routine manual	-0.0007	(0.0008)	0.0011**	(0.0005)	-0.0003	(0.0011)
FGN × exp. non-routine manual	-0.0013***	(0.0003)	-0.0018***	(0.0002)	-0.0008	(0.0016)
Experience unknown task	0.0057**	(0.0021)	0.0017	(0.0012)	-0.0026	(0.0023)
FGN × exp. unknown task	-0.0071***	(0.0019)	0.0046***	(0.0009)	0.0161**	(0.0059)
Experience by establishment quality, reference: lowest quality						
Exp. lower establishment quality	0.0000	(0.0005)	-0.0012*	(0.0006)	0.0014	(0.0009)
FGN × exp. lower est. quality	-0.0008	(0.0008)	-0.0018***	(0.0003)	-0.0024*	(0.0013)
Exp. higher establishment quality	0.0016**	(0.0006)	0.0005	(0.0008)	0.0025**	(0.0010)
FGN × exp. higher est. quality	-0.0014**	(0.0006)	-0.0017***	(0.0002)	-0.0033**	(0.0012)
Exp. highest establishment quality	0.0029***	(0.0009)	0.0006	(0.0012)	0.0014	(0.0013)
FGN × exp. highest est. quality	-0.0008	(0.0005)	-0.0013***	(0.0003)	-0.0040***	(0.0010)
Exp. unknown establishment quality	0.0100***	(0.0017)	0.0013	(0.0011)	0.0149***	(0.0036)
FGN × exp. unknown est. quality	0.0024	(0.0016)	0.0048***	(0.0011)	0.0299***	(0.0042)
Observations	776,135		14,061,421		3,212,590	

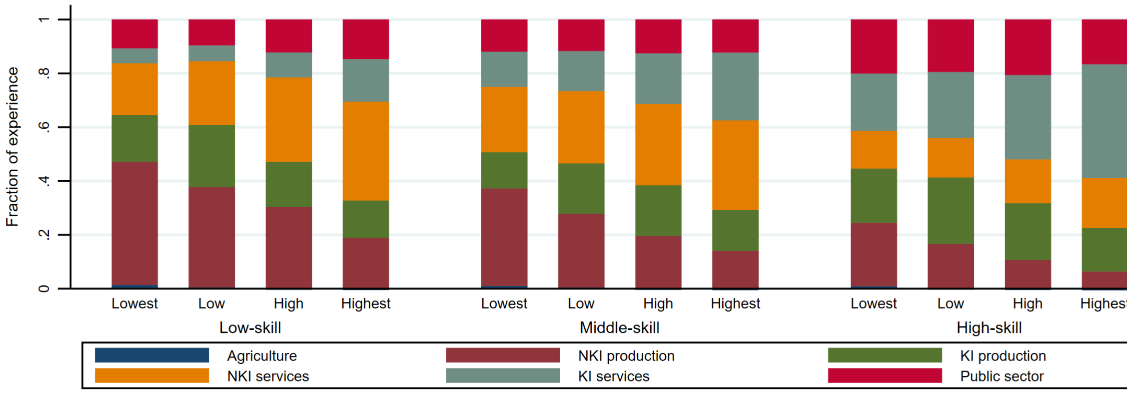
Notes: Referring to columns (2)–(5) of Table 4, this table summarizes the results for the additionally considered experience categories. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Driscoll-Kraay standard errors are given in parentheses. For further notes see Table 4.
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.

Table A5: Dynamic agglomeration effects by skill group (no full interaction with the foreign indicator)

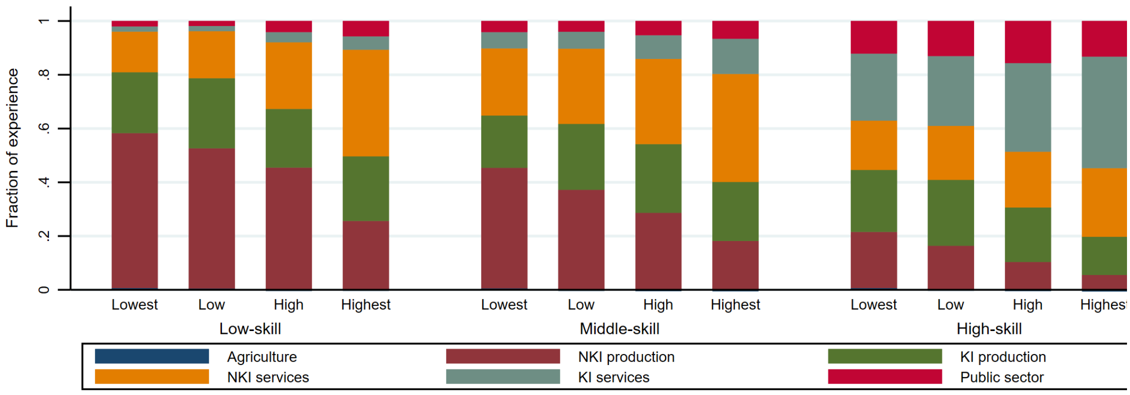
	Low-skilled		Middle-skilled		High-skilled	
Total experience	0.0181***	(0.0013)	0.0451***	(0.0031)	0.0345***	(0.0036)
Foreign (FGN) × total exp.	0.0099***	(0.0014)	-0.0116***	(0.0011)	-0.0029*	(0.0014)
Total experience^2	-0.0005***	(0.0000)	-0.0005***	(0.0000)	-0.0010***	(0.0001)
FGN × total exp.^{2}	-0.0000	(0.0000)	-0.0000***	(0.0000)	-0.0003***	(0.0000)
Experience by the density category, reference: experience in least dense regions						
Experience lower density	0.0003*	(0.0002)	0.0010***	(0.0001)	0.0014***	(0.0002)
FGN × exp. lower density	-0.0000	(0.0004)	0.0000	(0.0001)	0.0005	(0.0011)
Experience higher density	0.0016***	(0.0003)	0.0015***	(0.0002)	0.0023***	(0.0004)
FGN × exp. higher density	-0.0002	(0.0003)	0.0002	(0.0003)	0.0022**	(0.0009)
Experience highest density	0.0019***	(0.0003)	0.0021***	(0.0002)	0.0036***	(0.0006)
FGN × exp. highest density	-0.0003	(0.0005)	0.0013***	(0.0003)	0.0014	(0.0009)
Experience by industry, reference: low knowledge production						
Exp. agriculture	0.0007	(0.0009)	-0.0036***	(0.0004)	-0.0025**	(0.0009)
Exp. knowledge-intens. production	0.0026***	(0.0001)	0.0050***	(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	0.0086***	(0.0006)	0.0084***	(0.0005)	0.0066***	(0.0009)
Exp. non-routine interactive	0.0052***	(0.0004)	0.0032***	(0.0002)	0.0041***	(0.0010)
Exp. routine cognitive	0.0039***	(0.0003)	0.0056***	(0.0004)	0.0071***	(0.0011)
Exp. non-routine manual	-0.0010	(0.0008)	0.0010*	(0.0005)	-0.0001	(0.0010)
Exp. unknown task	0.0038*	(0.0021)	0.0021	(0.0013)	-0.0019	(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	0.0013**	(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	0.0103***	(0.0017)	0.0014	(0.0011)	0.0157***	(0.0037)
Observations		776135		14061421		3212590
R^2		.19		.244		.234

Notes: 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 A4). ***, ** 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 et al. (2014), Bellmann et al. (2020), own calculations.



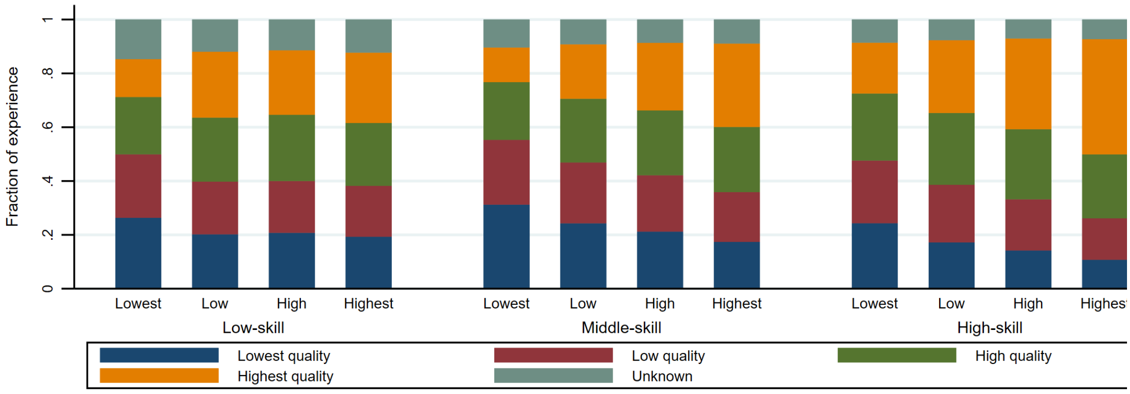
(a) Native workers



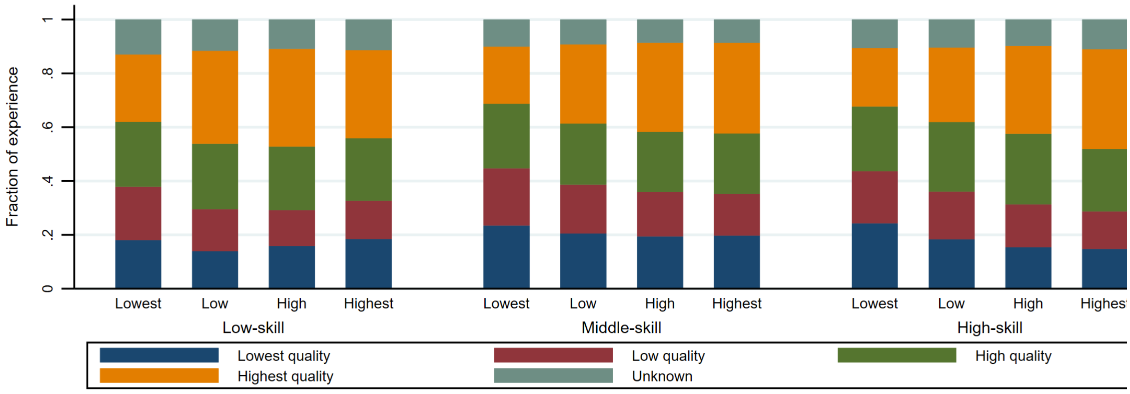
(b) Foreign workers

Figure A2: Composition of work experience w.r.t. sectors by labor market density and skill level for foreign and native 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*. Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613.
Source: IEB, Gehrke et al. (2010), own calculations.



(a) Native workers



(b) Foreign workers

Figure A3: Composition of work experience w.r.t. establishment quality by labor market density and skill level for foreign and native 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. Unit of observation is person-year covering the period 2000–2019. The total number is 18,050,613.
Source: IEB, Bellmann et al. (2020), own calculations.

Table A6: Dynamic agglomeration effects for middle-skilled foreign workers

	All		European guest worker nationalities		Turks	
	(1)	(2)	(3)	(4)	(5)	(6)
	Total experience					
Total experience	0.0378***	0.0354***	0.0441***	0.0418***	0.0353***	0.0339***
	(0.0015)	(0.0021)	(0.0025)	(0.0032)	(0.0011)	(0.0016)
Total experience^2	-0.0005***	-0.0005***	-0.0006***	-0.0006***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Experience by the density category, reference: experience in least dense regions					
Experience lower density	0.0016***	0.0011***	-0.0001	-0.0005*	0.0017***	0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Experience higher density	0.0032***	0.0019***	0.0024***	0.0012**	0.0039***	0.0028***
	(0.0002)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Experience highest density	0.0055***	0.0038***	0.0047***	0.0031***	0.0057***	0.0043***
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Observations	636248	636248	199492	199492	274419	274419
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)	.250	.256	.248	.254	.253	.257

Notes: Unit of observation is person-year. Dependent variable is a worker's log daily wage. Each model includes fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density". Further control variables are: sex, level of qualification, part-time status, tenure and its square, 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. 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. Middle-skilled workers are those with a completed apprenticeship. European guest workers refer to nationals from Greece, Italy, Portugal, Spain and the former Yugoslavia.
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.

Table A7: Dynamic agglomeration effects for high-skilled foreign workers

	All		European guest worker nationalities		Turks	
	(1)	(2)	(3)	(4)	(5)	(6)
	Total experience					
Total experience	0.0389***	0.0250***	0.0446***	0.0358***	0.0278***	0.0177***
	(0.0031)	(0.0046)	(0.0039)	(0.0050)	(0.0042)	(0.0059)
Total experience^2	-0.0013***	-0.0013***	-0.0012***	-0.0012***	-0.0011***	-0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	Experience by the density category, reference: experience in least dense regions					
Experience lower density	0.0021*	0.0023**	0.0128***	0.0126***	0.0028	0.0043
	(0.0011)	(0.0010)	(0.0035)	(0.0034)	(0.0039)	(0.0041)
Experience higher density	0.0049***	0.0047***	0.0151***	0.0154***	0.0071*	0.0084**
	(0.0009)	(0.0009)	(0.0029)	(0.0030)	(0.0038)	(0.0039)
Experience highest density	0.0050***	0.0049***	0.0130***	0.0132***	0.0034	0.0049
	(0.0009)	(0.0009)	(0.0034)	(0.0034)	(0.0039)	(0.0042)
Observations	167101	167101	26883	26883	20658	20658
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)	.249	.255	.252	.257	.241	.252

Notes: Unit of observation is person-year. Dependent variable is a worker's log daily wage. Each model includes fixed effects for occupation, sector, region-year and worker as well as instrumented "ln employment density". Further control variables are: sex, level of qualification, part-time status, tenure and its square, 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. 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. High-skilled workers are those with completed tertiary education. European guest workers refer to nationals from Greece, Italy, Portugal, Spain and the former Yugoslavia.
Source: IEB, Gehrke et al. (2010), Dengler et al. (2014), Bellmann et al. (2020), own calculations.