The Dynamic Impact of Refugee Immigration on Native Workers *

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Abstract

We study the effects of low and medium-skilled refugee immigration on natives' labor market outcomes. Using individual-level panel data on the German workforce for 2011–2019 and exogenous regional variation from processing authorities' distances, we find that a larger inflow of refugees to a district increases the probability of full-time employment. Fewer outflows of employment drive this effect. The yearly estimates suggest positive labor demand responses in the short run—in occupations that supply services to the refugees—and positive labor supply effects in the medium run—in manufacturing occupations. Finally, we find null effects on wages, the task composition of jobs, and job changes but positive mobility responses.

Keywords: refugee migration, labor market outcomes, complementarities
JEL Codes: J15, J21, J31, J61

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1 Introduction

How immigration affects native workers in the host country continues to be an unsettled debate in academics and policy. Apart from economic migration, there have recently been historically large episodes of refugee migration, i.e., in 2015–2016 from the Middle East and in 2022 from Ukraine. While there is abundant economic literature about the labor market effects of immigration on natives (e.g., Dustmann et al., 2016; Edo, 2019), less is known about the effects of recent refugee migration episodes in OECD countries. Refugees are different from other groups of migrants along several dimensions (Becker and Ferrara, 2019; Dustmann et al., 2017). On the one hand, refugees have different motives to migrate, less security, and less preparation for employment take-up abroad. Consequently, their economic and social integration follow on average slower trajectories than those of economic immigrants (e.g., Chin and Cortes, 2015; Brell et al., 2020; Brücker et al., 2020). Moreover, refugees are often subject to residency restrictions (Fasani et al., 2022) and employment bans (Fasani et al., 2021), all of which dampen their labor market impact on natives, at least in the short run. On the other hand, the refugee arrivals to Germany induced additional regional labor demand (e.g., Auer and Götz, 2023; Berbée et al., 2022) and they occurred at a time of labor market tightness and skills shortages in certain occupations. Hence, it is *a priori* unclear what effect the refugees' arrival has on incumbent natives and how this changes over time.

In this paper, we study how the 2014–2016 inflow of refugees to Germany affected the labor market outcomes of individual native workers over time. We analyze the dynamic effects of refugee migration which help us to distinguish initial labor demand effects from later labor supply effects, as refugees only enter the labor market slowly (see Figure 1). We focus on Germany, the largest receiving country in Europe in absolute terms. About 1.16 million individuals sought asylum for the first time in 2015 and 2016. In 2019, asylum-seekers and refugees together accounted for about 2% of the country's population and 1% of all workers.[1] As such, this recent refugee migration episode to an OECD country is larger than others that have previously been studied (e.g., Glitz, 2012; Foged and Peri, 2016).[2]

Our empirical strategy builds on a dispersal policy and an instrumental variable approach. During the peak of arrivals, the allocation quotas of the dispersal policy were often not met (Berbée et al., 2022; Bredtmann, 2022; Brücker et al., 2020; Gallegos Torres, 2023; Gehrsitz and Ungerer, 2022), leading to refugees being placed in districts with available accommodation, often in areas with higher unemployment (Brücker et al., 2020). Furthermore, refugees are free to choose their place of residence after a maximum of 3 years or after finding employment subject to social security contributions of at least 15 hours per week. These issues raise concerns that the regional allocation of refugees is not exogenous but affected by endogenous regional sorting. We, therefore, build a novel instrument based on the observation that asylum seekers were typically placed close to the responsible branch office of the Federal Office for Migra-

[1] From now on, we will speak of refugees subsuming all individuals who arrived as asylum-seekers, the majority of which have obtained protection in the meantime.

[2] Glitz (2012) studies the arrival of more than 700,000 ethnic Germans 1996–2001, with an average inflow rate of 0.83%. One larger recent event is the Venezuelan exodus to Colombia, which currently represents almost 4% of the Colombian population (Delgado-Prieto, 2023). Other episodes of forced migration impacted only very local labor markets (e.g., Card, 1990; Borjas and Monras, 2017).

tion and Refugees (BAMF), which handles their asylum applications, and they often continue residing there.[3] Most of these offices have existed since 1993; hence their location long precedes the 2014–2016 refugee arrivals. We use the distance from the centroid of a district to the closest responsible BAMF branch office to construct our distance instrument (in the spirit of a shift-share IV) in order to tackle endogenous regional sorting.

To shed light on different adjustment mechanisms, we study how individual-level employment, real daily wages, job task composition, occupation, and regional labor market changes develop over time for different subpopulations and occupation groups. In particular, the data allow us to go beyond aggregate regional effects and answer, instead, how the immigration shock affects employed vs. non-employed natives already in the labor market.

We use a long-differences approach with IV to causally estimate the effects of refugee arrivals from 2014–2016 on the yearly labor market outcomes of native workers (similar to Autor et al., 2014; Yagan, 2019; Delgado-Prieto, 2023). To follow individuals over time (akin Foged and Peri, 2016), we use administrative individual-level panel data representing 2% of all German workers subject to social security contributions for the years 2011–2019 as contained in the Sample of Integrated labor Market Biographies (SIAB) provided by the Federal Employment Agency (Frodermann et al., 2021).

The results show that a 1 pp. higher inflow of refugees 2014–2016 to a district led to a 0.6 pp. higher probability of being full-time employed for native individuals from 2015 onward. In the short run, the employment gains are significant in commercial services, as well as health and education sectors, likely reflecting labor demand effects—especially since refugees were initially restricted from working and only gradually entered the labor force. In the medium run, these positive employment effects are only significant for manufacturing professions and commercial services—in line with a labor supply phase, when refugees start to provide labor and complementarities arise. Importantly, refugees predominantly work in precisely these professions, suggesting important complementarities between refugees (in low-skilled jobs) and natives (in high-skilled jobs). The employment gains from refugee immigration are large and significant for females in the short run (2015) and males in the medium run (2018 and 2019), which reflects occupational segregation by gender (Cortes and Pan, 2018).

Our paper contributes to the important and contested economic literature on the impact of immigration on labor markets in several ways. First, we complement the literature studying labor market effects from (refugee) immigration by studying a setting where refugees enter employment with some delay. Thus, their share in employment differs from that in the population due to employment restrictions and a lack of qualifications. We study the large 2014–2016 refugee immigration to Europe and its effect on Germany, as an example of a large OECD country. Existing work has focused on the impact of Syrian refugee immigration in bordering countries. In Turkey, Syrian refugees led to a reduction in natives' informal employment while at the same time increasing natives' formal employment (e.g., Tumen, 2016; Aksu et al., 2022; Ceritoglu et al., 2017; Del Carpio and Wagner, 2015). Similarly, in Jordan, natives living in regions exposed to more Syrian refugees do not exhibit worse labor market outcomes than those less exposed (Fallah et al., 2019). For Germany, the empirical evidence is scant: using a

[3]By 2020, 54% of recognized refugees were still residing in their initial district of assignment (Weber, 2022).

difference-in-differences approach, Gehrsitz and Ungerer (2022) find no displacement effect on native workers during the period (2016–2017) but only on previous immigrants.[4] Berbée et al. (2022) and Auer and Götz (2023) empirically show large and significant labor demand effects from refugee immigration, though they are short-lived.

Second, by focusing on the yearly dynamics of the effects, we identify different labor demand and supply effects over time. Furthermore, we study the effect on native workers (employed and non-employed) already present in the labor market at the time of the refugee inflow. The aforementioned papers (Berbée et al., 2022; Auer and Götz, 2023; Gehrsitz and Ungerer, 2022) use aggregate district-level data and estimate regional employment effects. Studies using individual-level worker data and estimating the dynamic effects from the 2014–2016 refugee arrivals on natives' labor market outcomes for a more extended period have been missing so far. We do both and, hence, complement and expand the existing literature.

Third, we expand the scant literature on the effects of refugee immigration on individual labor market outcomes by developing a novel identification strategy. A major challenge in this literature is how to solve endogenous regional sorting. The literature has mainly relied on regional approaches usually combined with a shift-share IV [5], shocks within particular skill-cell groups[6], and natural experiments.[7] Alternatively, dispersal policies provide a particularly well-suited setting to generate exogenous variation in the arrival of immigrants (Foged and Peri, 2016; Dustmann et al., 2019; Glitz, 2012). We identify exogenous variation in the refugee population shock by relying on a particular aspect of the refugee dispersal policy in Germany, i.e., the responsible BAMF branch offices differ by country of origin. These responsibilities and locations can be considered exogenous as we argue below.

Finally, the positive economic conditions in the host country at the time of the immigration shock provide a good setting to complement the literature. We analyze the medium-run effects of predominantly low- and medium-skilled immigrants on the resident workers in a country where unemployment has steadily decreased in recent years and is currently at 5.5%. Whether refugees take away jobs has been forefront in the public debate but needs more empirical evidence. Estimates show that Germany needs 400,000 immigrant workers annually to account for its loss in workforce (Gerber and Winters, 2023). Hence, it is of high political importance to understand who gains and who loses from refugee immigration to optimize migration and labor market policies. Our results mainly show winners, reflecting the economy's capacity to absorb additional labor without harming incumbent workers. However, there are also some hints of potential losers, namely young individuals out of the labor force at the time of the shock. Using individual-level panel data, we provide evidence of two adjustment mechanisms for our positive employment effects on native incumbent workers: an increase in full-time work instead of part-time work (intensive margin) and regional sorting by changing regional labor markets. We complement our individual-level analysis with a regional analysis of commuter flows.

[4] This is mainly a mechanical effect given that refugees will be included in the foreigners "unemployment rates" 18 months after arrival (the latest).

[5] For area-based studies, see for example: Card (2009); Altonji and Card (1991); Cortes and Tessada (2011); Dustmann et al. (2016).

[6] For example: Aydemir and Borjas (2011); Borjas (2003); Monras (2020).

[7] Mainly using unexpected migration waves, e.g., from refugees. Borjas and Monras (2017) describe some historical forced migration episodes.

The rest of the paper is organized as follows. Section 2 describes the dispersal policy and the responsibilities of the BAMF branch offices. Section 3 discusses some theoretical considerations. Section 4 describes the employment data and the refugee inflow data we use. Section 5 describes our empirical approach and instrumental variable, and Section 6 reports the main results. Finally, Section 7 concludes the paper.

2 The 2014–2016 Refugee Inflow and the BAMF Branch Offices

2.1 Refugee Inflow and Dispersal Policy

The arrival of asylum-seekers to Germany increased from 2014 onward, peaking in late 2015. Germany alone received about half a million first-time asylum applications in 2015, representing 35.2% of all applications in the European Union (Eurostat, 2016). This strong influx ceased in early 2016 when the European Union and Turkey came to an economic agreement for stopping irregular migrants entering via Turkey to the Greek Islands. Figure 1(a) shows the stocks of immigrants from the top 8 refugee-origin countries in Germany 2010–2018.[8] The stock has been steadily increasing but there is a structural break in its growth-rate from 2014 onward. Arrivals were relatively steady until 2013. They more than doubled between 2013 and 2014 and quadrupled between 2014 and 2015. Since then, arrivals have been rapidly decreasing. In the empirical analysis, we measure the inflow of refugees between January 1, 2014, and December 31, 2016. However, due to the asylum process and initial employment restrictions, we do not see the share of refugee-origin workers in employment increasing at the same time as the arrivals, but only from 2016 onwards (see Figure 1(b)).

Asylum-seekers in Germany are entitled to receive asylum-seeking benefits from the moment they declare their willingness to apply for asylum (see Appendix A.1 for further details). They are allocated across German districts according to an administrative dispersal policy which proceeds, generally, in two steps.[9] First, after arrival at the border, asylum-seekers are assigned to a federal state, taking into account state population share and tax revenue (based on the quotas from the "Königssteiner Schlüssel"). Within each state, asylum-seekers are assigned to an initial reception facility (IRF) in the districts (*Kreise*, NUTS-3, corresponding approximately to counties in the US), based on nationality, distance, and capacity of the IRFs. Asylum-seekers have to reside in the IRF they have been assigned until a decision on their application has been reached up to a maximum of 18 months, otherwise losing their entitlement to social benefits.[10] In a second step, refugees are assigned across districts to follow-up accommodations if their asylum claim is accepted or if they have good perspectives of being allowed to stay in Germany. They have to reside there for up to three years. Some states require the refugees to stay in the state or in the district where their application was processed (*Wohnsitzauflage*).[11] However, back in 2015 the authorities were trying to quickly free up space for new

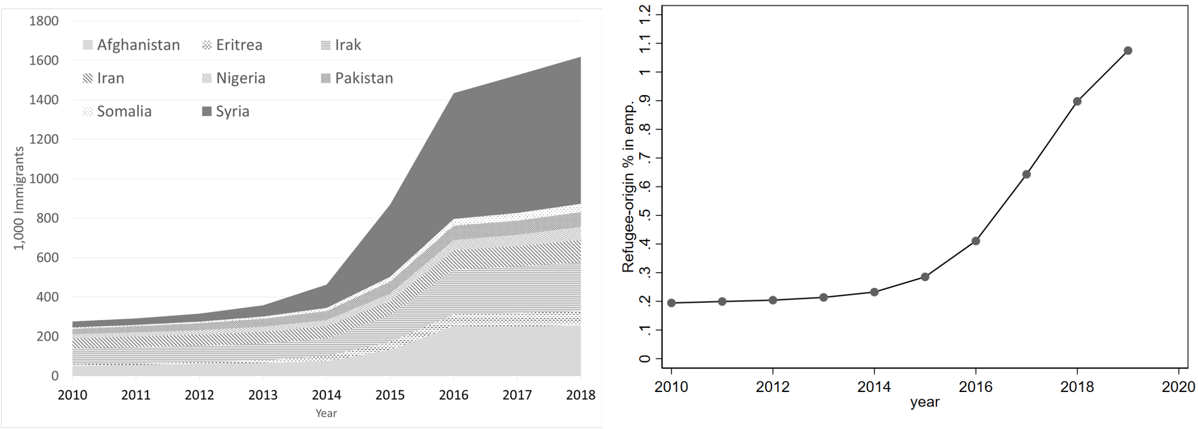
[8]The top 8 asylum-seeking countries, as defined per the Federal Employment Agency are: Afghanistan, Eritrea, Iraq, Iran, Nigeria, Pakistan, Somalia, and Syria.

[9]The states of Baden-Württemberg, Bavaria, and Schleswig-Holstein used a three-step process during these years. They first allocated refugees to the administrative districts (*Regierungsbezirke*) and then to the districts.

[10]Asylum-seekers have to stay at in the first location of assignment (*Residenzpflicht* until a decision on their application has been reached but for at least three months. This is usually the Initial Reception Facility.

[11]This does not apply to refugees whose decision was met before January 1, 2016. Other exceptions are granted

Figure 1: Immigrants from the Top 8 Refugee-Origin Countries, Stocks and Employment Shares



(a) Immigrant arrivals

(b) Employment of refugee-origin workers

Notes: Figure (a) shows the yearly stocks of immigrants from the top 8 refugee origin countries in Germany: Afghanistan, Eritrea, Iran, Iraq, Pakistan, Somalia, and Syria for the years 2010–2018. Figure (b) shows the shares in total employment of the same countries until 2019, i.e., number of refugee origin workers / number of total workers in Germany.
Source: Destatis (*Wanderungsstatistik*) and Federal Employment Agency. Own depiction.

arrivals in the initial reception facilities; therefore sending asylum-seekers to the follow-up accommodation even before a final decision on their application had been made. As a result, many asylum-seekers waited for the final decision in the follow-up accommodation (Geis and Orth, 2016). After this three year period, refugees are free to chose their place of residence. This is also possible if they find a job that meets certain minimum requirements. The within-state distribution quotas depend mainly on population size though the details differ across federal states.[12]

Had the dispersal policy been implemented rigorously, we would see no variation in refugees' arrivals after normalization by population at baseline. However, Figure 2(a) shows substantial variation even within federal states. In addition, asylum seekers, as well as recognized refugees, have been found to disproportionately live in districts with higher unemployment rates (Brücker et al., 2020; Weber, 2022). This finding implies an endogeneous allocation of newly arrived refugees to worse economic conditions which likely continues to correlate with ongoing labor market trends. Figure A.1 in the Appendix shows the standardized coefficients of a regression from our main explanatory variable (refugee arrivals 2014–2016) and pre-treatment district level controls. The only covariate significantly correlated with these arrivals is the unemployment rate, corroborating the findings by Brücker et al. (2020).

The reasons for these (endogeneous) deviations from the dispersal policy are likely (i) limited housing availability (Brücker et al., 2020), (ii) non-compliance on the side of refugees (e.g.,

in case the core-family lives in a different district, if starting a new training/studies, and if sufficient job has been found. Furthermore, four states in Germany do not have this residence requirement (Brandenburg, Bremen, Mecklenburg-Vorpommern, and Thuringia).

[12]These distribution systems are regulated under the laws of each federal state, so in practice, one can consider having sixteen different distribution and accommodation systems (Beinhorn et al., 2019). Berbée et al. (2022) provide details about the state-specific distribution quotas.

moving on), and (iii) non-compliance on the side of districts (e.g., political lobbying) (Lange and Sommerfeld, 2024). In addition to apparent endogeneity in the initial allocation, additional regional sorting may kick in once asylum seekers can move freely (36 months after arriving at the latest). By 2020, the majority of recognized refugees that arrived in Germany between 2015–2019 had stayed in their initial district (54%) (Weber, 2022).[13] Those who moved did so predominantly to large cities (which also display high unemployment rates) and districts in the North and West regions of Germany, displaying lower housing availability and higher average unemployment rates.[14] Hence, not only were asylum-seekers often allocated to districts with higher unemployment, but even when they were allowed to move, they did so to districts with higher unemployment. Thus, contrary to the standard economic migration literature, refugees regionally sort into regions with bad labor market conditions.

2.2 Responsibilities of BAMF Branch Offices

The Federal Office for Migration and Refugees (BAMF) in Germany is responsible for processing asylum applications. It has branch offices (*BAMF Außenstellen*) in every federal state which are linked to one or more initial reception facilities (IRF). These branch offices process asylum applications, grant the resulting migration status and coordinate regional integration courses. Since 1993, the BAMF decentralized their operations and set up 48 branch offices across the federal states (BAMF, 2023). Different branch offices specialize in the handling of applications from certain countries of origin, thereby trying to increase efficiency. These responsibilities by origin country are already taken into account in the first step of the allocation process (EASY-System at the border). During the peak of refugee arrivals in late 2015, authorities tried to take into account the proximity to the responsible BAMF branch office when allocating refugees across districts (second step).[15] Moreover, refugees often continue residing in the vicinity of the initial reception facilities throughout and even after the asylum application process. As a consequence, asylum-seekers are clustered by origin countries around certain districts (see Figure A.2 in the Appendix).

Since 2016, all federal states are responsible for processing applications of all top 10 asylum-seeking countries of origin, as defined by the BAMF.[16] For states with more than one BAMF branch office processing the same nationality, there is within-state variation regarding which branch office is nearest. In addition, there is within-state variation regarding which nationality is processed—and thus clustered—where. Based on these observations and anecdotal evidence, we will use the distance to the closest responsible BAMF branch office to instrument refugees' arrivals by nationality.

Figure 2 shows the dispersal of refugees across the country and its correlation with the location of BAMF branch offices. Figure 2(a) shows newly arrived asylum seekers from the

[13] 44% of recognized refugees have moved to another district than where they lived three months after arrival, and 18% have moved to another federal state (Weber, 2022).

[14] Additionally, Weber (2022) shows that districts in the fourth quartile of the unemployment distribution had a net immigration gain of 18% from refugees that moved. This is because refugees often move to large cities that also exhibit high unemployment.

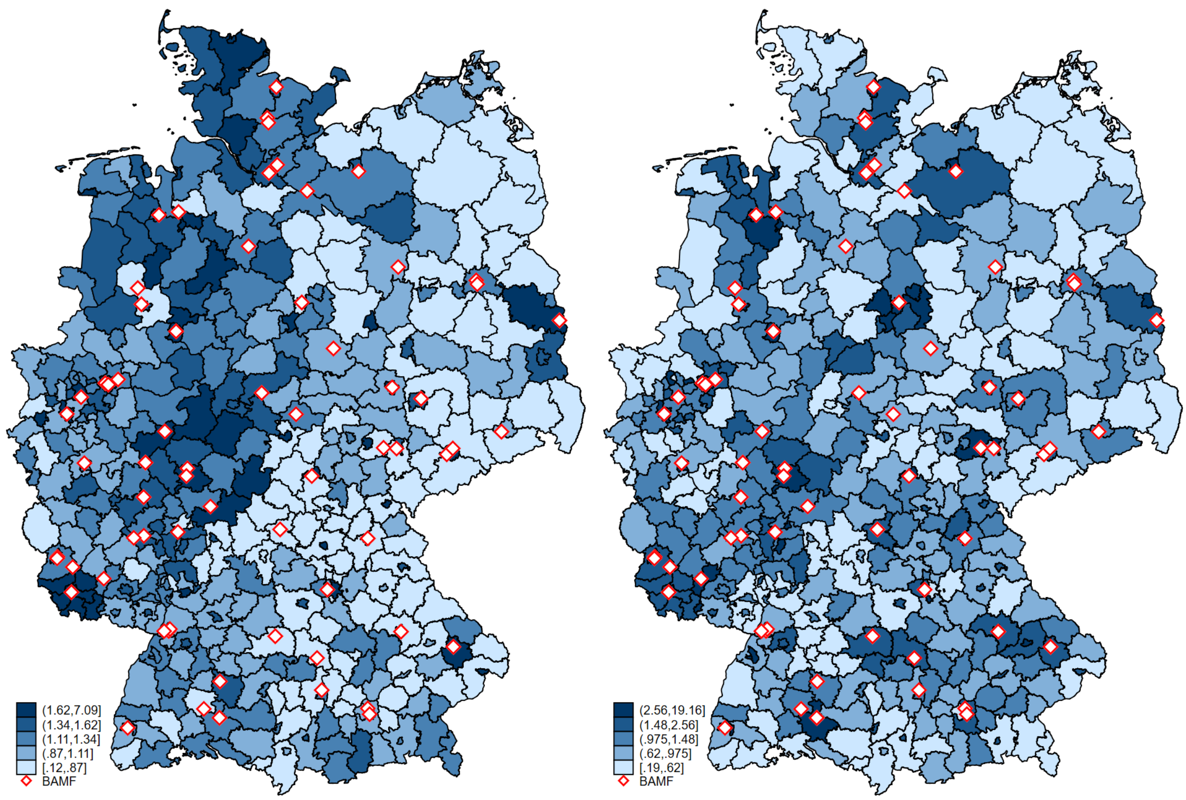
[15] This was confirmed by interviews with stakeholders from the responsible authorities in some federal states.

[16] In response to the large inflow of 2015/16, the BAMF opened several new branch offices. This was often implemented as an enlargement of the already existing branch office.

top 8 sending countries (having arrived between January 1, 2014 and December 31, 2016)[17] as a share of the 2011 population in each district. This will be the main explanatory variable, subject to endogeneity concerns (as outlined above). The white diamonds show the location of the BAMF branch offices that were responsible for the top 8 nationalities in 2016. In addition, Figure A.2 in Appendix A shows the corresponding maps for the individual nationalities. All eight maps show a certain degree of spatial correlation between the responsible BAMF branch office and the share of migrants from the corresponding home country.

We will use the distance from a district's centroid to the closest BAMF branch office to build a distance IV, which we describe in detail in Section 5.2. Figure 2(b) shows the predicted arrivals from the distance IV which gives more weight to closer responsible BAMF branch offices. Visual inspection suggests a substantial spatial correlation, that will later be supported empirically. Our reasoning behind the visual correlation between both maps in Figure 2 is that many asylum-seekers stay close to the original BAMF branch office to which they were initially assigned.

Figure 2: Top 8 Refugee-Origin Countries: Arrivals per Population and BAMF Branch Offices



(a) Refugee arrivals 2014–2016 (% of pop.)

(b) Distance IV

Notes: Figure (a) shows the arrivals of asylum-seekers from the top 8 refugee-origin countries as % of the population in a district (fixed in 2011). Figure (b) shows the regional variation of our instrument (using distance to BAMF, Section 5.2). The white diamonds represent the BAMF branch offices. *Source:* Destatis and BAMF. Own graph.

[17] See Section 4 for further details. The top 8 sending countries refers to those identified by the employment agency: Afghanistan, Eritrea, Iran, Iraq, Pakistan, Somalia, and Syria.

3 Theoretical Considerations

3.1 How Refugees are Different from Economic Migrants

Initial Motives. Refugee migration differs from standard economically driven migration in several ways. Refugees generally do not flee for economic reasons, have little time for preparation (i.e., to invest in host-country-specific human capital), have lower language skills, and bring fewer qualifications. Additionally, institutional barriers—such as employment bans and residence restrictions—contribute to a slower integration of refugees into the host country's labor markets (e.g., Brell et al., 2020; Brücker et al., 2020; Brücker et al., 2020; Chin and Cortes, 2015; Dustmann et al., 2017; Edin et al., 2003). However, there are few reasons to expect a relatively better labor market integration for refugees than for other migrants. First, refugees have no incentives nor the option for return migration, which increases pressure to integrate in host countries. Second, the likelihood of staying permanently in the host country is higher for some refugees than for other migrants, translating into additional human capital investments such as language courses and additional training (e.g., Cortes, 2004; Chin and Cortes, 2015).

Legal status. In addition, the asylum recognition process itself may have bi-directional effects on refugees' labor market integration. Brücker et al. (2020) show that a delay by 6 months in the asylum-process reduces the probability of employment by 11%, while getting a positive asylum decision increases it by 30%. Hence, both the length and type of recognition matter for the labor market integration of refugees. During 2015–2016 the asylum-process was accelerated which resulted in approximately 60% of all applications being decided during the first 6 months, and over 90% within 12 months (BAMF, 2016; BAMF, 2017).[18] However, even a positive decision on the asylum application usually only grants temporary protection in Germany. There is a notion of temporariness that hinders labor market integration (Dustmann et al., 2017). This, again, differs from economic migrants who usually already have a work contract that helps them with their residence permit. Overall, refugees enter employment with a delay. Nonetheless, various factors may lead to a fast take-up of training and potential anticipation effects among natives.

Labor market restrictions. Although it is clear that there was a sizeable one-time shock in arrivals during 2014–2016, the employment take-up of refugee-origin workers takes some time to realize since they cannot immediately access the labor market (see Figure 1(b)). Germany enforces an employment ban on refugees during the first 3 months after their arrival. During this time, they cannot add to the labor supply but only to labor demand. However, actual employment take-up is much slower: One year after arriving in Germany, only 3% of refugees are employed (Brücker et al., 2020). Three years after arrival, their employment rate reaches 37%.[19] Furthermore, given that individuals from some origin countries are more likely to re-

[18] The average duration for reaching a decision on asylum applications was 7.9 months in 2015 and 8.7 months in 2016 (BAMF, 2016; BAMF, 2017; Brenzel and Kosyakova, 2019). This is in contrast to the 11.3 months recorded in 2014.

[19] Given the employment restrictions and language requirements, the labor market integration of the 2013–2016 arrivals was initially slower than that of the 1990–2013 refugee arrivals (Brücker et al., 2020). However, 3.5 years after arrival, the 2013–2016 cohort catches up to the previous cohort: about 45% have already started their first job

main in Germany, investments in human capital (i.e., language) might also differ by country of origin. Altogether, refugees are different than economic migrants and enter the labor market at a much slower pace.

Refugees' Jobs. In 2018, 44% of refugee-origin workers were employed in low-skilled jobs, 52% in medium-skilled, and 5% in high-skilled jobs (Brücker et al., 2020).[20] We provide more details on refugees' employment rates and skill-type of jobs in Section A.2 in the Appendix. Table A.2 further describes the occupational groups in which refugees are working. 32.2% of working refugees have jobs related to "Transport, logistics, protection and security", and 27.6% perform jobs related to "Raw material extraction, production, manufacturing". These shares are much larger than among natives.[21] In these occupations, we expect to see the largest labor supply effects from refugee immigration which could affect natives via complementarities or substitution effects.

3.2 Labor Demand Effects from Refugee Immigration

The effects from immigration in the host country are typically analyzed as a labor supply shock. However, immigrants might also induce labor demand effects. Labor demand increases upon refugee arrivals due to two factors, (i) public expenditure (more case workers are needed, workers in shelters, public administration and support programs, etc.) and (ii) consumer demand also increases (either via in-kind provision of services, or via consumption funded by the monthly cash-allowance). Hence, immigrants add to the consumer base (Borjas, 2013) and they consume a disproportionate share of their income in locally provided goods and services (Berbée et al., 2022). These labor demand effects will kick-in right away upon immigration, while labor supply effects are delayed as refugees may be subject to employment bans (Fasani et al., 2021) and enter the labor market slower than other migrants (e.g., Becker and Ferrara, 2019; Brell et al., 2020; Chin and Cortes, 2015; Verme and Schuettler, 2021). The labor supply effects will only take place once refugees have gained labor market access. Thus, from the dynamics of the labor market effects of refugee migration, we can distinguish (short-run) labor demand effects from (medium-run) labor supply effects. Our dynamic analysis will reflect the timing of the effects.

3.3 Labor Supply Effects from Refugee Immigration

We think of labor supply effects in a model of limited substitutability with two nationality groups (natives and refugees) and three education groups (Ottaviano and Peri, 2012; Peri, 2012; Card, 2009). While most refugees arriving in Germany were low-skilled, there was also a small but relevant group of high-skilled refugees. The latter group has been found to provide labor on average later than the former group, partly due to human capital investments, e.g., into

(Brücker et al., 2020).

[20]These shares are very similar to the ones reported in Table A.1 in the Appendix with the exception that the share of workers performing medium-skilled jobs is somewhat smaller, and the share of those performing high skilled jobs larger in the data from the Federal Employment Agency than in the IAB-BAMF-SOEP survey.

[21]For Germans, the largest occupational group is "Company organization, accounting, law, administration" (22%) followed by "Raw material extraction, production, manufacturing" (21%). Only 11.6% of employed Germans work in jobs related to "Transport, logistics, protection and security".

language skills and recognition of qualifications. However, they are also more likely to suffer from downgrading when taking up a job (Brücker et al., 2020). Therefore, we expect that in our analysis period (over four years after the refugee inflow), refugees enter the labor market mainly in low- and medium-skilled jobs. This is confirmed by the official statistics (see Appendix A.2). Hence, native high-skilled workers, who are usually considered complementary to immigrants, are expected to benefit. Whether low- and medium-skilled workers also benefit is less clear due to the interplay of substitution effects and complementarities.

A simplistic model of perfect substitutability between native and refugee employees predicts employment or wage losses for low and medium-skilled workers after the refugees' arrival on the labor market. However, in a model with limited substitutability between natives and refugees, this effect is most likely reversed such that low and medium-skilled natives benefit. Such an effect has been shown for low-skilled native workers in Denmark by Foged and Peri (2016) who find that refugees "push" natives into more demanding jobs, particularly in terms of complex communication tasks.

We therefore expect to find positive labor market effects for high-skilled natives and zero or small positive effects for low- and medium-skilled natives. Furthermore, refugees might fill vacant low-skilled jobs that cannot be filled by native workers, e.g., due to high reservation wages of the native population. Thus, refugees and natives might not compete with each other, rather refugees may add to overall employment. This could allow the (more productive) execution of high-skilled jobs that could not be performed before, if complementary (low- or medium-skilled) workers were missing. Under this scenario, refugees would not exert negative labor market effects on either low- or medium-skilled workers.

3.4 The German Labor Market Situation

The German labor market performed well between 2011 and 2019 (our period of analysis). The unemployment rate decreased by 30% between these years, and by 2019 the unemployment rate was at a historical minimum since 1991: only 5.5%. This steady decrease in unemployment was accompanied by a 7% increase in the number of employed individuals within the same period, with 38.2 million employed individuals in 2011 and 41 million in 2019.

Meanwhile, reported vacant jobs increased by 66% from 466,288 in 2011 to 774,345 in 2019. This positive development is the result of a combination of labor market reforms introduced in the early and mid 2000s ("Hartz reforms"), a large decline in unemployment in East Germany (due to demographic change), the role of the dual apprenticeship system, changes in the retirement age, the introduction of more flexible employment forms such as temporary agency work (Schneider et al., 2019), as well as a process of decentralization within the otherwise rather rigid system of collective wage bargaining (Dustmann et al., 2014). Hence, the arrivals of refugees coincided with a particularly good period for the German economy and a situation of labor shortages.

4 Data

Our main variables come from a number of sources: administrative employment data at the individual level, aggregate refugee inflows at the district level, the location of the BAMF branch offices, and other regional characteristics at the district level.

Employment data. We follow individuals over time by using the Sample of Integrated Labor Market Biographies 1975–2019 (SIAB 7519) from the Research Data Centre (FDZ) from the Federal Employment Agency (*Bundesagentur für Arbeit*) (Frodermann et al., 2021). This is a 2% random sample drawn from the Integrated Employment Biographies (IEB) that contains all workers subject to social security contributions in Germany.[22] We analyze the period 2011–2019, using 2013 as the base year. We restrict the sample to individuals aged 20 to 64 who appear in the SIAB in 2013 and have at least one post-treatment observation. To have a balanced panel, we fill their missing observations (for the years before or after 2013) with a zero in our employment outcomes unless they died. Furthermore, we calculate all the outcomes as of June 30 of each year.[23] As outcomes, we consider a dummy for full-time employment, real daily wages and their growth rates (in 2015 €), the main task type for each job (Dengler et al., 2014), and changes in occupation (at the 3-digit level), and labor market region. The main task type classification measures the share of the usual five different task groups (analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks, and manual non-routine tasks) in each 3-digit occupations as obtained from the BERUFENET Expert database (2013) (Dengler et al., 2014).[24] We condense these categories to only abstract and routine tasks following Dustmann et al. (2023).

A limitation of the data, is that it is not possible to identify German-born individuals, but only German citizens. Similar to D'Amuri et al. (2010) our definition of "native" German workers are those who have never changed their nationality in all the years for which we have data. Overall the sample is quite balanced, 67.14% of observations appear during all nine years of observation, and 86.76% appear during seven years or more. Our final sample consist of 469,281 German nationals. Furthermore, around 90% of the sample are original observations, and 10% are filled gaps.

Table A.3 shows summary statistics of the outcome and control variables used for the empirical analysis for native workers. On average, the native workers in our sample are 41.4 years old, have 14.4 years of experience in total and 7.5 years in the current job. Most of them are medium-skilled (74%) and only a small fraction (9%) are low-skilled. On average, the overall employment rate (excluding trainees) in our sample was 81% in the pre-treatment period (2011–2013). However, only 61% were full-time employed. By skill levels, only 25% of the low-skilled workers were full-time employed (36% had any employment); 63% of the medium-skilled and 70% of the high-skilled were full-time employed (85% and 89% respectively had

[22] As of 2019, 74% of all workers in Germany were subject to social security contributions (Destatis, 2021b). Access to these data is only possible at the premises of the Research Data Centre (IAB-FDZ) or via a remote platform (JoSuA).

[23] This is a standard procedure when using the SIAB, since wages are only reported on June 30 every year (Dauth and Eppelsheimer, 2020).

[24] The BERUFENET Expert database relies on expert knowledge about the tasks performed in nearly all jobs performed in Germany. It is similar to the Occupational Information Network (O*NET) (Dengler et al., 2014).

any employment). The average pre-treatment daily wage was 112 euros. This wage was almost two times larger for a high-skilled individual than for a low-skilled one (or 85.96 euros more); the wage of a medium-skilled worker was 28% larger than that of a low-skilled worker. On average, 82% of the tasks of low-skilled workers are routine tasks. For medium-skilled workers is 71% and for high-skilled workers it is only 35%. Pre-treatment, 9% of workers had changed their regional labor market, compared to 2013, and about 27% changed their 3-digit occupation, this change was larger among the low-skilled.

Immigration data. For the immigration shock, we use customized data extracts from the Central Registry of Foreigners (AZR), administered by the BAMF (BAMF, 2019). We have district-level half-yearly data on asylum-seekers by month of arrival 2013–2017.[25] More specifically, for a particular cutoff date (June or December each year) the data indicate how many refugees are registered in a district at this cutoff date, who arrived in Germany up to 18 months prior, and is disaggregated by month of arrival. As the best measure for the inflow, we take the arrivals from the top 8 refugee-origin countries between January 2014 and December 2016 (normalized by the district's population in 2011). We measure inflows of refugees rather than differences in stocks for two reasons (Lange and Sommerfeld, 2024): (i) the political debate centers around newly arrived refugees, (ii) this group is more homogeneous than what would be measured by net differences of stocks. This is because measuring differences in stocks at the district level would include refugees who have been in the country for a long time and are, therefore, free to move across districts (entailing an additional risk of endogenous regional sorting). Figure 2(a) shows the regional distribution of the refugee inflow. Importantly, all districts have been treated, yet to a different degree. Additionally, the BAMF provided us with the monthly allocations by nationality from the EASY algorithm to the initial reception facilities in the federal states from 2011–2018. We use these data for robustness checks (as an alternative shift).

Location and responsibilities of the BAMF branch offices. The BAMF provided us with the lists of branch-offices and the countries they were responsible for during 2013–2018 (BAMF, 2020). These lists were updated many times during the year but not regularly. Hence, we created a half-yearly panel of responsibilities at the district level. Since the lists only contain the BAMF branch office's name, code, and district, we manually checked the exact GPS locations using Google Maps. For our analysis, we keep the active branch offices in the first half of 2016. We then calculate the distance in minutes (by car) from the centroid of a district to each BAMF branch office.[26]

District-level covariates. To check if the inflow of refugees correlate with other district characteristics, we rely on covariates such as unemployment rate, population density, an indicator for urbanity, GDP per capita, etc. for the year 2011 from INKAR (Bundesinstitut für Bau, 2019).

[25]This is the same data on refugee arrivals used by Berbée et al. (2022) and Lange and Sommerfeld (2024).

[26]For this we use the command "osrmtime" in Stata (Huber and Rust, 2016).

5 Empirical Approach

5.1 Empirical Specification

We aim at estimating the causal effect of the refugee immigration shock between 2014 and 2016 on individual workers in the host country in terms of labor market outcomes.

We model the one-time immigration shock as time-invariant, focusing on the dynamics of the resulting effect.[27] For this, we run separate regressions for the years 2011–2019 where we take long-differences of varying length, similar to Autor et al. (2014); Yagan (2019); Delgado-Prieto (2023), as follows:

$$\Delta y_{idt} \equiv y_{idt} - (1/3) \sum_{j=2011}^{2013} y_{idj} = \beta_0 + \beta_t S_{d,1416} + \beta_2 Urban + \phi_{g(i,2013)} + \epsilon_{idt} \tag{1}$$

The left-hand side indicates the difference in outcomes of domestic worker i in district d between the current year t and the pre-treatment average value: $y_{idt} - (1/3)\sum_{j=2011}^{2013} y_{idj}$. Taking the differences with respect to pre-treatment averages instead of using only one baseline year smoothes pre-treatment variation in individual outcome levels. Furthermore, it is a way of controlling for individual-level time invariant unobservable characteristics. Our variable of interest is $S_{d,1416}$: the arrivals of asylum-seekers between 2014–2016 in district d ($A_{d,1416}$) as a share of the district population in 2011: $S_{d,1416} = A_{d,1416}/pop_{d,2011}$.[28] We merge this shock to the district of residence of native workers in 2013. To control for differential trends in industry, wage decile, and age groups, we include the fixed-effect $\phi_{g(i,2013)}$, which is an interaction of 9 age-groups, 10 wage-deciles, and 88 industries (2-digit level) fixed-effects. All of these covariates are fixed pre-treatment (in 2013). Hence, we measure the average effect of living in a district with more vs. fewer refugee arrivals within 7,920 groups of workers defined by their age group, wage decile and industry, i.e., workers with similar observable characteristics who are employed in different districts. Controlling for pre-treatment selection is important, as some districts might be more populated by particular types of workers if, for example, a particular industry is strong there. These workers could be prone to different types of shocks other than refugee immigration but such effects will be controlled for by our approach.

Hence, the dynamics of the effect will be given by the β_t coefficients from the yearly long-differences regressions. The main explanatory variable, $S_{d,1416}$, remains constant over time, i.e., the samples and explanatory variable are fixed across the yearly regressions and only the outcome (full-time employment, wages, job task content, occupation and regional labor market changes) varies for each year.

Depending on the outcome under consideration, the sample consists of a panel of different groups of the labor force which follow throughout 2011–2019:

(i) When analyzing employment outcomes, the sample consists of a panel of the labor force

[27] Similar to Dustmann et al. (2017), because of the sharp increase in arrivals, we are not confronted by dynamic responses to past migration shocks (Jaeger et al., 2018).

[28] As mentioned in Section 4, we measure arrivals to a district within the past 18 months at two points in time, June 30, 2015 and December 31, 2016. Hence, our main explanatory variable is the sum of those two arrival groups.

(employed and non-employed workers) in 2013, with at least one post-treatment observation, filling in zero values for gap years; see Section 4.

(ii) When analyzing wages, we restrict the sample to an unbalanced panel of workers that have been full-time employed in 2013 and any other year throughout 2011–2019 (i.e., being full-time employed in any pair of post-treatment years, including the baseline). For wages, we restrict the sample only to the full-time employed since we only have information on daily wages.

(iii) When analyzing job task contents, we use an unbalanced sample of all employed workers (any employment) in 2013 and any other year throughout 2011–2019 (i.e., being employed in any pair of years, including the baseline).

(iv) When analyzing mobility, we use an unbalanced sample of all individuals with a registered district of residence in 2013 and any other year throughout 2011–2019 (i.e., having information on residence in any pair of years, including the baseline).

When analyzing effect heterogeneities, e.g., by skills, sex or age group, we split the sample by individual characteristics.

5.2 Identification and Instrument

Although asylum seekers are distributed regionally by a dispersal policy, the explanatory variable can be endogenous with respect to local labor market trends because, first, asylum seekers are apparently allocated disproportionately into districts with relatively high unemployment rates (potentially due to available housing, non-compliance or political lobbying, as explained in Subsection 2.1). Second, a maximum of 36 months after arrival, refugees are permitted to move freely, which may introduce regional sorting. Moreover, they are free to move whenever they have found a job. From the migration literature, we would expect them to move to economically better-performing regions, hence biasing OLS estimates upwards. However, this is not the case in the German context: even when refugees are allowed to move, they do so to high-unemployment districts (predominantly large cities, see Subsection 2.1). Therefore, OLS estimates might be downward biased (if refugees' location is correlated with worse economic conditions). Third, during the peak of arrivals, registrations were delayed, which led to underreporting in 2015. Although we try to circumvent this problem, if measurement error is still in our AZR data, this will lead to an attenuation bias in the OLS estimates. We propose the following instrument to address the endogeneity of the treatment variable.

Distance IV (DIV). In order to measure the exogenous part of the administrative allocation of asylum seekers across districts, we make use of the fact that asylum seekers are allocated close to a BAMF branch office responsible for the specific country of origin and often continue residing there. Hence, the closer a BAMF branch office, the more asylum seekers from that origin country are expected. This instrument resembles a shift-share IV in spirit. We use the arrivals during 2014–2016 at the state level as the shift and the distances from the centroid of a district to the closest BAMF branch office as the share. The shift is given by the arrivals of asylum-seekers from each nationality (country c) that arrived in a particular federal state (s) during 2014–2016 to Germany ($A^{1416}_{c,s}$). As exogenous shares, we use the travel distance by car from the centroid of a district to the closest BAMF branch office responsible for a particular country of origin ($T_{c,d}$).[29] We normalize these distances within each state (so that they add up to one) and use them as weights to spread out the arrivals of asylum-seekers within state across districts.[30] Finally, we sum across nationalities and normalize this by the 2011 district's population, P^{2011}_d.

$$DistanceIV^{1416}_d = \sum_{c \in Refugee} \underbrace{A^{1416}_{c,s}}_{shift} \times \underbrace{NormTravel^{2016}_{d,c}}_{share} \times \frac{1}{P^{2011}_d} \tag{2}$$

One concern with this distance instrument is that BAMF branch offices could potentially have been installed where there was a sufficiently large existing migrant community (e.g., to facilitate a sufficient supply of translators, etc.). If this were the case, our instrument would resemble a standard past settlement IV. To address this concern, Figure A.4 shows the regional distribution of a past settlement instrument (based on past migrant communities, subsuming all top 8 origin countries in 2011) together with the location of BAMF branch offices. It shows no discernible regional correlation. On average, the population of the top 8 refugee-origin countries in the German districts in 2011 was 0.26%. We further regress an indicator for the location of branch offices per nationality for which they are responsible on the share of the migrant community who possess said nationality (see Table A.4). This exercise only shows a statistically significant correlation, at the 1% level, for Afghans. This might be the reflection of a notable Afghani diaspora in Germany, as it represents the largest Afghan community in Europe, yet is still small in absolute terms.[31] Overall, however, there were hardly any migrants from the top 8 sending countries before 2013. This fact also explains why a past settlement approach bears little empirical relevance in the current setup.

Figure 3 shows a graphical first stage between the share of arrivals 2014–2016 and the distance to the closest BAMF branch office. From all of the above, we expect a higher (lower) population share of refugees closer to (further from) a BAMF branch office. This hypothesis about the relevance of our novel instrument is supported visually by Figure 3. It shows how the population share of refugees in a district decreases with a longer driving distance to the next BAMF office (in minutes). We find the same pattern when plotting this relation for all top 8 origin countries separately (Figure A.5 in the Appendix). They thus graphically support the relevance of our instrument.

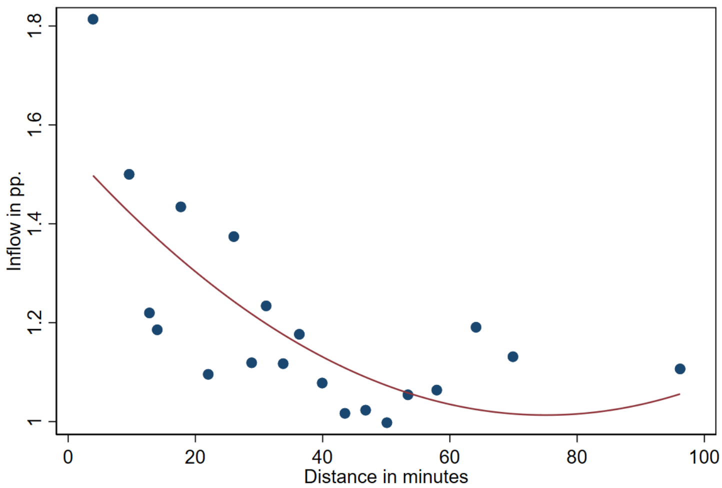
For this to be a valid instrument, we need our predicted inflow (based on the distance to the closest BAMF branch office) to not be correlated with local labor market conditions. Figure A.3 in the Appendix shows that the "urban" dummy is the only strong predictor of our instrument. Therefore, we will control for this variable and assume that conditional on this urban indicator our instrument is as good as randomly assigned. Additionally, following

[29]Our distance IV bears some resemblance to those used recently in the migration/refugee literature, e.g., Delgado-Prieto (2023); Akbulut-Yuksel et al. (2022); Del Carpio and Wagner (2015); Huang and Kvasnicka (2019).

[30]The following equation shows how we construct the shares: $NormTravel^{2016}_{d,c} = \frac{T_{c,d}}{\sum_{d \in states_s} T_{c,d}}$

[31]There were previous migration waves from Afghanistan to Germany (e.g., in the 1970s and early 1990s) due to previous wars.

Figure 3: Asylum Seekers' Arrivals (2014–2016) by Distance to the Closest BAMF Branch Office



Notes: The figure shows a binned scatterplot and a quadratic fit from arrivals of the top 8 refugee-origin countries between 2014–2016 by districts, grouped into 20 equal-sized bins. The x-axis shows the travel distance in minutes between the centroid of a district and the closest BAMF branch office. The bins are weighted by the total population in the district in 2011. *Source:* BAMF. Own depiction.

Autor et al. (2014) we check whether the instrument is correlated with pre-treatment outcomes. Table 1 shows the results of regressions on our pre-treatment outcomes, i.e., the difference between 2013-2011, on our distance instrument (DIV) and the same covariates as equation 1. Reassuringly, our instrument is not correlated with these pre-treatment outcomes. These results provide evidence supporting the parallel-trends assumption.

Table 1: Instrument and Pre-Treatment Outcomes

	Wage (in 2015 €)	Full-time emp.	Part-time emp.	Not employed
Distance IV	0.0644	-0.0001	0.0002	0.0001
	(0.0605)	(0.0004)	(0.0005)	-0.0006
Observations	250,172	469,281	469,281	469,281

Notes: The table shows the results OLS regressions of our pre-treatment outcomes, measured as the difference between the outcome variable in 2013 and 2011, on our distance based instrument, an urban dummy, and the FE interaction of age, wage decile, and industry (following the controls in equation 1).

First stage and Placebo. We show the relevance of our instrument in column (1) of Table 2. The Kleibergen-Paap F-statistic above 10 suggests that the variation generated by differences in the responsibilities of the various BAMF offices is very relevant.

In the spirit of a placebo regression, column (2) of Table 2 shows that there is no correlation between our instrument and the inflow of immigrants from EU-13 countries, who are free to choose their location (similar to Foged and Peri, 2016).[32] Hence, our instrument does not predict standard economic migration.

Typically, with an IV approach the results should be interpreted as a LATE (i.e., the average treatment effect for the compliers), however, our setting does not directly fit that framework. Instead, the IV estimator with a continuous instrument should be interpreted like a weighted

[32]EU-13 countries are the ones who have joined the European Union since 2004: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia.

Table 2: First Stage and Placebo

	Arrivals 2014-2016	Δ EU 2014-2016
	(1)	(2)
Distance-based IV	0.1695 ***	0.0218
	(0.0363)	(0.0219)
Age-wage-ind FE	Yes	Yes
Observations	469,281	469,281
KP F-stat	21.856	0.9923

Notes: The dependent variable in column (1) is the arrivals of asylum-seekers in a district between 2014–2016 (our treatment variable). In column (2), the dependent variable is the change in stocks between 2014–2016 of EU-13 immigrants. We estimate the regressions using our main sample where we control for an urban dummy and the FE interaction of age groups, wage deciles, and industries, as in equation 1.
Source: Destatis (2021a); BAMF (2019, 2020)

average of different groups of effects (Angrist and Pischke, 2009, p. 181 ff.). One way to think about this is in terms of a discretized instrumental variable. For simplicity, think about the distance IV as if it was a binary instrument. In that view, compliers from the distance IV would be those districts that only host a large number of refugees because of the proximity to a BAMF branch office.

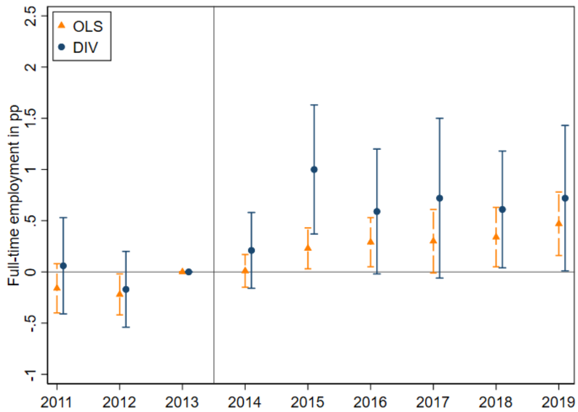
6 Results

The following empirical results are based on the sample of the labor force (employed and unemployed workers) observed in SIAB in 2013. The treatment is measured as the refugee inflow between 2014 and 2016, with the peak inflow happening in late 2015. Therefore, the interpretation of the coefficients for 2014–2016 should take into consideration that the treatment was not yet fully realized. These years also coincide with potential labor demand effects. The coefficients prior to 2013 serve as pre-treatment checks. In all panels, it is reassuring to see flat pre-trends in the pre-treatment period, which supports the plausibility of the parallel-trends assumption. The outcomes are measured relative to the 2011–2013 average. Only the 2011–2012 outcomes are measured relative to 2013, as otherwise, we would be mechanically setting the differences to zero.

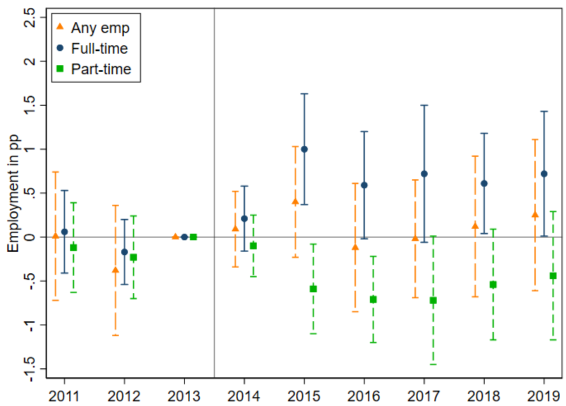
Main Employment Effect. Our main result shows that a 1 percentage point (pp.) increase in the population share of newly arrived refugees in a district leads to an increase in the probability of being full-time employed in the post-treatment period for natives by about 0.6 pp., on average (Figure 4a and Table B.1 in the Appendix). The estimated employment effect is largest in 2015 when the refugee influx peaked, and most refugees were still banned from working. The estimated effect remains large and relevant up until 2019, the end of the observation period, hinting at potential positive effects on natives from refugees' incipient labor supply.

This coefficient is statistically significant at the 5% level in 2015 and throughout 2018–2019. The average of our treatment variable, i.e., newly arrived asylum seekers between 2014 and 2016 as a share of the district population in 2011, is 1.18 %. This refugee inflow, together with the estimated average effect, therefore implies an increase in the probability of being full-time

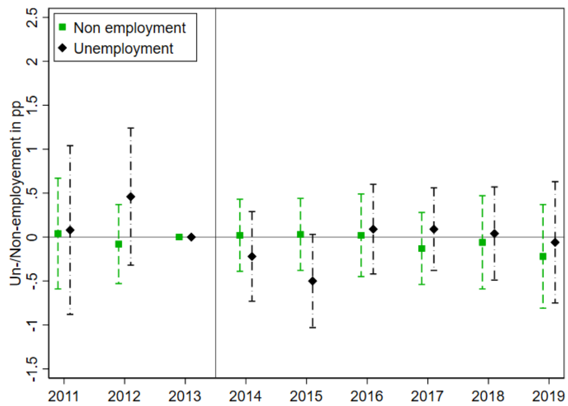
Figure 4: Main Effects on Employment



(a) Full-time employment



(b) Full-, part-time and any employment



(c) Un- and non-employment

Notes: The graph shows the IV coefficients for $\beta_t * 100$ from equation (1) for the yearly regressions and corresponding 95% confidence intervals. The sample consists of 469,281 individuals who were observed in SIAB in 2013 (employed or unemployed). Figure (a) shows the OLS and IV coefficients only for full-time employment as an outcome. Figures (b) and (c) show all different employment outcomes (measured as dummies): any employment (without trainees), full-time, part-time, unemployment and non-employment. Standard errors are clustered at the district level. Table B.1 in the Appendix shows the results displayed in these graphs.

employed for natives by 0.71 pp., an increase of 1.16% with respect to average pre-treatment full-time employment rate of 61%.[33] The OLS results (depicted as orange dashed lines in Figure 4(a)) are smaller than the 2SLS results, which is in line with our arguments about a downward bias due to the negative regional selection of refugees. To analyze all possible employment outcomes, we also coded dummies for being part-time employed, having any employment, being unemployed (officially registered), and being not employed (i.e., having a missing spell). For completeness, Figures 4(b) and (c) show all possible margins of adjustment. While full-time employment increased for the incumbent workforce in districts with more refugees, part-time work decreased on average by 0.5 pp. Hence, there was no effect on overall employment at the extensive margin for incumbent native workers but an adjustment at the intensive margin. Furthermore, we see no effects on the likelihood of being non-employed, and only a small and marginally significant reduction on unemployment in 2015. Next, we investigate how the inflow and outflow margins were affected.

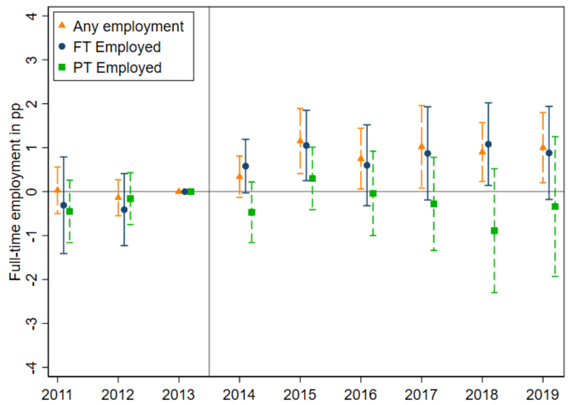
Employed and Unemployed Individuals Pre-Treatment. In the spirit of Dustmann et al. (2017), we analyze whether the (full-time) employment effects come from inflows out of unemployment or less outflows out of employment. To see whether refugee immigration affects more strongly the employment of incumbent or unemployed natives, we split the sample between those individuals in any kind of employment in 2013 and those unemployed in 2013 (Figure 5).

For those unemployed in 2013, we find no statistically significant effects, so we rule out inflows from unemployment to full-time employment as the main channel driving the employment gains from above (Figure 5(b)). Instead, we find that the effects are driven by those already employed in 2013, meaning that the inflow of asylum-seekers reduced the outflows of full-time employment. Figure 5(a) further shows that the estimated coefficients are very similar for full-time employees (solid blue line) and for those in any employment (long-dashed orange). Furthermore, we do not see an increase in working full-time for those who worked part-time in 2013 compared to individuals in less intensively treated districts. Hence, taking together, the results shown in Figures 4 and 5 show that incumbent workers in high inflow refugee districts profited by staying longer in full-time employment and not transitioning to part-time jobs, compared to workers in low-refugee districts. The employment gains are driven by those workers who were already employed pre-treatment.

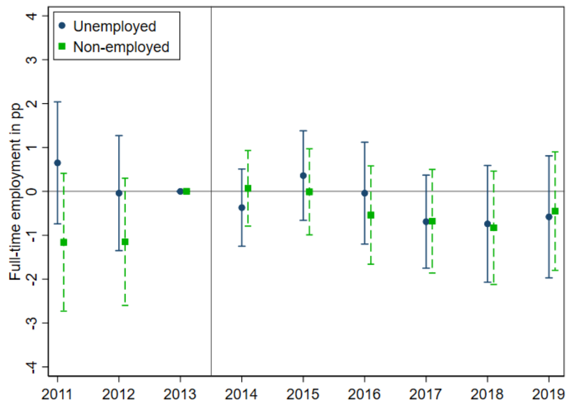
Recovering Non-Employed Individuals. One caveat of the data is that we can only observe individuals who are officially registered as employed or unemployed (at the employment agency). Hence, we might be missing individuals who are not employed and not registered or out of the labor force. These groups could be most affected by refugee immigration because refugees could be close substitutes and hinder their labor market (re)entry. In an attempt to recover some of these workers, we expand our sample to individuals who had any spell in 2011 or 2012 but not in 2013 and to those who entered the SIAB at age 23 in 2014. Figure 5(b) (dashed green lines) shows that the results remain essentially unchanged but they exhibit some pre-

[33]This employment effect is large but comparable in magnitude with the one found by Dustmann et al. (2016)—although with the opposite sign—who use a similar empirical approach and data.

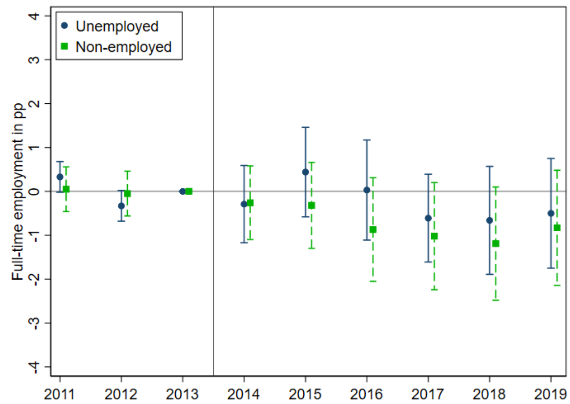
Figure 5: Full-time Employment Effects by Subsamples of the Workforce in 2013



(a) Subsample: Any employment, FT and PT employed



(b) Subsample: Unemployed and non-employed, not controlling for pre-trends



(c) Subsample: Unemployed and non-employed, controlling for pre-trends

Notes: The graph shows the IV coefficients for $\beta_t * 100$ from equation 1 for the yearly regressions and corresponding 95% confidence intervals. The sample in panel (a) consists of 420,292 individuals who had any type of employment in SIAB in 2013 (orange lines), of 304,878 individuals who were full-time employed (blue lines), and of 119,349 who were part-time employed. The sample in panel (b) consists of 49,932 individuals who were registered as unemployed in SIAB in 2013. When recovering the non-employed individuals we gain additionally 35,811 individuals. Standard errors are clustered at the district level. Table B.2 in the Appendix shows the full results for all these subsamples.

trends. When controlling for pre-trends, Figure 5(c), the results including the non-employed sample show more negative point estimates for 2017–2019, although not statistically significant at the 5% level. Overall, we find null effects for this “imputed non-employed” sample but some hints of small negative effects. In Subsection 6.2, we perform heterogeneity analysis by individual characteristics to dig deeper into the possible adverse effects.

Sensitivity Checks. To ensure the robustness of our main results, we conduct various sensitivity checks. Appendix C shows that using different specifications of the instrument, either by using only the BAMF branch offices in place in 2014 or by using the EASY arrivals as shift instead of the AZR data, do not change our main results. Furthermore, our results remain essentially unchanged when including other regional covariates or using only a 1-digit industry fixed effect as controls. Additionally, we test a TWFE specification instead of our preferred long-differences one. The results are in line with our main results, but the point estimates are almost twice as large. Finally, to further check pre-trends, we run our main analysis with a placebo sample 2001–2009, taking 2003 as the base year.[34] One concern is that the event-study graphs might include a structural beak at the base year, even if our treatment variable has no causal effects since individuals tend to upgrade as time passes. The results show no structural break after the placebo base year (2003) and all the coefficients are not as large as in our main analysis. Hence, we discard the fact that a general structural break might drive our results.

6.1 Mechanisms: Labor Demand and Labor Supply Effects

Our dynamic effects could be in line with initial labor demand effects from refugee immigration and later labor supply effects. We investigate this idea further by estimating effects across occupation groups using sample splits. To disentangle such effects empirically, we estimate the same main equation 1 but for individual occupation groups (measured in 2013) while excluding industry from the fixed-effects.

Labor Demand Effects. If the arrival of refugees stimulates labor demand (as in Berbée et al., 2022 and Auer and Götz, 2023), we expect to see effects in occupations related to (i) administration and law, (ii) health, social affairs and education, and (iii) commercial services (catering, hospitality) right after refugees’ arrival. Table 3 shows the results separately by individuals’ pre-treatment occupation, where we expect to find employment gains in rows 6-8. These results are in line with our expectations, albeit only at weak significance. In 2015, workers in “Health, social affairs, teaching and education” professions were 2 pp. more likely to be full-time employed than at baseline (significant at the 5% level). Workers in “Commercial services, trade in goods, distribution, hotel and tourism” were 1.6 pp. more likely to be full-time employed (significant at the 10% level). The estimated coefficients for occupations in administration are not statistically significant but go in the expected direction. Taken together, we interpret these results as support for initial labor demand effects.

Labor Supply Effects. We expect to see labor supply kicking in 2017–2019 when refugees slowly start picking up employment. Refugees work predominantly in occupations related to (i) transport and logistics (32%) and (ii) manufacturing (28%; Appendix Table A.2). We, there-

[34] These results are available upon request.

fore, expect to see labor supply effects in rows 2 and 5 of Table 3 starting from about 2017. While the effects in transport and logistics are close to zero and statistically insignificant, native employment in manufacturing starts growing at statistically significant levels as of 2018. Finding employment growth here for natives suggests relevant complementarities between refugees and native workers. We interpret the timing of the effects in light of labor supply effects from refugee immigration. Overall, we see few significant employment effects on natives in Table 3 after 2017. Two mechanisms could potentially explain this finding. Either there are hardly any substitution effects or complementarities within the occupation groups, or labor shortages work in a way to fully absorb refugee labor without (negatively) affecting natives. Additionally, since we are only looking at active workers present since 2013 (and before) in the employment data, the complementarities in manufacturing could arise if more experienced workers can now work more/longer training the new workers, e.g., refugees taking up apprenticeships. In Section 6.4, we describe possible negative effects on those native workers not yet in the labor force.

Table 3: Main Results by Occupation Groups

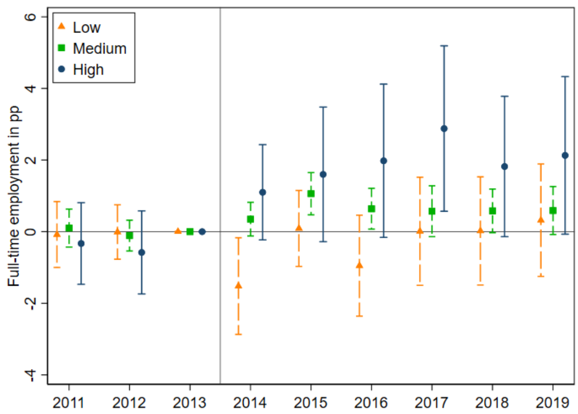
Occupational group	2011	2012	2013	2014	2015	2016	2017	2018	2019	N	KP F-stat
1 Agriculture, forestry, animal husb.	0.0090	0.0051	.	0.0108	0.0081	0.0283	0.008	0.0048	-0.0035	6,202	23.2065
	(0.0257)	(0.0184)	.	(0.0215)	(0.0067)	(0.0230)	(0.0279)	(0.0261)	(0.0245)		
2 Manufacturing	0.0033	0.0013	.	0.0007	0.008	0.0025	0.006	0.0144	0.0153*	95,274	18.9166
	(0.0059)	(0.0041)	.	(0.0047)	(0.0067)	(0.0065)	(0.0073)	(0.0090)	(0.0088)		
3 Construction	-0.0124	0.0019	.	0.0146	0.0114	0.0138	0.0056	0.0244	0.0220	25,023	22.0953
	(0.0102)	(0.0104)	.	(0.0133)	(0.0145)	(0.0140)	(0.0145)	(0.0183)	(0.0147)		
4 Natural sciences,IT	-0.0250	-0.0339	.	0.0191	0.0184	0.0043	0.0196	0.0051	-0.0001	16,524	8.9833
	(0.0196)	(0.0221)	.	(0.0180)	(0.0228)	(0.0281)	(0.0274)	(0.0252)	(0.0366)		
5 Transport, logistics, security	0.0071	0.0033	.	-0.0048	0.0001	-0.0038	0.0029	0.0043	0.0023	49,187	28.1124
	(0.0057)	(0.0045)	.	(0.0064)	(0.0052)	(0.0054)	(0.0095)	(0.0070)	(0.0068)		
6 Commercial services,hotel and tourism	-0.0018	-0.0017	.	0.0047	0.0156*	0.0108	0.0144	0.0099	0.0147*	48,683	19.1661
	(0.0084)	(0.0064)	.	(0.0054)	(0.0093)	(0.0088)	(0.0089)	(0.0096)	(0.0086)		
7 Accounting, law and administration	0.0028	-0.0013	.	0.0063	0.0074	0.0100	0.0096	0.0065	0.0069	96,738	17.9219
	(0.0083)	(0.0065)	.	(0.0070)	(0.0073)	(0.0069)	(0.0082)	(0.0107)	(0.0094)		
8 Health, social services, education	0.0093	0.0050	.	-0.0012	0.0206**	0.0142	0.0169	0.0046	0.0144	73,874	20.4147
	(0.0079)	(0.0060)	.	(0.0056)	(0.0087)	(0.0088)	(0.0112)	(0.0097)	(0.0109)		
9 Social sciences, culture	0.0094	-0.0115	.	0.0255	0.0400	0.0213	0.0339	0.0149	-0.0012	11,333	15.1983
	(0.0257)	(0.0193)	.	(0.0233)	(0.0378)	(0.0295)	(0.0310)	(0.0257)	(0.0284)		
Urban dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Age group*wage decile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		

Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019 and corresponding standard errors. Every row represents the subsample of occupation groups, defined by the occupation of a worker in 2013, and the columns show the yearly coefficients. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.2 Heterogeneities by Individual Characteristics

Employment Effects by Skill Groups. Refugees work disproportionately in low (45%) and medium-skilled (45%) jobs (see Appendix Table A.1), which appears to be an effect from downgrading (Brücker et al., 2020). Therefore, in the labor supply phase after 2017, we could expect to find smalle negative or null substitution effects for low-skilled and positive effects from complementarities for high-skilled natives, while the expectations are unclear for the medium skilled. Figure 6 shows the estimated employment effects on natives by splitting up the sample by pre-treatment skill level based on education groups.

Figure 6: Employment Effects by Skill Groups



Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and corresponding 95% confidence intervals for the yearly regressions by skill-groups. The sample consists of 37,954 low-skilled workers, 345,858 medium-skilled workers, and 79,855 high-skilled workers. Table B.3 in the Appendix shows the full results.

Low-skilled native incumbent workers exhibit negative effects in 2014, though at large confidence intervals (as this unskilled group is small in Germany). This could hint at a substitution between refugees and low-skilled workers, although during 2014–2016, the employment rate of refugee-origin workers was very low. Hence, substitution effects are pretty unlikely. Alternatively, low-skilled workers could have anticipated a low-skilled labor supply shock and decided to take up additional training. However, due to data limitations, we cannot test this hypothesis. Medium-skilled workers display slightly positive coefficients that are only statistically significant at the 5% level in 2015–2016 and marginally significant thereafter. At the same time, for high-skilled employees, the full-time employment growth is large, significant, and growing over time as refugees enter the labor market. This again fits well the hypothesis of complementarities between refugees and natives, especially between refugees in low-skilled jobs and high-skilled natives.

Since our low-skilled sample (defined by education) is relatively small, we run heterogeneities by wage-decile at baseline (see Table B.4 in the Appendix). We find positive and significant full-time employment effects for medium-wage workers (wage decile 4) during the labor demand phase (2014–2016) and larger and significant effects for high-wage workers (wage decile 9) throughout the post-treatment phase, and for wage decile 10 only in 2017. Both effects go in line with our findings for medium and high-skilled workers. However, we also find some indication of positive effects (although only marginally significant for one years) for low-wage workers (wage decile 2), which suggest that low-skilled workers were not harmed by refugee migration.

Overall, our results imply positive employment effects on incumbent native workers that are in line with early labor demand effects and delayed labor supply effects. For the labor supply phase after 2017, the occupation and skill groups results suggest positive complementarities between refugees in low-skilled jobs and especially high-skilled natives.

Employment Effects by Gender. During the labor demand phase, refugees receive support mainly from workers in health, social services and education, commercial services (accommodation and food) and administration. These occupations are female-dominated, so we expect to find the initial employment gains to be concentrated among women. Splitting up the sample by gender shows that women experienced positive employment effects in 2015 that are statistically significant, i.e., when refugees are hosted, administered, and supported (Figure B.1(a)). Meanwhile, the positive employment effects for males are statistically significant in 2018, i.e., when refugees start working themselves. Refugees work predominantly in male-dominated occupations such as logistics and manufacturing. Together, this disaggregation by gender provides additional hints to our interpretation of labor demand and supply effects. However, the results by gender are overall not statistically different from each other.

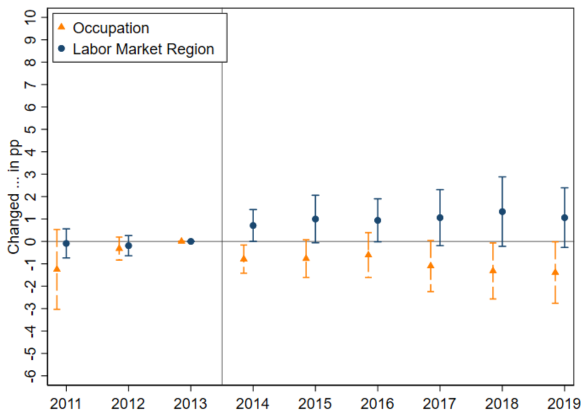
Employment Effects by Age Group. By age groups, the reduced outflows out of full-time employment are driven by the youngest (aged 22–33 in 2013) and the oldest (aged 50–58) employees (Figure B.1(b)). These are also the groups with the highest employment elasticities. Particularly, we hypothesize that women and men remain longer in the labor force by, e.g., postponing early retirement. We see results along these lines when we further split the age groups by gender (Figure B.2). This figure reiterates that young and elderly females show the strongest positive effects in 2015, whereas elderly males show the strongest positive effects in 2018–2019.

So far, the literature has found large employment losses among older workers upon immigration (Dustmann et al., 2017). Our results imply employment gains for older incumbent workers upon immigration. A high labor supply elasticity of older workers can reconcile both sets of results. This way, older workers reduce employment most strongly when immigration reduces employment, as in past episodes. By contrast, the refugee immigration episode we studied leads to employment gains that benefit older incumbent workers more strongly in the medium-run. While there seem to be mainly winners and almost no losers when looking at the employment effects of refugee migration on native workers, we now look at mobility responses, wages, and tasks. These could be potential margins of adjustment where we could see adverse effects.

6.3 Further Outcomes: Mobility Responses, Wages, and Tasks

Individual Mobility Responses. Workers can respond by either changing their occupation or changing their current labor market region.[35] Figure 7 shows that workers in more intensively treated districts are less likely to change their occupation than workers in control districts. Workers were on average 1 pp. less likely to change their occupation.

Figure 7: Mobility Responses: Changes in Occupation and Labor Market Region



Notes: The sample is an unbalanced panel of all workers who have been employed in 2013 and in any other year (for occupation) and who have moved to different labor market regions. The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and 95% confidence intervals for the yearly regressions, where the outcomes are: the changes in occupation, and changes in the labor market region where they reside. Both coded as dummies and measured with respect to 2013.

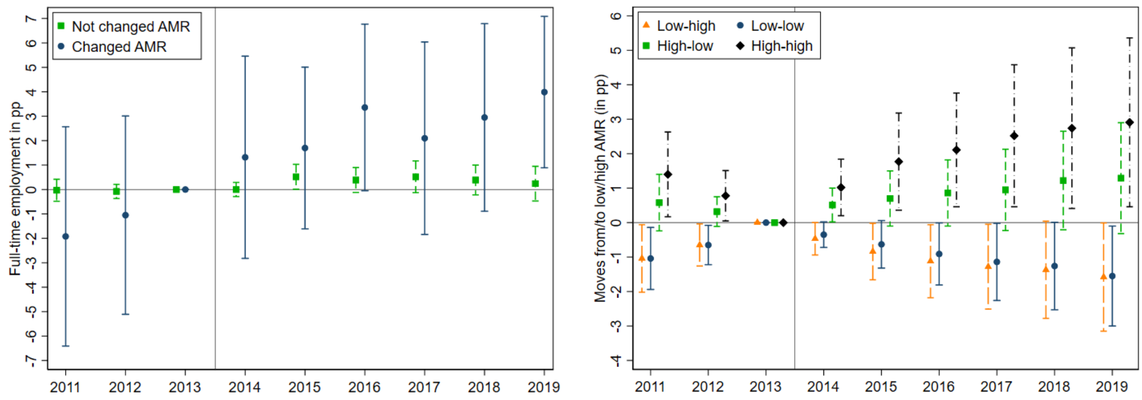
More interestingly, the likelihood of changing their labor market region increases by about 1 pp. in the post-treatment period. The changes in the labor market region are mainly driven by younger workers (aged 22–33) and somewhat by those aged 34–49 (see Figure B.3). Figure B.4 shows that low-skilled workers were neither more likely to change their occupation nor their labor market region. In contrast, medium-skilled workers were less likely to change occupations than workers in low-inflow districts, although the effects are only marginally significant. Interestingly, medium-skilled workers seemed to be more likely to change their labor market region (positive but not significant point estimates). High-skilled workers in high-refugee districts, however, were more likely to change their labor market region compared to high-skilled workers in low-refugee districts throughout the entire post-treatment period.[36] Finally, the point estimates for change in the type of occupation are statistically not significant for high-skilled workers. What stands out is the increase in their probability of changing labor market regions. Two questions arise from this analysis. Do the movers drive our employment effects? And, do they move to districts with a lower inflow of refugees?

Figure 8(a) provides suggestive evidence for the first question. It shows the change in full-time employment by type of mover. We need to be cautious when interpreting these effects, as moving out is an endogenous choice, and we cannot add any causal interpretation to them. On

[35] There are 254 labor market regions in Germany as defined by the "Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR)".

[36] The confidence intervals are large due to smaller samples for low and high-skilled workers.

Figure 8: Employment Effects by Mover Status and Mobility to High/Low Migration Areas



(a) Employment effects

(b) Moves to a high/low refugee LMR

Notes: Panel (a) shows the results for our main outcome (change in full-time employment) by mover status (mover or not). The sample in panel (a) is an unbalanced panel of all individuals who have moved out (or not) from their initial labor market region (LMR) in 2013. On average 402,479 individuals stayed in ther initial LMR in the post-treatment period, and only 23,603 moved out. Panel (b) shows whether individuals moved from a high/low to a high/low refugee inflow labor market region. This variable is coded as a dummy equal to one if the individual lives in a district with above median refugee-inflow in 2013 and moved to a high/low refugee inflow region. The population-weighted median inflow was 1.15%.

average, the point estimates for the stayers (green squares) are 0.4 pp., two-thirds of our main effect. The average point estimate for the movers is 2.5 pp., but since the movers are a small subsample, these are imprecisely estimated. Only about 5.5% of our sample moved in the post-treatment period. So, our effect does not seem to be driven by the movers. Figure 8(b) gives us a possible answer to the second question. The graph shows, for all skill levels, the probability of moving from a high/low labor market region (LMR) to a high/low refugee inflow LMR. Overall, we see positive point estimates for the probability of moving from a high to a low refugee-inflow LMR (dashed green lines), although not statistically significant. This result could hint at a "native flight effect" away from those labor market regions that experienced a large refugee inflow. In addition, we also find positive and statistically significant effects on the probability of moving from a high to a high refugee inflow LMR. These positive coefficients suggest that workers residing in high refugee inflow LMRs in 2013 were more likely to move to other high refugee inflow LMRs post-treatment. Hence, our mover's effects likely combine some "native flight" and movers to other high refugee LMRs. We take this result with a pinch of salt, given that the outcome variable (high/low refugee inflow LMR) is based on our treatment variable (the share of refugees). Hence, we are defining the outcomes also based on the treatment, which explains the pre-trends.

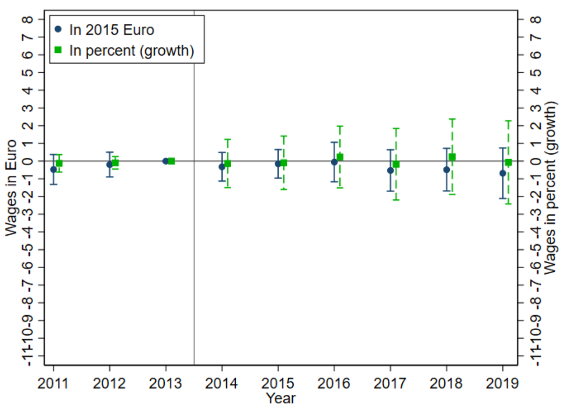
Regional mobility responses. Additionally, we can look at in- and out-migration, and commuter flows using the official regional statistics (see Figure B.5 in the Appendix). First, we look at native movers across district borders. None of our results are statistically different from zero. However, we see a small spike in outflows in 2014 (panel b) and a similar spike in inflows in 2015 (panel a). Thus, there is some evidence for a small but non-persistent native outmigration and a slight increase in inflows following the refugee arrivals. This pattern is in line with the findings by Glitz et al. (2023). The authors find that the refugee inflows displaced the native population in neighborhoods by less than 1:1, i.e., more refugees arrived than the overall population growth. They rationalize their results by indicating that refugees could have positive effects on local amenities (higher rental prices).

Similarly, we investigate how commuter flows changed after the refugee arrivals (see Figure B.6). The effect for inbound commuters is quite imprecisely estimated, but the point estimates are all close to zero. For outbound commuters, we see a positive and increasing trend. Hence, we find evidence supporting our findings from the individual-level regressions when looking at changes in the LMR: outbound commuters increase in districts with a larger share of refugees.

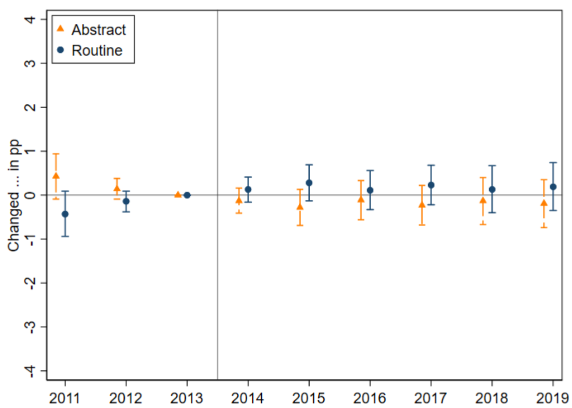
Wages. To investigate the effect on wages rather than employment, we use a sample of continuously employed full-time workers (in any pair of years, including 2013). The left panel of Figure 9 shows zero wage effects for full-time workers on average, no matter whether measuring the percentage growth (dashed green lines) or in Euros (solid blue lines). The yearly regressions show that asylum-seekers' arrival did not seem to depress the wages of native workers. Figure B.7 shows that these effects are statistically indistinguishable from zero for all skills groups. Hence, these results suggest zero substitution effects between refugees and native workers, supporting our positive employment effects. Given that refugees are mainly employed in low and medium-skilled jobs, we would expect these groups to be more negatively affected if refugees and natives were substitutes in the labor market. Our results, however, hint at imperfect substitutability between refugees and natives; and support our hypothesis that refugees might take up jobs usually not performed by native workers.

As a limitation, we only have information only daily wages. Thus, we cannot disentangle the effect of a change in hourly wages or working hours to shed further light on more detailed margins of adjustment.

Figure 9: Wages and Tasks



(a) Wages



(b) Tasks

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and corresponding 95% confidence intervals for the yearly regressions using as outcomes changes in wages (in 2015 Euros and in percent change) and changes in the job's main task. We grouped analytical non-routine and interactive tasks as "abstract", and cognitive routine, and manual (routine and non-routine) tasks as "routine".

Job Task Composition. Next, we check whether the job task components of natives have changed in response to the refugee arrivals. Following the argument of Foged and Peri (2016), low-skilled natives could be promoted to better jobs with more communication-intensive tasks, using their comparative advantage in the language. For studying the effect on job task components, we use a sample of continuously employed individuals (by pair of years) in any type of employment. We group jobs by their main task into abstract (analytical and interactive) and routine (including manual). The right panel of Figure 9 shows on average null effects for the main tasks component of the job. The vast majority of results for the different subsamples by education and gender are statistically insignificant (Figure B.8). Again, all the coefficients are statistically indistinguishable from zero across skill groups. A positive point estimate for low-skilled workers in 2015 suggests a slight increase in predominantly routine jobs for this year. On the other hand, positive—but very imprecise—point estimates for high-skilled workers suggest an increase in abstract jobs, especially during 2018–2019, when refugees start supplying labor which would again support the complementarity among refugees and high-skilled workers. However, there is no indication of similar effects for low-skilled workers as in Foged and Peri (2016).

6.4 Only winners?

So far, our analysis by occupations and individual characteristics has shown positive employment effects of refugee migration. When we examine other outcomes such as mobility, wages, and tasks, we do not find any evidence of the adverse effects previously reported in the literature (e.g., Dustmann et al., 2017). However, a deeper analysis of the non-employed is still pending. We show in Figure 5(c) that—after controlling for pre-tends—there is some indication of negative effects for the unemployed and non-employed in 2013. Together, these groups represent 15% of the total extended sample. To further explore these potential adverse effects, we perform sample splits by individual characteristics. Our results show that women and young people are the most affected by the refugee inflow, as they experience fewer transitions to full-time employment. These results may not be surprising, as these groups are less attached to the labor force. These negative effects seem large and statistically significant at the 5% level in 2017–2019, coinciding with the time when refugees start supplying labor. Thus, similar to Dustmann et al. (2017), this could be due to the high costs of laying off current workers in a highly regulated labor market, leading firms to quickly adjust their hiring behavior and maybe substitute younger workers for the refugee immigrants. Nevertheless, although females and the young represent about 55% and 41% of the pooled non-employed sample, they account only for 9% and 7% of the extended sample. Hence, the large effects shown in Table C.2 could be amplified by the relatively small size of these subgroups. It is important to keep in mind that although these effects seem large, they are concentrated in a few specific subgroups.

7 Conclusion and Discussion

Germany has seen a large and unexpected influx of refugees which peaked in 2015 and now makes up 2% of the population. While refugees are banned from working at first, they slowly start entering the labor market due to a lack of host-country human capital. This inflow came at a time when the German labor market was in good condition, with record lows of unemployment and growing skill shortages in some occupations and regions. We study the effect of refugee arrivals on individual natives' labor market outcomes. We focus on employment outcomes since Germany's wage-setting process is relatively rigid. Nevertheless, we also check wage changes, changes in main job tasks, and mobility responses.

Refugees are allocated across German districts by a dispersal policy. However, deviations from the established quotas occurred during the peak of the inflow, and, in addition, refugees are free to move after some time. In Germany, refugees often select into large urban centers, exhibiting high unemployment rates. Hence, there is a negative regional selection of refugees. We address this identification challenge by developing a novel instrument that relies on the responsibilities of the BAMF branch offices for processing asylum claims. These different responsibilities generate regional variation in refugees' population share and country of origin composition. Using a novel distance-based instrument—from the centroid of each district to the closest BAMF branch office—together with individual-level panel data, we can follow individuals over time, partly similar to Foged and Peri (2016), which allows us to causally identify the labor market effects of refugee migration and disentangle the dynamics of the effects. We attempt to shed light on different adjustment mechanisms by separating employed vs. unemployed individuals, females vs. males, young vs. old, and different occupational groups.

Our results show that the arrival of refugees raises the probability of full-time employment among natives: A 1 pp. increase in refugees' arrivals to a district increases the probability of full-time employment among natives by 0.6 pp. These employment gains appear to be driven initially by labor demand effects from hosting and administering refugees. Later, refugees slowly start providing labor themselves, which might exert substitution effects, especially among low-skilled natives. However, our results show no indication of adverse substitution effects by skill groups. As expected, the results also show strong positive complementarities between refugees and high-skilled natives regarding employment. Regional labor markets seem to adapt by reducing outflows of full-time employment, especially by young and old workers. Likely, elderly workers stay longer in full-time employment than they otherwise would have. On top of the overall positive employment effects, the effects we estimate for wages and the main task component of the job are statistically indistinguishable from zero. We further investigate workers' mobility and find an increase in the probability of changing the labor market region after the arrival of refugees. Young and high-skill workers drive these results. On the bright side, this relocation was higher to other districts that also received a large inflow of refugees. On the down side, when recovering the non-employed we find evidence of adverse employment effects in 2017–2019 for females and young individuals, who were not-employed at the time of the refugee shock.

Taken together, we interpret our results as showing that the arrival of refugees did not substitute native workers, not even low-skilled employees but likely hindered the transition to full-time employment for some small subgroups, such as females and young non-employed individuals. At the same time, the results imply strong employment complementarities between refugees and natives, which benefit especially high-skilled natives.

Our results provide important insights into the labor market effects of refugee migration in the host countries, a crucial topic for forming public opinion and designing policy measures. Our analysis shows that not only the skill composition matter to define who wins and loses after a migration shock but also gender, the type of jobs where men and women specialize, and their labor market attachment at the time of the shock. Additionally, it is crucial to describe the labor market conditions of the host countries as these contribute to our understanding of the potential negative or positive effects of refugee migration.

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A Additional Background Information on Refugees in Germany

A.1 Asylum Seekers Benefits

By the Asylum Seekers Benefits Act *(Asylbewerberleistungsgesetz)*, asylum-seekers are entitled to social benefits until they receive a decision on their application. These benefits are usually granted in-kind while still residing in an IRF and in cash when living in the follow-up accommodation. A single adult (without children) or a single parent received around 360€ worth of monthly benefits (excluding housing and health insurance). Once a positive decision is granted (recognized refugees, subsidiary protected, and persons with a national ban on deportation), they fall under SGB II or SGB XII and receive unemployment benefit II. Hence, are entitled to the same social benefits as any other German national. For this, they need to register at their local employment agency (Job Center) and are usually required to participate in training courses (*Aktivierungsmaßnahmen*).

A.2 Employment of Refugee Origin Workers

We describe the employment of refugees using data from the Federal Employment Agency as of 2019. Since this is administrative data, it is the most reliable for describing employment statistics of refugee-origin workers. However, these data have some drawbacks. First, the administrative data on employment does not distinguish legal status, i.e., we cannot know whether a worker is a refugee or an asylum-seeker but only the country of origin. Second, it lacks information on the arrival date, thus mixing early arrivals with later ones. Third, it shows a selected sample of immigrants from refugee-origin countries, namely those who are already registered with the Employment Agency or who have taken up employment. However, since registration at the Employment Agency is needed for receipt social benefits, this caveat might play a minor role. Table A.1 shows the employment rates for all workers from the top 8 asylum-seeking countries by nationality and the share of those workers employed in low-, medium-, and high skilled jobs.[37]

[37] The skill levels correspond to the jobs performed. The German names are "Helfer" (low skilled), "Fachkraft" (medium skilled), and "Spezialist/Experte" (high skilled).

Table A.1: Employment Rates and Job Skill Levels (July - August 2019)

	(1) Population in working age	(2) # Workers	(3) Emp. Rate (%)	(4) Type of job skill (%) Low	(5) Medium	(6) High
All top 8	1,045,107	362,652	34.7	45.2	45.1	9.5
Eritrea	58,789	28,454	48.4	68.0	30.4	1.6
Pakistan	54,577	24,669	45.2	40.8	41.2	18.0
Iran	88,068	36,196	41.1	26.7	46.0	27.0
Nigeria	46,820	18,494	39.5	62.3	31.0	6.6
Afghanistan	175,053	65,820	37.6	41.7	54.4	3.8
Somalia	33,900	11,831	34.9	69.4	28.5	1.9
Iraq	149,131	45,634	30.6	49.0	45.6	5.1
Syria	431,325	131,554	30.5	42.2	47.3	10.4

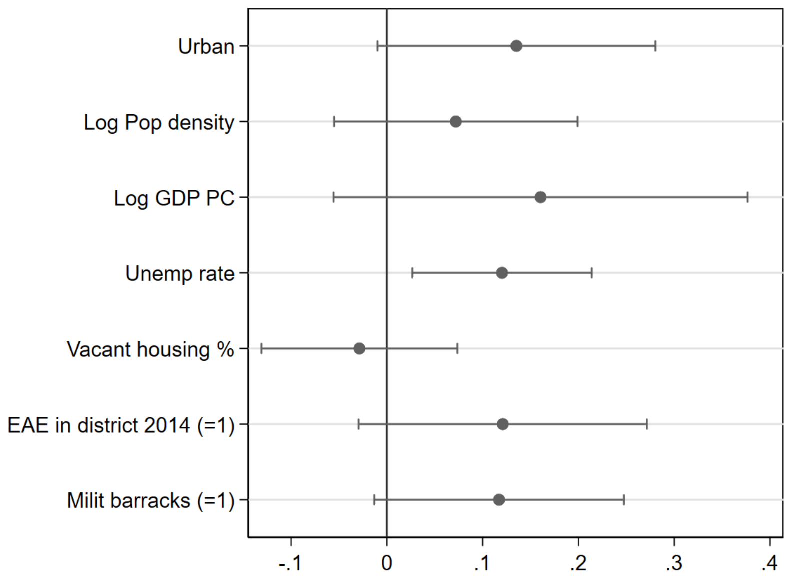
Notes: Column (1) shows the absolute number of working age population by nationalities, column (2) the number of workers, and column (3) the employment rate. Source: Federal Employment Agency (2019b,a)

Table A.2: Occupation Groups - Refugee Origin Workers

Classification of occupations (KldB 2010)	% of all refugee orig. workers	% of all workers
Transport, Logistics, Safety and Security	32.24	2.59
Raw Material Extraction, Production and Manufacturing	27.61	1.37
Commercial services, trade in goods, sales, hotel and tourism	12.68	1.19
Health, social affairs, teaching and education	12.66	1.15
Construction, architecture, surveying and building technology	6.55	0.74
Business organization, accounting, law and administration	3.59	0.74
Natural Science, Geography and Informatics	2.63	0.71
Agriculture, forestry, animal husbandry, horticulture	0.97	0.35
Humanities, social sciences, media, culture, design	0.85	0.19

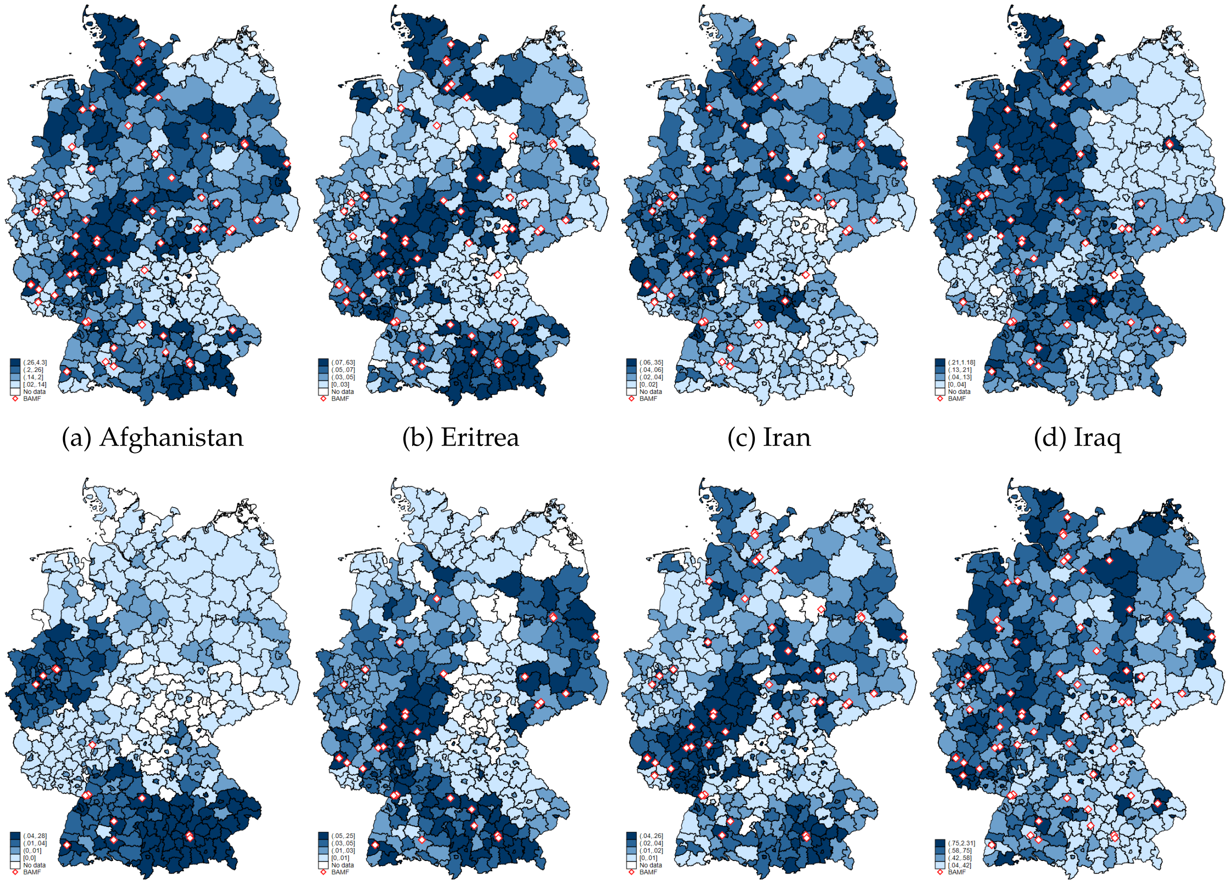
Notes: The table displays the occupation groups where refugee origin workers worked in 2019. The columns show the percentages relative to all refugee origin workers and relative to all workers.

Figure A.1: Balance Test: Refugee arrivals (2014–2016) and district covariates (in 2011)



Notes: The graph shows standardized beta coefficients with 95%-confidence intervals of a regression of our main explanatory variable (inflow of refugees between 2014–2016) on pre-treatment covariates (measured in 2011). Only the coefficient for the unemployment rate is statistically significant at the 5% level. Other—a priori—more relevant covariates such as the presence of a military barrack, an initial reception facility (present in 2014), or the predicted arrival share (using the established allocation quotas) do not have a statistically significant correlation with our main explanatory variable. Standard errors are clustered at the district level.
Source: BAMF, Destatis. Own graph.

Figure A.2: Arrivals of Refugees from top 8 Nationalities 2014—2016 and BAMF Branch Offices in 2014 and 2016

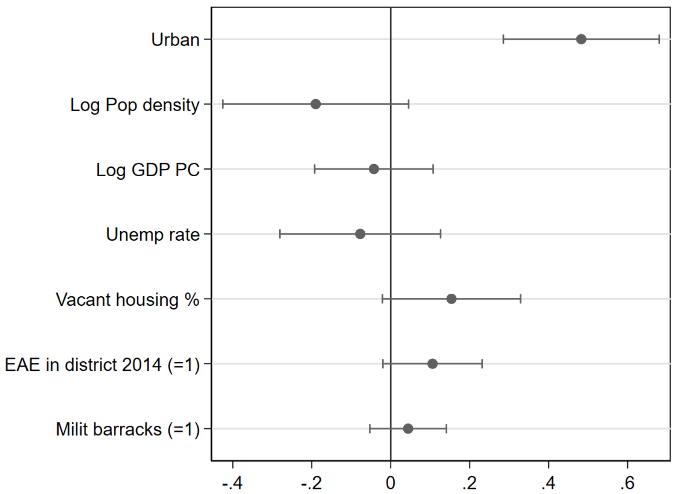


(a) Afghanistan (b) Eritrea (c) Iran (d) Iraq

(e) Nigeria (f) Pakistan (g) Somalia (h) Syria

Notes: The maps show the share of arrivals 2014–2016 as a percentage of all residents in a district in 2011. The diamonds show the location of the BAMF branch offices in 2016, which were responsible for the indicated nationalities.
Source: AZR, BAMF

Figure A.3: District Characteristics as Predictors of our Instrument



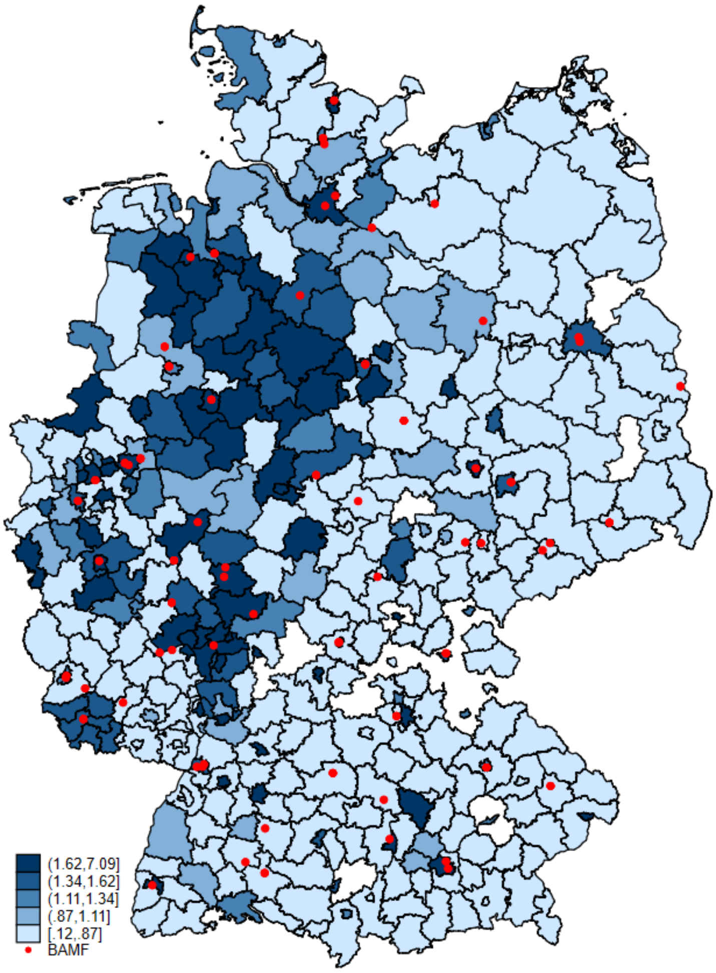
Notes: The graph shows standardized beta coefficients with 95%-confidence intervals of a regression of our distance based instrument on pre-treatment covariates (measured in 2011). Standard errors are clustered at the district level. *Source:* BAMF, Destatis. Own graph.

Table A.3: Summary Statistics for Low, Medium and High Skilled Germans

	All	Low-skilled	Medium-skilled	High-skilled
Age (in years)	41.37	36.000	41.700	41.830
	(10.460)	(11.770)	(10.440)	(9.530)
Experience (in years)	14.43	8.310	15.300	12.920
	(9.390)	(9.640)	(9.430)	(8.050)
Job tenure (in years)	7.490	6.130	7.830	6.360
	(7.470)	(8.150)	(7.690)	(6.150)
Education, no Abitur nor vocational train.	0.090	1.000	.	.
	(0.290)	.	.	.
Vocational training and/or Abitur	0.740	.	1.000	.
	(0.444)	.	.	.
College education	0.170	.	.	1.000
	(0.380)	.	.	.
Share of employed (w/o trainees)	0.810	0.360	0.850	0.890
	(0.340)	(0.430)	(0.300)	(0.240)
Share of FT employed (2011-2013)	0.610	0.250	0.630	0.700
	(0.450)	(0.390)	(0.450)	(0.410)
Share of PT employed (2011-2013)	0.190	0.100	0.200	0.170
	(0.360)	(0.270)	(0.370)	(0.350)
Share of unemployed (2011-2013)	0.100	0.450	0.08	0.03
	(0.260)	(0.440)	(0.230)	(0.120)
Share of not-employed (2011-2013)	0.060	0.080	0.050	0.070
	(0.160)	(0.180)	(0.150)	(0.180)
Avg. individual wage (2011-2013)	111.98	77.75	99.75	163.71
	(57.470)	(32.67)	(44.65)	(71.90)
Abstract %	0.349	0.175	0.284	0.647
	(0.456)	35.96	43.00	45.43
Routine %	0.650	0.824	0.715	0.352
	(0.456)	(0.359)	(0.430	0.454
Change in AMR %	0.090	0.100	0.080	0.130
	(0.280)	(0.300)	(0.260)	(0.330)
Change in occupation	0.270	0.420	0.260	0.260
	(0.440)	(0.490)	(0.440)	(0.440)
Observations	469,281	39,154	346,023	80,820

Notes: The top panel shows the control variables for our main sample and by skill levels. All of these variables are as of 2013 (baseline). The bottom panel shows the outcome variables measured pre-treatment (2011–2013 average). The total observations by skills do not add up to the total because there are 3,284 observations for which we have no information on education.
Source: SIAB 7519.

Figure A.4: Past Settlement IV and BAMF Branch Offices



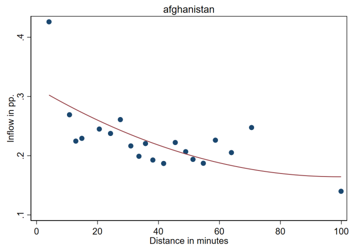
Notes: The map shows the share of migrants as per the past settlement IV and the location of the BAMF branch offices in 2016. Own depiction.

Table A.4: BAMF Responsibilities by Nationalities and Share of Immigrants Pre-treatment

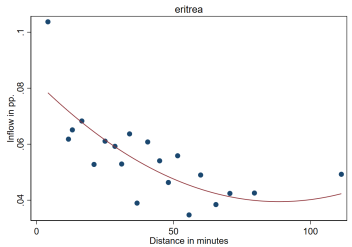
	Afghanistan	Eritrea	Irak	Iran	Nigeria	Pakistan	Somalia	Syria	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of nationals in d	0.816***	-0.026	-0.642*	1.244	3.575*	0.045	-1.069	0.754	0.210
in 2011	(0.222)	(1.478)	(0.288)	(0.804)	(1.771)	(0.482)	(1.833)	(0.685)	(0.167)
R^2	0.249	0.231	0.254	0.222	0.231	0.186	0.222	0.250	0.255
N	394	394	394	394	394	394	394	394	394
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column represents an OLS regression of a dummy equal one if there is a BAMF branch-office responsible for country of origin c in district d on the share of nationals from country of origin c living in district d in 2011 and some covariates. The covariates include a dummy for urban, log GDP per capita, log population density, unemployment rate, and female share. All variables as of December 2011. The regressions are weighted by the district's population in 2011.

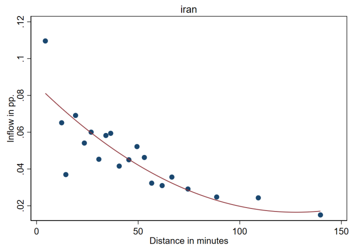
Figure A.5: Binned Scatterplots: Refugee Arrivals as Population Share 2014–2016 and Distance to the Closest Responsible BAMF Branch Office in 2016



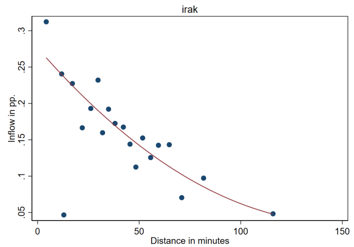
(a) Afghanistan



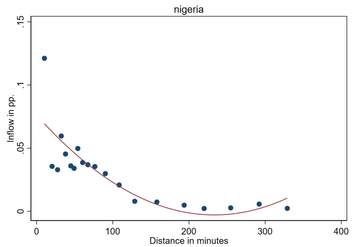
(b) Eritrea



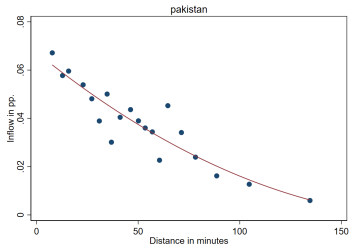
(c) Iran



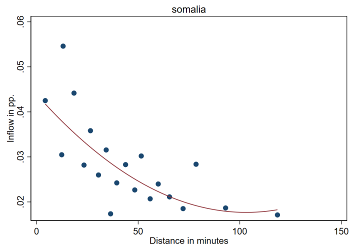
(d) Iraq



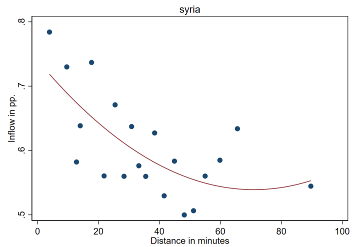
(e) Nigeria



(f) Pakistan



(g) Somalia

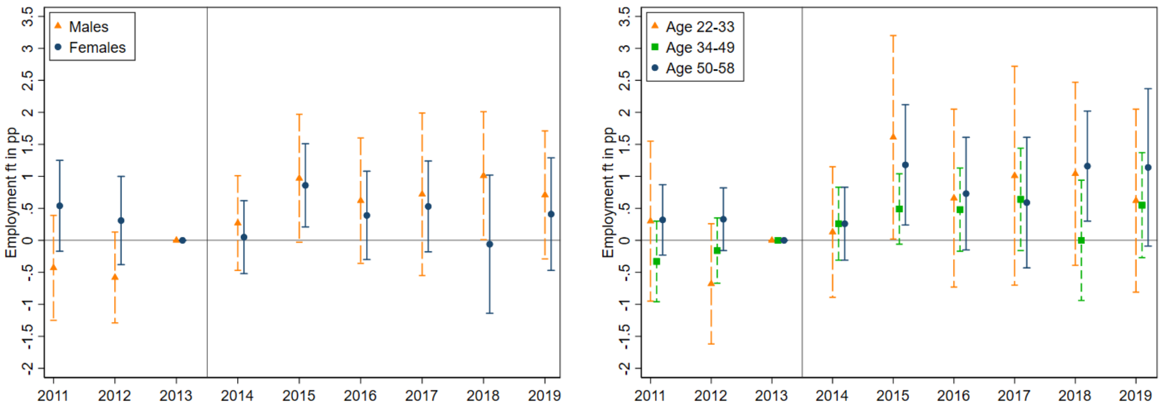


(h) Syria

Notes: The figures show binned scatterplots and a quadratic fit from the arrivals of each top 8 refugee-origin country between 2014–2016 by districts, grouped into 20 equal-sized bins. The x-axis shows the travel distance in minutes between the centroid of a district and the closest BAMF branch office by nationality. The bins are weighted by the total population in the district in 2011.
Source: BAMF. Own depiction.

B Additional Figures and Tables

Figure B.1: Employment Effects by Sex or Age Groups



(a) Sex

(b) Age in 2013

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and 95% confidence intervals for the yearly regressions by sex and age groups. The sample in panel (a) consists of 250,358 men and 218,059 females. The samples in panel (b) of 132,382 for age group 22-33, 206,416 for age group 34-49, and 130,483 for age group 50-58. The age refers to the year 2013. Table B.3 in the Appendix shows the full results.

Figure B.2: Employment Effects by Sex and Age Groups (ii)

(a) Females by age group

(b) Males by age group

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and 95% confidence intervals for the yearly regressions by sex and age groups.

Table B.1: Main Results for All Employment Outcomes, All Workers in SIAB 2013

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Full-time emp (OLS)	-0.0016	-0.0022**	.	0.0001	0.0023**	0.0029**	0.0030*	0.0034**	0.0047**
	(0.0012)	(0.0010)	.	(0.0008)	(0.0010)	(0.0012)	(0.0016)	(0.0015)	(0.0016)
N					469,281				
Full-time emp (2SLS)	0.0006	-0.0017	.	0.0021	0.0100**	0.0059*	0.0072*	0.0061**	0.0072**
	(0.0024)	(0.0019)	.	(0.0019)	(0.0032)	(0.0031)	(0.0040)	(0.0029)	(0.0036)
KP F-stat					21.7818				
N					469,281				
Employed (w/o vocational)	0.0001	-0.0038	.	0.0009	0.004	-0.0012	0.000	0.0012	0.0025
	(0.0037)	(0.0038)	.	(0.0022)	(0.0032)	(0.0037)	(0.0034)	(0.0041)	(0.0044)
KP F-stat					21.7818				
N					469,281				
Employed all	-0.0018	-0.0046	.	0.0014	0.0033	-0.0027	-0.0017	-0.0008	0.0008
	(0.0034)	(0.0032)	.	(0.0023)	(0.0033)	(0.0039)	(0.0036)	(0.0043)	(0.0046)
KP F-stat					21.7818				
N					469,281				
Part-time emp.	-0.0012	-0.0023	.	-0.001	-0.0059**	-0.0071**	-0.0072**	-0.0054*	-0.0044
	(0.0026)	(0.0024)	.	(0.0018)	(0.0026)	(0.0025)	(0.0037)	(0.0032)	(0.0037)
KP F-stat					21.7818				
N					469,281				
Not employed	-0.0003	-0.0005	.	-0.0012	-0.0009	-0.0008	-0.0022	-0.0015	-0.0029
	(0.0034)	(0.0023)	.	(0.0020)	(0.0020)	(0.0023)	(0.0021)	(0.0025)	(0.0029)
KP F-stat					21.7818				
N					469,281				

Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019. The outcome are all different employment dummies (stated on the left): full-time employment, any employment (without vocational training), part-time employment, and non-employment. The top panel shows the results for an OLS estimation on the full-time dummy, the following panels show the results for the 2SLS estimates for all employment outcomes. The results are estimated on the main sample, i.e., for all individuals who appeared in SIAB in 2013. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.2: Main Results for Full-time Employment, by Employment Subsamples

	2011	2012	2013	2014	2015	2016	2017	2018	2019
All in SIAB	0.0006	-0.0017	.	0.0021	0.0100**	0.0059*	0.0072*	0.0061**	0.0072**
	(0.0024)	(0.0019)	.	(0.0019)	(0.0032)	(0.0031)	(0.0040)	(0.0029)	(0.0036)
KP F-stat					21.7818				
N					469,281				
Any employment	0.0003	-0.0014	.	0.0034	0.0115**	0.0075**	0.0102**	0.0090**	0.0100**
	(0.0027)	(0.0021)	.	(0.0024)	(0.0038)	(0.0035)	(0.0048)	(0.0034)	(0.0041)
KP F-stat					20.5791				
N					419,349				
Full-time emp.	-0.0031	-0.0041	.	0.0058*	0.0105**	0.006	0.0087	0.0108**	0.0088
	(0.0056)	(0.0042)	.	(0.0031)	(0.0041)	(0.0047)	(0.0054)	(0.0048)	(0.0054)
KP F-stat					20.4372				
N					301,224				
Part-time emp.	-0.0045	-0.0016	.	-0.0047	0.003	-0.0004	-0.0028	-0.0089	-0.0034
	(0.0036)	(0.0030)	.	(0.0035)	(0.0036)	(0.0049)	(0.0054)	(0.0072)	(0.0081)
KP F-stat					20.787				
N					98,177				
Unemployed	0.0065	-0.0004	.	-0.0037	0.0036	-0.0004	-0.0069	-0.0074	-0.0058
	(0.0071)	(0.0067)	.	(0.0045)	(0.0052)	(0.0059)	(0.0054)	(0.0068)	(0.0071)
KP F-stat					29.7422				
N					49,932				
Non-employed	-0.0116	-0.0115	.	0.0007	-0.0001	-0.0054	-0.0068	-0.0083	-0.0045
+ unemployed	(0.0080)	(0.0074)	.	(0.0044)	(0.0050)	(0.0057)	(0.0060)	(0.0066)	(0.0069)
KP F-stat					27.2667				
N					85,743				

Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019. The outcome is a dummy equal to one if the individual is full-time employed. The top panel shows the main results, the following panels show the results for different subsamples by employment status in 2013. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.3: Main Results for Full-time Employment, by Individual Characteristics

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Males	-0.0043	-0.0058	.	0.0027	0.0097*	0.0062	0.0072	0.0101**	0.0071
	(0.0042)	(0.0036)	.	(0.0038)	(0.0051)	(0.0050)	(0.0065)	(0.0051)	(0.0051)
KP F-stat					21.7688				
N					250,358				
Females	0.0054	0.0031	.	0.0005	0.0086**	0.0039	0.0053	-0.0006	0.0041
	(0.0036)	(0.0035)	.	(0.0029)	(0.0033)	(0.0035)	(0.0036)	(0.0055)	(0.0045)
KP F-stat					22.076				
N					218,059				
Age group 1	0.003	-0.0068	.	0.0013	0.0161**	0.0066	0.0101	0.0104	0.0062
	(0.0064)	(0.0048)	.	(0.0052)	(0.0081)	(0.0071)	(0.0087)	(0.0073)	(0.0073)
KP F-stat					20.1899				
N					132,382				
Age group 2	-0.0033	-0.0016	.	0.0026	0.0049*	0.0048	0.0064	0.0000	0.0055
	(0.0032)	(0.0026)	.	(0.0029)	(0.0028)	(0.0033)	(0.0041)	(0.0048)	(0.0042)
KP F-stat					22.168				
N					206,416				
Age group 3	0.003	0.003	.	0.003	0.0118**	0.0073	0.0059	0.0116**	0.0114*
	(0.0028)	(0.0025)	.	(0.0029)	(0.0048)	(0.0045)	(0.0052)	(0.0044)	(0.0063)
KP F-stat					23.0188				
N					130,483				
Low-skilled	-0.0008	-0.0001	.	-0.0152**	0.0009	-0.0095	0.0001	0.0002	0.0032
	(0.0047)	(0.0039)	.	(0.0069)	(0.0054)	(0.0072)	(0.0077)	(0.0077)	(0.0080)
KP F-stat					28.4855				
N					37,954				
Medium-skilled	0.0010	-0.0011	.	0.0035	0.0106***	0.0064**	0.0057	0.0058*	0.0059*
	(0.0027)	(0.0022)	.	(0.0024)	(0.0030)	(0.0029)	(0.0036)	(0.0031)	(0.0034)
KP F-stat					23.5908				
N					345,858				
High-skilled	-0.0033	-0.0058	.	0.0110	0.0160*	0.0198*	0.0288**	0.0182*	0.0213*
	(0.0058)	(0.0059)	.	(0.0068)	(0.0096)	(0.0109)	(0.0118)	(0.0100)	(0.0112)
KP F-stat					13.7646				
N					79,855				

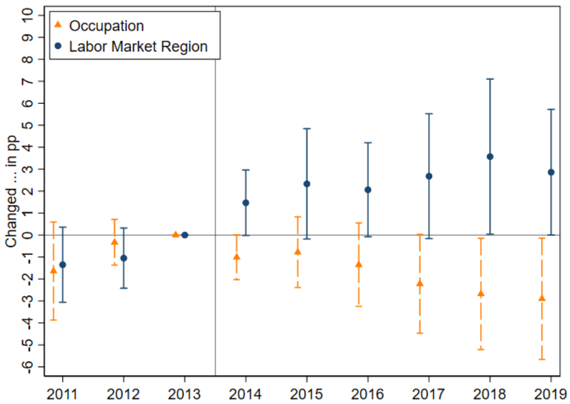
Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019. The outcome is a dummy equal to one if the individual is full-time employed. The left-hand column shows the characteristics for which we estimate the results (sex, age group, and skills). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.4: Heterogeneities for the Full-time Employment Outcome, by Wage-Deciles Pre-treatment

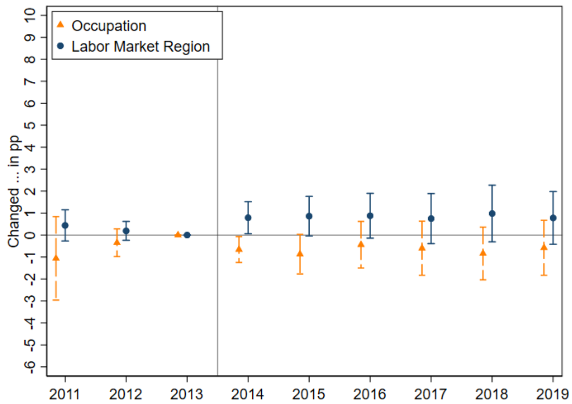
	2011	2012	2013	2014	2015	2016	2017	2018	2019
Wage decile 1	-0.0042	-0.0035	.	-0.0057	0.0026	-0.0039	-0.0071	-0.0058	-0.0081
	(0.0031)	(0.0031)	.	(0.0036)	(0.0049)	(0.0053)	(0.0059)	(0.0055)	(0.0073)
KP F-stat					30.8858				
N					41,602				
Wage decile 2	0.0110	0.0010	.	0.0070	0.0200 *	0.0090	0.0160	0.0117	0.0170
	(0.0070)	(0.0040)	.	(0.0100)	(0.0110)	(0.0110)	(0.0100)	(0.0130)	(0.0110)
KP F-stat					23.6905				
N					42,405				
Wage decile 3	0.0120	-0.0008	.	-0.0042	-0.0059	0.0024	0.0011	0.0004	0.0088
	(0.0124)	(0.0082)	.	(0.0059)	(0.0090)	(0.0091)	(0.0108)	(0.0106)	(0.0103)
KP F-stat					26.5682				
N					46,484				
Wage decile 4	-0.0069	-0.0091	.	0.0227 **	0.0197 **	0.0113	-0.0038	-0.0021	-0.0049
	(0.0099)	(0.0087)	.	(0.0084)	(0.0092)	(0.0106)	(0.0113)	(0.0118)	(0.0122)
KP F-stat					22.9377				
N					47,274				
Wage decile 5	0.0079	0.0026	.	-0.0058	0.0094	-0.0042	0.0036	0.0032	0.0108
	(0.0075)	(0.0066)	.	(0.0063)	(0.0078)	(0.0075)	(0.0114)	(0.0095)	(0.0097)
KP F-stat					23.0915				
N					48,456				
Wage decile 6	0.0098	0.0036	.	0.0028	0.0075	0.0037	0.0118	0.0108	-0.0020
	(0.0100)	(0.0074)	.	(0.0064)	(0.0084)	(0.0080)	(0.0120)	(0.0124)	(0.0123)
KP F-stat					20.3847				
N					48,934				
Wage decile 7	-0.0059	-0.0047	.	-0.0097	0.0103	-0.0015	0.0030	0.0061	0.0078
	(0.0067)	(0.0051)	.	(0.0061)	(0.0076)	(0.0088)	(0.0102)	(0.0096)	(0.0087)
KP F-stat					21.4341				
N					50,002				
Wage decile 8	-0.0013	0.0035	.	0.0038	0.0080	0.0121	0.0116	0.0044	0.0079
	(0.0083)	(0.0059)	.	(0.0057)	(0.0074)	(0.0084)	(0.0106)	(0.0107)	(0.0123)
KP F-stat					17.2786				
N					50,121				
Wage decile 9	-0.0193 **	-0.0066	.	0.0121 **	0.0226 **	0.0244 **	0.0211 **	0.0223 **	0.0195 *
	(0.0089)	(0.0055)	.	(0.0054)	(0.0080)	(0.0087)	(0.0095)	(0.0088)	(0.0110)
KP F-stat					17.652				
N					50,589				
Wage decile 10	0.0021	-0.0063	.	0.0091	0.0097	0.0097	0.0197 **	0.0088	0.0128
	(0.0065)	(0.0074)	.	(0.0065)	(0.0066)	(0.0079)	(0.0092)	(0.0105)	(0.0104)
KP F-stat					12.4033				
N					51,281				

Notes: The table displays the effects on full-time employment for all workers by wage deciles (pre-treatment). Hence, those unemployed will be part of wage decile 1.

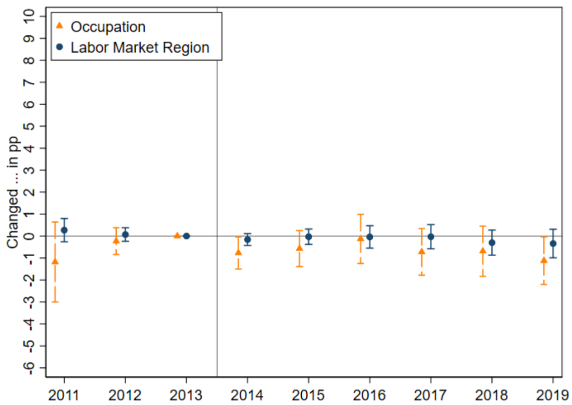
Figure B.3: Mobility Responses by Age Groups: Changes in Occupation, and in Regional Labor Market



(a) Age group 1 (22–33 in 2013)



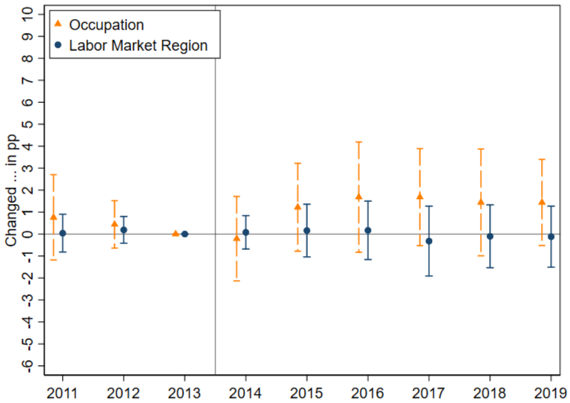
(b) Age group 2 (34–49)



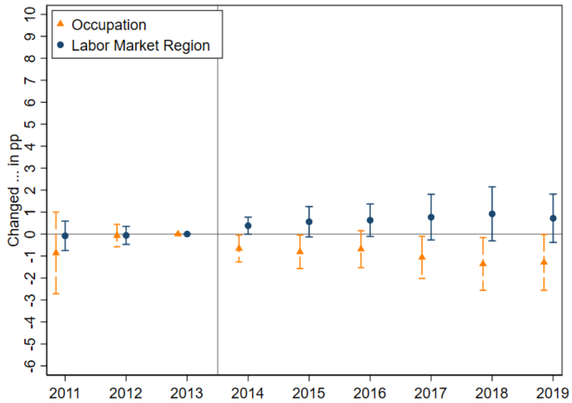
(c) Age group 3 (50–58)

Notes: The sample is an unbalanced panel of all workers who have been employed in 2013 and in any other year, by age groups. Subfigures (a) to (c) show as outcomes the changes in occupation, and regional labor market with respect to 2013 and are coded as dummies.

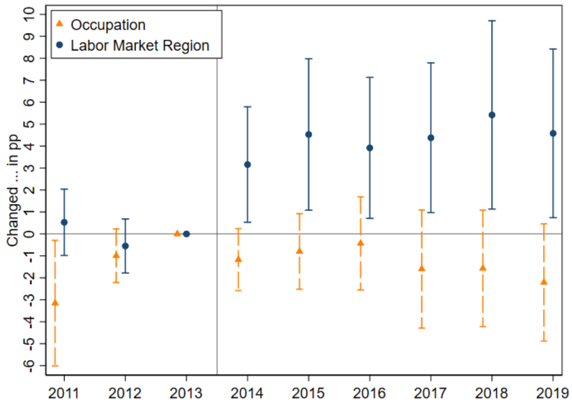
Figure B.4: Mobility Responses by Skill Groups: Changes in Occupation, and in Regional Labor Market



(a) Low-skilled



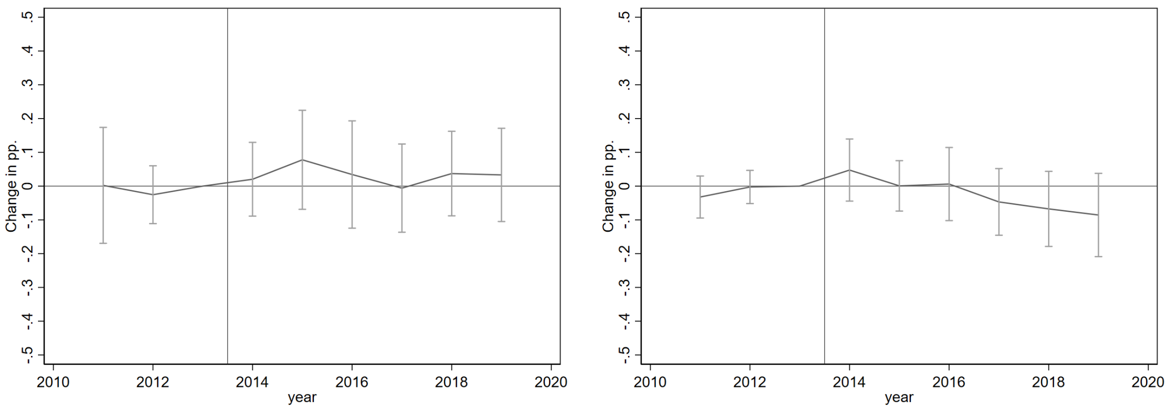
(b) Medium-skilled



(c) High-skilled

Notes: The sample is an unbalanced panel of all workers who have been employed in 2013 and in any other year, by skill groups. Subfigures (a) to (c) show as outcomes the changes in occupation, and regional labor market measured with respect to 2013 and are coded as dummies.

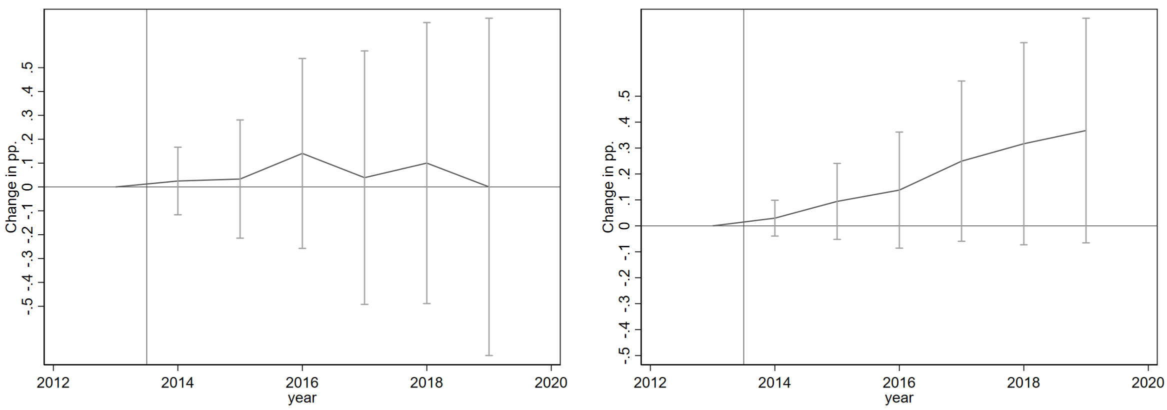
Figure B.5: Migration across District Borders



(a) Inflows (b) Outflows

Notes: The graphs show the IV coefficients for β_t from equation 1 and 95% confidence intervals for the yearly regression. We run the regressions using district-level data. The outcome variables are inflows and outflows from German citizens relative to the district's population in 2011. The regressions are weighted by the total population in the district in 2011. *Source:* Destatis.

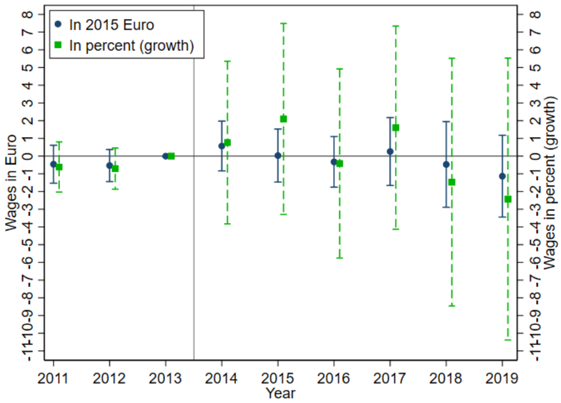
Figure B.6: Commuter Flows



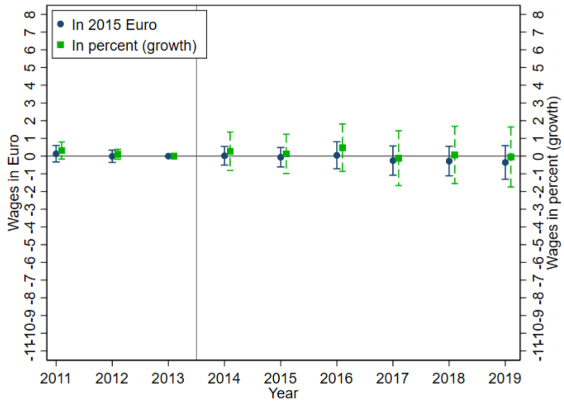
(a) Inbound (b) Outbound

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and 95% confidence intervals for the yearly regression. We run the regressions using district-level data. The outcome variables are inbound and outbound commuters who are German citizens relative to the district's population in 2011. The regressions are weighted by the total population in the district in 2013 since the data on commuter flows is only available since this year. *Source:* Bundesagentur für Arbeit - Statistik.

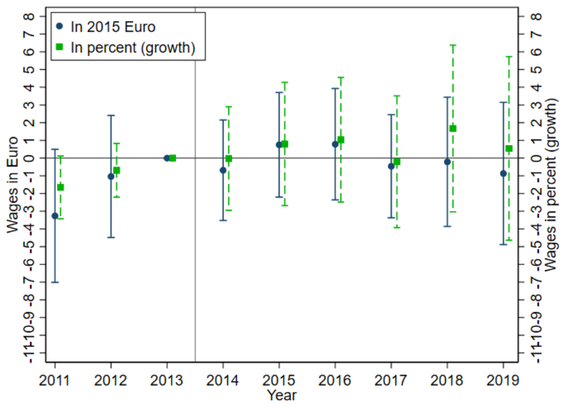
Figure B.7: Wage Changes by Skill Groups



(a) Low-skilled



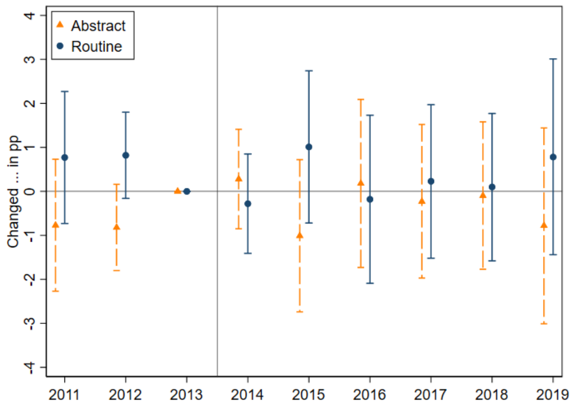
(b) Medium-skilled



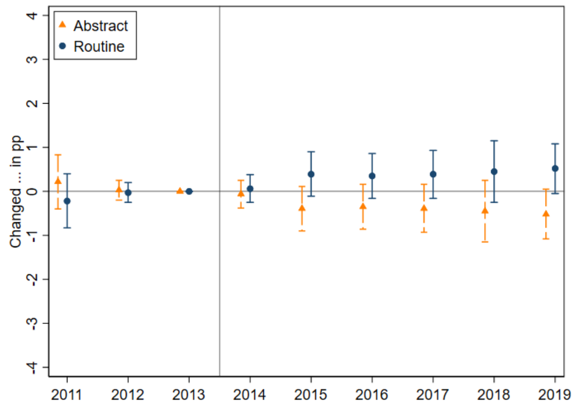
(c) High-skilled

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and corresponding 95% confidence intervals for the yearly regressions using as outcomes changes in wages (in 2015 Euros and in percent change), by skill-levels.

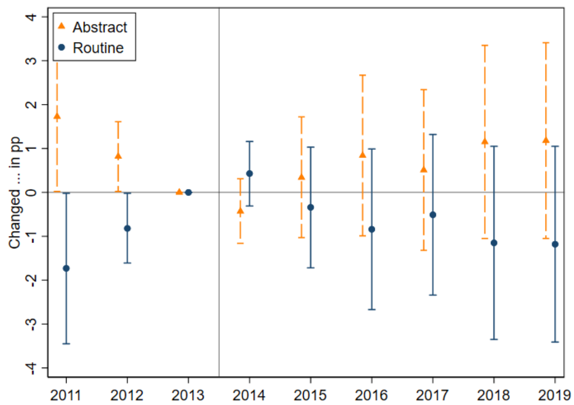
Figure B.8: Change in Main Task Component of the Job by Skill Groups



(a) Low-skilled



(b) Medium-skilled



(c) High-skilled

Notes: The graphs show the IV coefficients for $\beta_t * 100$ from equation 1 and corresponding 95% confidence intervals for the yearly regressions using as outcomes changes in the job's main task, by skill-levels. We grouped analytical non-routine and interactive tasks as "abstract", and cognitive routine, and manual (routine and non-routine) tasks as "routine".

C Sensitivity Checks

Table C.1 shows our main results using different specifications of the instruments and adding further covariates. The first row shows our main results for comparison.

Using the Distances to the 2014 BAMF Branch Offices. Since the BAMF opened new branch offices in 2015–2016, the concern might be that the offices in place in 2016 are less exogenous than the ones already in place in 2014. Therefore, we rebuilt our instrument using only the distances to the BAMF offices already in place in 2014. It is worth noting that the new offices usually enlarged the already existing branch offices. The second row of table C.1 shows the results. The instrument has less power (smaller F-stat), but the results remain very similar.

Using EASY Arrivals as Shift. The current instrument is built using the AZR data provided by the BAMF. As mentioned in Section 2, these data might suffer from a lag in reporting, given that asylum-seekers were not immediately registered after arrival. The EASY data would provide a more accurate picture of the precise time of arrival. However, from anecdotal evidence, we know that in many cases, the EASY registration also had to be done ex-post (after the actual arrival and even allocation of refugees). Furthermore, the AZR data might provide a more accurate picture since refugees might have had registered until the end of 2016. Since both datasets have pros and cons, we use the EASY arrivals instead of the AZR data as the ”shift” part of our instrument for comparison. The third row of Table C.1 shows these results. Again, the instrument has a smaller F-stat, but the point estimates remain very similar.

Inclusion of Further Regional Covariates. We include further regional covariates to check that we are not omitting any relevant regional variable. Our results remain largely unchanged, including further regional covariates (population density, GDP pc, female share, unemployment rate, etc.). See the fourth row of Table C.1.

Using only 1-digit Industry FE. Since we lose some observations when including FE interactions at the 2-digit industry, we re-estimate our results using only 1-digit industry FE in our interactions (see the bottom of table C.1). The results remain largely unchanged.

Using a TWFE specification. Finally, we use a two-way fixed-effect model to check sensitivity of our empirical strategy to a different model. We estimate the following equation, where the base year is 2013 and the year*shock interactions are instrumented by interactions of year*instrument:

$$y_{idt} = \alpha_i + \phi_t + \sum_{r=-2}^{-1} \beta_r S_{d,1416} + \sum_{r=1,r\neq 0}^{6} \beta_r S_{d,1416} + \epsilon_{idt} \tag{3}$$

Figure C.1 shows the results. Overall, the results follow a very similar pattern than the ones from our main specification (see Figure 4), but the point-estimates of the TWFE model are slightly larger and statistically significant at the 5% level throughout the post-treatment period. On average, the estimates from our preferred long-differences model are 0.64 pp. while the average of the TWFE post-treatment coefficients are 1.29 pp. Almost twice as large, as in our main specification.

Figure C.1: Robustness: TWFE Specification on Employment

Notes: The graph shows the OLS and IV coefficients for $\beta_r * 100$ from equation (3) for the two-way fixed effects model. The sample consists of 469,281 individuals who were observed in SIAB in 2013 (employed or unemployed).

Table C.1: Robustness: Results using Different Variations of the Instrument and Covariates

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Main results (2 dig WZ)	0.0006	-0.0017	.	0.0021	0.0100**	0.0059*	0.0072*	0.0061**	0.0072**
	(0.0024)	(0.0019)	.	(0.0019)	(0.0032)	(0.0031)	(0.0040)	(0.0029)	(0.0036)
F-stat					21.7818				
Using 2014 distances	-0.0008	-0.0035	.	0.0027	0.0080**	0.0096**	0.0094	0.0075**	0.0088*
	(0.0027)	(0.0023)	.	(0.0028)	(0.0035)	(0.0048)	(0.0064)	(0.0037)	(0.0051)
F-stat					15.3718				
Using EASY shift	0.0037	0.0001	.	0.0020	0.0103**	0.0044	0.0067	0.0039	0.0047
	(0.0030)	(0.0024)	.	(0.0021)	(0.0041)	(0.0034)	(0.0042)	(0.0031)	(0.0036)
F-stat					14.2728				
Adding more covars	-0.0018	-0.0042**	.	0.0023	0.0107**	0.0067*	0.0087*	0.0075**	0.0087**
	(0.0025)	(0.0020)	.	(0.0022)	(0.0040)	(0.0037)	(0.0048)	(0.0033)	(0.0041)
F-stat					20.5327				
N					469,281				
Main results (1 dig WZ)	0.0003	-0.0020	.	0.0025	0.0107**	0.0063*	0.0077*	0.0067**	0.0080**
	(0.0024)	(0.0020)	.	(0.0020)	(0.0037)	(0.0033)	(0.0043)	(0.0030)	(0.0039)
F-stat					21.6943				
N					469,570				

Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019. The upper panel shows our main results using the distances to the 2016 BAMF offices. Instead, the second row uses distances to the 2014 BAMF offices. The third row uses the EASY-arrivals as the shift part of our instrument instead of the AZR aggregates. The fourth row adds more regional covariates (GDP per capita, population density, female share, unemployment rate). The bottom panel uses only 1-digit industries for the fixed-effects interaction in our main specification. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C.2: Heterogeneities by sex, Age, and Skills, for the Un- and Non-Employed in 2013

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Males	0.005	-0.005	.	0.0003	0.0024	0.0033	0.0063	0.0003	0.0082
	(0.0052)	(0.0052)	.	(0.0081)	(0.0061)	(0.0062)	(0.0074)	(0.0078)	(0.0078)
KP F-stat					28.385				
N					38,346				
Females	-0.0028	0.0028	.	-0.0057	-0.0088	-0.0197*	-0.0247**	-0.0227**	-0.0225**
	(0.0043)	(0.0043)	.	(0.0051)	(0.0082)	(0.0107)	(0.0112)	(0.0090)	(0.0101)
KP F-stat					26.164				
N					47,397				
Age group 1	0.0063	-0.0063	.	-0.008	-0.0046	-0.0190*	-0.0244**	-0.0249**	-0.0155
	(0.0040)	(0.0040)	.	(0.0067)	(0.0083)	(0.0106)	(0.0105)	(0.0091)	(0.0100)
KP F-stat					24.836				
N					35,246				
Age group 2	-0.001	0.001	.	0.0003	-0.0052	-0.0085	-0.0042	-0.0086	-0.0059
	(0.0050)	(0.0050)	.	(0.0071)	(0.0067)	(0.0081)	(0.0082)	(0.0092)	(0.0101)
KP F-stat					28.287				
N					31,518				
Age group 3	-0.0100**	0.0100**	.	0.002	0.0030	0.0135	0.0099	0.0107	0.0036
	(0.0042)	(0.0042)	.	(0.0105)	(0.0096)	(0.0110)	(0.0109)	(0.0094)	(0.0091)
KP F-stat					27.8624				
N					18,979				
Low-skilled	-0.0017	0.0017	.	-0.0048	-0.0057	-0.0123*	-0.0061	-0.0036	0.0042
	(0.0026)	(0.0026)	.	(0.0065)	(0.0075)	(0.0066)	(0.0067)	(0.0075)	(0.0084)
KP F-stat					28.0505				
N					25,671				
Medium-skilled	0.0041	-0.0041	.	0.004	0.0071	0.0014	-0.0067	-0.0105	-0.0102
	(0.0038)	(0.0038)	.	(0.0060)	(0.0084)	(0.0086)	(0.0092)	(0.0096)	(0.0091)
KP F-stat					28.719				
N					52,666				
High-skilled	-0.0207	0.0207	.	-0.0049	-0.0306	-0.0255	-0.0074	-0.0143	-0.0116
	(0.0155)	(0.0155)	.	(0.0207)	(0.0331)	(0.0318)	(0.0072)	(0.0073)	(0.0085)
KP F-stat					12.0073				
N					7,271				

Notes: This table shows the results for coefficients for β_t of equation 1 for the years 2011–2019, for the pooled subsample of the unemployed and non-employed in 2013. The outcome is being full-time employed (difference of the current year minus the pre-treatment average). Each panel shows the results by gender, age, and skills. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$