Market Structures, Prejudice, and the Residual Wage Gap Between Refugees and Natives

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Working Paper †

July 5, 2026

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Abstract

I exploit regional variation in Germany to estimate the impact of labor market structures and prejudice on both the overall and residual wage and employment gaps between refugees and natives. I first demonstrate that persistent wage and employment gaps exist for more highly educated refugees after controlling for demographic differences. Highly educated refugees receive substantially lower returns to their accumulated human capital outside of Germany than highly educated natives, indicating that vocational training requirements and language barriers may form a significant obstacle to entry into highly skilled professions. Furthermore, there exists significant variation by region, implying that certain local conditions are favorable or unfavorable for refugees. Using survey responses on social attitudes toward refugees, I do not find evidence that higher regional prejudice increases the wage gap. However, overall wage gaps and residual wage gaps are lower in regions with more binding minimum wages, while employment gaps are unaffected. I also find suggestive evidence that the overall wage gap is lower in regions with higher union coverage. Residual wage gaps may also be higher in regions with stronger vocational degree requirements for highly skilled workers. These results indicate that labor markets characterized by greater wage compression and fewer vocational training requirements are conducive to reducing refugee–native disparities.

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†I would like to thank Francine Blau, Michèle Belot, Lawrence Kahn, Plamen Nikolov, Leila Salarpour, Evan Riehl, Seth Sanders, and all others who have provided helpful feedback and guidance. Any mistakes are my own.

I. Introduction

Since 2014, the integration of refugees has become a key policy concern in several European countries. This is particularly true in Germany: between 2014 and 2023, more than 2.7 million asylum applications were received. The greatest spike during this period came in 2015 and 2016, when 800,000 Syrians, fleeing civil war, arrived in Germany. In subsequent years, new asylum applications ranged in the hundreds of thousands, from a low of 120 thousand in 2020 to over 350 thousand in 2023.[1] While the inflow of new refugees has ebbed in more recent years, many refugees from last decade's surge have remained in Germany. These refugees have faced greater difficulties in integrating into host country labor markets than other immigrants: Brell et al. (2020) document that the average refugee wage in many developed countries is as low as half the average native wage. Furthermore, they show that the wage gap may persist even after refugees spend significant time in some countries, including Germany. Similarly, Ruiz and Vargas-Silva (2018) estimate a persistent residual wage gap between more recent refugee cohorts and natives after controlling for observable characteristics. These gaps contrast with patterns from earlier refugee cohorts. For instance, Cortes (2004) finds that refugees who arrived in the United States between 1975 and 1980 had worse outcomes than other immigrants upon arrival but were able to catch up as they spent more time in the country, and they even closed the earnings gap with similarly educated U.S. natives.

Variation in overall and residual gaps across countries may be caused by several factors, such as prejudice, language barriers, occupational licensing restrictions, cultural differences, lower human capital of the specific refugee cohort, or transferability of human capital across countries. Any one of these factors may render the prior schooling obsolete in the new host country if employers are unwilling to hire highly-educated refugees. This concern is of particular relevance for Germany: I demonstrate that the residual wage gap is primarily driven by highly-educated refugees not receiving the same returns to education as natives with the same years of schooling.

While this residual gap does gradually diminish over years since migration in Germany, it remains very large for several years. Given that more recent refugee cohorts in Germany struggle relative to similarly educated Germans for such an extended period, it is worthwhile to examine factors that may ameliorate the residual gap as they slowly integrate into the labor market. Germany is an ideal country to investigate such factors: as I document, significant regional variation in wage and employment gaps exists within the country. I therefore exploit regional variation in social, institutional, and economic characteristics across the 38 administrative divisions within Germany over time.[2] I first estimate the effect of region-level prejudice and social norms on the residual refugee wage and employment gaps. I do so by

[1]See the December 2025 Current Figures report from The Federal Office for Migration and Refugees (BAMF) for more details on asylum statistics by year.

[2]As a robustness check, I also run my analysis by instead aggregating to the more granular 96 spatial planning regions within Germany. This has the advantage of producing more observations in the second stage, but it comes at a cost of precision in the first stage, in which I estimate wage and employment gaps. In many cases, I must drop specific spatial planning region-year cells since there are too few refugees in the data.

following the approach from Charles and Guryan (2008): I use survey questions on social attitudes regarding refugees to create an aggregated prejudice index at the regional level. I then regress regional residual wage gaps on my generated prejudice measures. According to Becker's (1957) theory on employer discrimination, only the "marginal" percentile of prejudice in a given region, which corresponds to the proportion of refugees in the workforce, should affect residual wage gaps. I therefore regress my estimated residual gaps on several percentile measures of prejudice. However, I do not find evidence that residual wage gaps are larger in regions with higher prejudice, and I find only very limited evidence of an effect on residual employment gaps.

I next test whether regional differences in institutions and labor market structures play a role. I do so by evaluating how the residual gap may be affected by regional variations in minimum wage bites, union coverage, and the prevalence of vocational degree requirements within highly skilled occupations. I ultimately find that both the overall wage gap and the residual wage gap after controlling for educational and demographic differences are lower in regions in which minimum wages are more binding. I also find no evidence that higher minimum wage bites increase overall or residual employment gaps. While there are some indications that greater union coverage reduces the overall gap, it does not appear to affect the residual gap. Finally, my results suggest that the residual gap may be lower in regions with lower vocational degree requirements for highly skilled occupations. These results imply that more compressed wage structures lower the gap between refugees and natives. Furthermore, since the residual gap is primarily concentrated among highly educated workers, greater vocational training restrictions specific to Germany may prevent otherwise skilled refugees from exploiting their accumulated education. The findings of this paper demonstrate that institutional and labor market conditions are important in shaping refugee labor market outcomes and in facilitating integration.

This paper contributes to the literature in three ways. First, it connects research on refugee outcomes with a body of prior literature studying the effect of minimum wage bites and union coverage on wage and employment gaps. Second, it demonstrates that wage-setting structures may be of greater importance to refugee labor market integration than prejudice. Third, it provides evidence that greater vocational training requirements in highly skilled fields may increase wage disparities between highly educated refugees and natives. Ultimately, this paper highlights the importance of labor market structures in ameliorating refugee-native wage gaps.

II. Background and Literature Review

It has long been understood that the differences in the labor market outcomes between immigrants and natives vary by cohort. Borjas (1987) was the first to apply the Roy Model to demonstrate that the immigrant-native wage gap can depend on the setting and the type of immigrant. Interestingly, refugees may be positively selected in this model: they may be highly skilled individuals who are nevertheless on the lower half of the income distribution within their home-country income distribution due to persecution. In such a case, Borjas (1987) predicts that refugees will move to new countries where they integrate into the upper half of the income distribution.

Despite this prediction, refugees in many cases earn lower wages than natives upon entry into the host country, and they do not necessarily fully catch up in terms of overall earnings and employment. Brell et al. (2020) record the mean wages of refugees by years since migration in the United States, Canada, and a number of European countries. Their results indicate that, while refugee earnings often increase relative to native earnings with years since migration, they do not reach the average earnings levels of natives in most developed countries. This discrepancy cannot always be explained by observable characteristics: other studies focusing on specific countries find that, even after controlling for differences in education and years since migration, a gap remains. For instance, Ruiz and Vargas-Silva (2018) show that refugees in the United Kingdom (many of whom immigrated in the early 2000s) lag behind similarly educated Britons in earnings, even after extended years of residence.

There are several potential reasons why the residual gaps for refugees may diverge over time and region. For one, it is possible that more recent cohorts enter countries in which their accumulated skills are not easily transferable to the new labor market. Furthermore, even if these refugees were otherwise qualified for high-skilled positions, it is also possible that their new host countries require different credentials for certain occupations, credentials that they did not obtain in their home countries. Recent cohorts may also lag further behind due to increased wage inequality over time: even if newer refugees are in the same percentile of the wage distribution as older cohorts, a greater residual wage gap could persist if earnings inequality increased over time and if refugees were in the bottom half of the distribution.

Even within certain countries, there may be regional variation in the residual wage gap for members of the same refugee cohort. This variation may be caused by factors that alter the overall wage distribution, such as minimum wage bites, union coverage, or regional differences in occupational structures. Another factor that may be social attitudes among natives regarding refugees: if recent refugee cohorts are exposed to greater discrimination in the labor market, they may have to accept lower wages.

I describe each of these potential factors in more detail below:

Transferability of Human Capital

Unlike other immigrants, refugees do not migrate for economic reasons, but rather in response to a crisis in their home country. As a result, they are unprepared for migration and are sometimes constrained in their choice of host country, which makes it more difficult for them to immigrate to countries advantageous to their accumulated skills. Borjas (1982) emphasizes this issue when he likens refugees to workers who are unexpectedly laid off and are thus unprepared for job search. This issue is especially pertinent for the recent cohort in Germany: there is a significant linguistic distance between German and Arabic, which means that a majority Middle Eastern cohort may find it more difficult than previous cohorts to learn the language.[3] Furthermore, high-skilled occupations in Germany often require

[3] Despite having access to self-reported measures of fluency in German, I do not address the causal effect of language ability in this paper due to the significant measurement error of self-reported fluency,

country-specific vocational certifications. Since these refugees do not initially possess these certifications, they may experience lower returns to their education and accumulated skills upon arrival than those of natives. Third, even if these requirements were not in place, employers may not value educational attainment from colleges in less developed countries.

If the transferability of accumulated human capital were the only issue affecting refugees, one might still expect them to converge toward native earnings as they invest in host country-specific human capital. Cortes (2004) asserts that refugees who entered the United States between 1975 and 1980 faced high marginal returns to adjusting their human capital to the host nation. Additionally, since some refugees may expect to stay in the host country longer than non-refugee immigrants, they may have a stronger incentive than non-refugee immigrants to invest in host country-specific human capital. Chin and Cortes (2015) further show that more rapid refugee upgrading in the wage distribution is positively correlated with investment in language skills and post-migration education.

It does not appear that such convergence in earnings occurs in other settings. Ruiz and Vargas-Silva (2018) find that the wage gap between natives and refugees in the United Kingdom persists over time. Furthermore, when documenting mean wages, Brell et al. (2020) find that refugee earnings in countries like Germany and Canada did not significantly improve relative to natives, at least in the first several years. They also show that large employment gaps for refugees compared to natives and other immigrants persist across many European nations. These findings suggest that more recent refugee cohorts face unique challenges to integration.

Prejudice

One factor that may partially explain regional variation in refugee-native gaps is prejudice. Discrimination arising from social attitudes against culturally different workers may be particularly pertinent, as prior research has shown that firms in multiple countries may discriminate against foreign workers. For instance, Oreopoulos (2011) uses a résumé field experiment in Britain and finds that employers are 40 percent less likely to call back foreign-sounding names. He also finds that statistical discrimination cannot fully explain this discrepancy. Taste-based discrimination is of particular concern for the newer, primarily Syrian refugee cohort, who may be settled in locations where the locals are not accustomed to non-Western cultures. For instance, Koopmans et al. (2019) analyze job vacancy selections among employers in Germany and find evidence of taste-based discrimination against those with "non-German" cultural values. Furthermore, Cumming and Heidinger (2025) exploit 2016-2023 SOEP survey data for Germany and show that perceived workplace, job-search, and housing discrimination among refugees, along with concerns about xenophobia, have increased since 2018.

Despite this concern, there are not many papers that directly estimate the effect of prejudice on residual wage gaps. Part of the reason for this is the difficulty in finding survey

the endogeneity of language skills with unobserved ability, and the lack of a suitable instrument for first-generation migrants. See Chiswick and Miller (1995), Dustmann and Van Soest (2002), and Yao and van Ours (2015) for discussions on the challenges of measuring the effect of fluency on labor market outcomes.

data that captures attitudes toward the specific group being analyzed. Charles and Guryan (2008) accomplish this by combining labor market data with a survey on prejudiced attitudes toward Black workers in the United States. They ultimately conclude that up to a quarter of the residual Black-White wage gap across U.S. states can be explained by prejudice. They empirically demonstrate that the "marginal" level of prejudice in a given region is the key factor: According to Becker (1957), if some employers are prejudiced, there will be a segregated equilibrium in which the discriminated group will work for less prejudiced employers. Thus, an increase in the median level of prejudice, all else being equal, should not impact the outcomes of the discriminated group if that group constitutes a minority of the workforce that is already sorted into less prejudiced firms.[4] Instead, the gap should be affected by an increase in the percentile of prejudice that corresponds to the proportion of workers who are members of the minority class. This implies that the marginal level of prejudice is on the lower tail of the distribution. [5]

While these predictions may hold for some minority groups, it is not clear that this model of discrimination would apply to recent refugees. Even with the large increase in asylum applications, refugees in Germany comprise less than two percent of the population and an even smaller share of the employed workforce. They thus likely do not have to compete as intensely for scarce job openings from non-prejudiced employers. In fact, the effect of prejudice on refugees may produce counterintuitive indirect effects for employment and wages: while prejudice may lead to discriminatory hiring practices, if refugees face greater pressure to assimilate culturally in order to avoid hostility from natives, higher average levels of prejudice could lead to faster human capital accumulation through increased fluency in the host-country language. Jaschke et al. (2022) construct an index designed to capture the extent to which refugees in Germany are threatened by natives. They find that refugees living in regions with higher threat indices are more likely to culturally assimilate but are not more likely to earn higher wages. This finding indicates that the labor market effect of prejudice may be reduced by competing mechanisms.

Empirical estimates of the effect of prejudice on residual gaps are relatively sparse in the immigration literature. To my knowledge, no study has applied Charles's and Guryan's (2008) strategy to the more recent cohorts of refugees arriving in 2014 or later. The only paper related to immigration that directly replicates Charles and Guryan (2008) is Carlsson and Roof (2016). They create an aggregate prejudice measure against first-generation and second-generation immigrants at the municipal level in Sweden. Like Charles and Guryan (2008), they find that the marginal level of prejudice corresponding with the proportion of workers who are immigrants explains a noticeable portion of the residual wage gap. That said, it must be noted that their findings are based on a sample that excludes immigrants with fewer than 15 years of residence. Their results may not apply to recent refugee cohorts.

[4]Note that this result does not necessarily apply if taste-based employer discrimination is not the driving factor. In fact, there may be other forms of taste-based discrimination that produce effects at the median. See my brief discussion on alternative mechanisms in Appendix B for more details.

[5]This framework also implies that an increase in the discriminated population, all else being equal, should negatively impact minority outcomes, as there would be fewer jobs available from non-prejudiced employers.

Local Labor Market Structures

In addition to prejudice, regional variation in Germany's wage and employment structures may cause differences in the residual wage gap between refugees and natives. For instance, if refugees are more concentrated on the left tail of the wage distribution, their wages would be disproportionately uplifted by minimum wages. Previous work has found that minimum wage bites, defined as the difference between minimum wages and the median wage and designed to capture how often the minimum wage binds, are an important factor in explaining pay gaps. Blau et al. (2026) exploit variation in effective minimum wages across U.S. states to investigate the effect on Black-White and male-female wage gaps. They find that women and Black workers in the lower tail of the female wage distribution are closer in wages to men and White workers at the same percentile in the male distribution in states with higher minimum wage bites. A similar approach is feasible for investigating wage gaps in Germany: beginning in 2015, Germany implemented a national minimum wage. While this wage floor has periodically increased to adjust for inflation, there is only one national nominal minimum wage in Germany. Still, the minimum wage bite varies geographically due to significant regional differences in the median wages across regions within Germany.[6]

Prior research has found that the 2015 implementation of the minimum wage in Germany led to increased wages and lower wage inequality within Germany, with only marginal decreases in employment (Bossler and Gerner 2020; Bossler and Schank 2023; Caliendo et al. 2025). Despite having a small effect on overall employment, there is evidence that the minimum wage policy led to a decline in "minijobbers," workers who make under 450 euros per month (Bossler et al. 2026). Thus, if refugees are more likely to be among this group, then higher minimum wage bites may be associated with large employment gaps.

If refugees are more concentrated in the left tail of the wage distribution, the residual gap may also be affected by variation in collective bargaining coverage. In Germany, about half of all workers are represented by a union, even though far fewer are dues-paying members. Prior research has found that higher union coverage is associated with lower pay gaps: when investigating international differences in the gender pay gap, Blau and Kahn (2003) find evidence that women perform comparatively better in countries with more centralized wage structures and higher union representation. Even so, these findings may not hold for refugees. For one, the effect of union representation is theoretically ambiguous. While workers on the left tail of the wage distribution may be lifted up, it is possible that refugees disproportionately work in occupations less likely to be covered by collective bargaining agreements.[7] If so, unions would disproportionately raise native wages relative to those of refugees, thereby increasing the residual wage gap. Furthermore, if widespread union coverage leads to a glut in labor supply, new entrants into the labor market with lower accumulated skills, such as refugees, may find it relatively more difficult to gain employment. Unions may also increase the residual employment gap. Suppose, for instance, that refugees initially struggle to acquire host-country-specific skills such as language fluency. In a more

[6]Many regions in former East Germany, for instance, have lower median wages than other regions.

[7]I am unable to precisely evaluate this possibility due to the small number employed refugees combined with the relatively low survey response rate for a question asking whether the respondent's wage was determined by a collective bargaining agreement.

flexible, more competitive labor market, they would earn lower wages to compensate. But if unions drive entry-level wages above that level, firms will not have an incentive to hire refugees. For these reasons, the theoretical effect of more centralized wage structures on residual gaps is ambiguous.

Finally, it is possible that barriers to entry specific to host countries may lower refugee employment and wages. This is of particular importance in Germany, where many occupations have specific vocational degree or occupational licensing requirements. Previous work has found that lowering such barriers can improve refugee labor market outcomes: Runst (2018) finds that deregulation of occupational licensing for certain crafts occupations increased immigrant employment in those fields. Refugees may thus be at a greater disadvantage in regions where more highly skilled occupations require specific qualifications, qualifications that they would not have been able to gain outside of Germany.

Refugee Settlement within Germany

Many countries in Europe quasi-randomly settle new asylum seekers into different regions and municipalities. This is the case in Germany, in which refugees are randomly allocated across the 16 federal states in proportion to a combination of the state-wide population and tax revenue.[8] Refugees are then further randomly allocated into districts within each state. Before 2016, refugees were allowed to take up residence outside of their originally assigned state after three months in Germany. However, the government passed the Integration Act in 2016, which extended this period to three years. And in seven states, laws further stipulate that refugees cannot reside outside of their initial municipality for a set period of time.[9] Exceptions exist: exemptions can be granted for employment reasons, the restrictions do not always preclude residence changes within a given state, and it may be difficult to enforce residency requirements. Nevertheless, the exogenous variation in the initial placement of refugees, along with initial residence restrictions, partially assuages concerns about selective migration within the country. Furthermore, this random placement helps address a concern from Charles and Guryan (2008): it is less likely that refugees living in regions with different prejudice levels differ in unmeasured characteristics that are correlated with labor market outcomes.

III. Data

I exploit data on both prejudice and labor market outcomes from the 2007-2024 waves of the German Socio-Economic Panel (SOEP), including the IAB-SOEP Migration Samples and the IAB-BAMF-SOEP Survey of Refugees. These are a series of longitudinal surveys

[8]The exact proportion allocated to each state is based on the BAMF's Königsteiner Schlussel formula. See Albarosa and Elsner (2023) for more details.

[9]Interestingly, these policies may themselves explain some of the residual wage gap. The intent of these policies was to discourage segregation into communities and encourage integration into German society, but an analysis by the Institute of Employment Research (2020) finds that the restrictions are associated with a decrease in employment and have no positive effect on German fluency.

consisting of both a general population sample and several supplementary immigrant samples. They contain data on earnings, employment, age, education, marital status, number of children, and many other covariates related to work, health, politics, attitudes, and family composition. Also included are five-digit KLDB occupational classifications. The first two digits of this code describe the broad type of occupation that an employee has (e.g., agriculture, fishing or forestry). The third digit narrows the classification further to occupational groups (e.g., farming). The fourth digit specifies an occupational subgroup (e.g., technical farming), and the fifth digit specifies the level of skill required for the occupation on a scale from 1 to 4. Specifically, a 1 indicates that the occupation does not require any education or vocational training, while a 2 indicates that the task involved requires at least two years of vocational training. A 3 indicates that highly specialized vocational training is typically required, and a 4 indicates that the tasks involved require a university degree.

Finally, the SOEP includes a question asking whether a respondent's wages are covered by a collective bargaining agreement, although the question was not asked in the 2020 and 2022 surveys. Apart from the SOEP, I use data on minimum wages in Germany from the German Federal Statistical Office.[10]

Since the SOEP does not directly report hourly wages, I construct a close proxy. Hourly wages are calculated by dividing monthly earnings at the time of the survey by actual hours worked per week and by 4.3 to assume a full working month. The resulting wages are winsorized at one third of the first percentile and three times the 99th percentile.[11] Wages are also inflation-adjusted to 2012 euros.

Migrant cohorts

In 2013, the SOEP introduced the first of several migration samples, which collect data on first-generation immigrants who arrived after 1994. This was followed by a sample of immigrants in 2014 who entered Germany between 2010 and 2013. In 2015, the first IAB-BAMF-SOEP sample, consisting primarily of recent refugees, was introduced. Along with previous migration samples, the refugee sample over time has been tracked and supplemented with additional refugees. Most refugees in my 2017-2024 sample are Syrian or Ukrainian, although a significant share are also from Afghanistan, Iraq, and East Africa. The migration samples record, among many other immigrant-specific variables, the year of migration into Germany, the country of origin, self-reported German reading, writing, and speaking ability (on a scale from one to five), and whether refugees took an integration course offered by the BAMF.

My sample universe consists of natives and of refugees ages 18 to 64 from survey years 2017 to 2024, and I only include refugees who immigrated in 2014 or later. I do not extend my analysis before 2017 because (1) most refugees were first surveyed in 2016 or later and

[10]The German minimum wage is sometimes increased during the middle of a calendar year. When this happens, I define the minimum wage for that year as a weighted average of the old and new wage based on the number of months each was in place.

[11]This approach for imputing hourly wages is the recommended method by DIW Berlin, the organization that conducts the SOEP surveys.

immigrated in 2015 or 2016, and (2) legal restrictions limit asylum seekers' ability to work during their first year in Germany.[12] I also use the 2016 survey year purely to evaluate native attitudes toward refugees, as that set of questions was asked in 2016 but not 2017.

Regional Level of Interest

Most papers that study the labor market effects of minimum wages or social norms within the United States evaluate aggregated data at the state level. This approach does not provide sufficient variation in Germany, as there are only 16 federal states, designated as NUTS1 regions for administrative purposes. Luckily, the remote-accessible version of the SOEP also includes regional indicators that are subdivided within the 16 states. These include the 38 NUTS2 government region / administrative districts of Germany, 96 spatial planning regions of Germany, and 401 smaller administrative districts. I elect to use the larger NUTS2 government regions to avoid sample size restrictions, as the SOEP does not include sufficient employed refugee observations for many of the more granular regions.[13] Since refugee residency is initially limited to the state of initial assignment, using the larger regions somewhat mitigates concerns of selective out-migration between smaller districts within the same state.

Aggregation of Prejudice Data

Before an aggregate regional measure of prejudice can be created, I first consider how to measure the level of prejudice of an individual in Germany. The SOEP is particularly advantageous for this purpose, as it includes survey data on a series of questions that gauge social norms, politics, and attitudes toward foreigners. For instance, respondents are asked annually about the political party they support in Germany. In addition, for every year since 1999, the SOEP asks respondents on a scale of one to three if they are (1) worried about immigration into Germany and (2) concerned about hostility towards foreigners. In addition, the 2016, 2018, and 2020 surveys include five questions specifically regarding attitudes toward refugees. These questions are all scaled from 1 to 10 and ask whether refugees are good for (1) Germany, (2) the economy, (3) culture, (4) in the short-run, and (5) in the long-run. I use these five refugee-specific questions for my primary prejudice index specification. An underlying assumption in using these questions is that the survey responses are not affected by regional variations in recent refugee inflows, and more specifically by regional variations in the labor market outcomes of new refugees. Since this is admittedly a very strong assumption, I also run a robustness check in which I use 2007-2014 survey responses to the two more general immigration questions as lagged proxies for attitudes toward refugees.

[12] In practice, very few surveyed refugee observations from 2016 or earlier were employed, making it infeasible to accurately estimate regional refugee-native gaps for any region in 2016 or earlier.

[13] I use the 96 spatial planning regions as a robustness check in my second-stage estimates. See the supplementary tables in Appendix A for more details.

IV. Empirical Strategy

The Residual Gap

I begin with a descriptive evaluation of the wage and employment gaps between refugees and natives. First, I estimate the residual gap between natives and recent refugees in a pooled regression. I do so using the following specification for all natives and refugees ages 18 to 64 who are surveyed between 2017 and 2024:

$$Y_{ict} = \alpha_0 + \alpha_1 Ref_i + \alpha \mathbf{X'_{ict}} + \delta_c + \delta_t + \epsilon_{ict} \tag{1}$$

Y_{ict} can represent either employment or the log real hourly wage (inflation-adjusted for 2012 euros) of individual i in region c and in year t, depending on the specification. Ref is a dummy variable indicating whether the individual is a refugee, δ_c and δ_t are spatial planning region and year fixed effects, and $\mathbf{X'_{ict}}$ is a vector of individual characteristics that includes age, age squared, education, gender, marital status, number of children in the household, and an interaction of gender with the latter two covariates.[14] ϵ_{ict} is an error term. The estimated coefficient $\hat{\alpha}_1$ represents the difference between refugee and native outcomes after controlling for differences in observable characteristics and for region and year fixed effects. I refer to this value as the residual gap or refugee penalty.

To evaluate potentially heterogeneous returns to education, I include in some specifications an interaction between refugee status and the education level. Note that since heterogeneous returns to education may themselves be affected by regional variations in prejudice or labor market structures, I do not include these interactions when evaluating the potential factors that may affect the residual gaps.[15]

In all cases for my individual-level estimates in this paper, survey weights are used, and standard errors are clustered at the NUTS2 region level in my primary specifications. As a robustness check, I often include in the appendix alternate specifications at the more granular spatial planning region level. For all second-stage estimates at the regional or region-by-year level, I weight by the inverse variance of the first-stage residual gap estimates. For all estimates involving refugee gaps, I only include region or region-by-year cells that have at least five refugee observations with wages.

[14] The SOEP imputes years of education based on whether an individual has completed secondary education, has obtained at least some post-secondary school education, or has earned some advanced degree. Instead of using these imputed values, I elect to use dummy variables indicating whether an immigrant has (1) only completed secondary education or (2) has had at least some post-secondary education. Using the imputed values for education does not materially affect the results.

[15] As an alternative, I implement a twofold Blinder-Oaxaca decomposition to characterize the overall gap and the extent to which differences in characteristics and returns to characteristics, particularly for education, play a role. The results using this approach can be found in Appendix Table A2, and I describe the decomposition in more detail in Appendix B. I do not use this approach to calculate the first-stage residual gaps described later because many region-year cells in my data have only a limited sample of refugee observations, and the decomposition requires separate regressions for refugees. I report the equation (1) results to provide consistency with my later residual gap calculations.

Estimating the Effect of Prejudice

After evaluating both the overall refugee–native wage gap and the residual gap, along with corresponding employment gaps, I determine whether regional variation in the residual gaps can be partially explained by prejudice against refugees. I therefore estimate the effect of prejudice at the region level by computing region-specific residual gaps across the pooled 2017-2024 time period, following the approach from Charles and Guryan (2008):

$$Y_{ict} = \alpha_0 + \alpha_{1c} Ref_i \times \delta_c + \mathbf{X'_{ict}}\alpha + \alpha_{2t} Ref_i \times \delta_t + \delta_c + \delta_t + \epsilon_{ict} \tag{2}$$

Here, Ref denotes refugee status, and the other variables are the same as described in equation (1).

The coefficient of interest, α_{1c}, represents the unexplained log wage gap between natives and refugees in a given spatial planning region c, also known as the refugee penalty for that region. $\hat{\alpha}_{1c}$ is thus the estimated unexplained wage gap in that region. I pool across all years from 2017 to 2024 rather than estimating separate gaps for each region-year cell. I take this approach when evaluating the effect of prejudice because there may be limited within-region variation in underlying prejudice over time, and any trend in survey responses may be driven by reactions to the overall increase in refugee inflow across all of Germany, rather than a true change in the prejudice distribution. In addition, I also only have refugee-specific attitude questions for every other survey year, so estimating the gap for each region-year cell would entail dropping half of all estimated gaps when evaluating the effect of prejudice. I include an interaction between refugee status and the survey year so that my pooled estimated residual gap accounts for national refugee-specific trends over time.

These estimated refugee penalties $\hat{\alpha}_{1c}$ are then used as dependent variables in the following second-stage regression:

$$\hat{\alpha}_{1c} = \tau_0 + \mathbf{Prej'_c}\pi + \epsilon_c \tag{3}$$

Since questions on attitudes regarding refugees are not asked every year, $\mathbf{Prej_c}$ is a vector of aggregated prejudice percentiles measured at the regional level using pooled data from the 2016, 2018, 2020, and 2023 survey waves[16] The vector π contains the primary coefficients of interest, as they capture the relationship between prejudice percentiles and the residual log wage gap.[17]

I follow Charles and Guryan (2008) to create $\mathbf{Prej_c}$. First, I standardize each answer to a given response θ_{ikt} from individual i to prejudice question k in year t, using the 2016 responses as the benchmark for the sample mean and standard deviation:

[16] These are the survey waves that contain the five refugee attitude questions.

[17] In an alternative specification, I also include as a control the estimated fraction of refugees ages 18 to 64 relative to refugees and natives combined. The underlying logic to this specification is that the proportion of refugees in the labor force determines the theoretical marginal level of prejudice. However, there is some concern that this control may be affected by selective out-migration to more promising labor markets. In any case, including it does not affect my results, so I elect to omit it.

$$\dot{\theta}_{ikt} = (\theta_{ikt} - \bar{\theta}_{k16})/\sqrt{var(\theta}_{k16})$$

I average standardized responses across questions for each individual and account for secular changes in survey responses resulting from national changes to refugee inflows by regressing individual-level prejudice on a set of year dummies. In doing so, I obtain a residual prejudice measure designed to reflect true underlying prejudice rather than temporal variation in stated attitudes.

I aggregate individual responses at the regional level to generate prejudice percentiles. Since Becker (1957) predicts that the marginal level of prejudice is a more important determinant of discrimination than the average level of prejudice, I test the following percentile measures:

$Prej_{c05}$ is the 5th percentile within region c between 2016 and 2023.

$Prej_{c10}$ is the 10th percentile within region c between 2016 and 2023.

$Prej_{c50}$ is the 50th percentile within region c between 2016 and 2023.

$Prej_{c90}$ is the 90th percentile within region c between 2016 and 2023.

If Becker's model of employer prejudice applies to immigrants in Germany, one would expect only the "marginal" level of prejudice to matter. Becker's model predicts that this "marginal" percentile corresponds to the proportion of minority workers in a given population. However, refugees make up less than two percent of the population in Germany, and there would not be sufficient variation in aggregated prejudice at the one percentile level across districts to yield precise estimates. Accordingly, I use the fifth percentile as the lowest measure in order to maintain a reasonable level of variation across regions. Even if there were sufficient variation in the first percentile, Becker's theory only holds if the marginal employer has some preference for natives over refugees. It is unclear that this condition would hold for the first percentile employer in even the most prejudiced regions, as they very plausibly would have no discriminatory preference. This implies that with perfect information, refugees may be able to completely sort into non-discriminating firms, which would mean that employer-based prejudice would produce no effect on the residual gap.

Minimum Wage Bites, Collective Bargaining, and Occupational Structures

I next investigate how regional variation in labor market conditions may influence the residual gap. For this, it is not necessary to pool residual gaps across the 2017–2024 survey years for each region since I no longer have to rely on survey questions asked every other year, nor am I analyzing a variable like prejudice, which likely has little true intertemporal variation. It is instead necessary in this case to analyze outcomes separately at the region-year level, as significant intertemporal variation may exist for factors such as minimum wage policies and collective bargaining. I therefore follow a different two-step approach that generates estimated residual gaps for each region-year cell ct. In the first stage, for each of these cells, I estimate the following regression:

$$Y_{ict} = \rho_0 + \rho_1 Ref_i + \mathbf{X'_{ict}}\rho + \epsilon_{ict} \tag{4}$$

The vector $\mathbf{X_{ict}}$ contains the same set of covariates as in equation (1). I repeat this approach for all regions and survey years from 2017 through 2024, so long as the given region-year cell contains at least five refugee observations with wages. This approach yields 280 estimated residual gaps $\hat{\rho_{ct}}$ between refugees and natives, and 210 gaps if I exclude survey years 2020 and 2022 due to their lack of a union coverage variable.

In the second stage, I regress these estimated gaps on region and year fixed effects and a series of variables designed to capture differences in labor market structures across regions and over time:

$$\hat{\rho}_{ct} = \lambda_0 + \lambda_1 bite_{ct} + \lambda_2 SQbite_{ct} + \lambda_3 Union_{ct} + \lambda_4 HSVOC_{ct} + \lambda_c + \lambda_t + \epsilon_{ct} \tag{5}$$

Standard errors are clustered at the region level, and estimates are weighted by the inverse variance of the estimated gaps in the first stage. My market structure variables are the following:

bite represents the minimum wage bite. This is calculated by taking the difference between the federally-set log minimum wage and the log median wage in each region among workers ages 18 to 64. The underlying intuition for this construction is that a statutory minimum wage lifts more workers up in regions where the prevailing wage structure is lower. *SQbite* is the square of this term.[18] Since refugees are concentrated in the lower portion of the wage distribution, higher minimum wage bites may disproportionally raise refugee wages and thus lower the gap.

Union represents the estimated proportion of employed natives ages 18 to 64 who are covered by some collective bargaining agreement. I do not include this variable in every specification since it is not available in survey years 2020 and 2022. If union coverage compresses the bottom of the wage distribution, then this variable should be associated with a lower wage gap. On the other hand, if refugees are disproportionately concentrated in less unionized jobs, increased union coverage may benefit native worker wages with no gain for refugees, thus widening the gap.

Finally, *HSVOC* is a proxy for the intensity of vocational degree requirements among high-skilled workers by region and year. My reason for creating and including such a proxy is that since the residual gap is primarily driven by differences between highly educated refugees and natives, it may be larger in regions in which highly educated refugees need to gain German vocational training qualifications to enter into high-skill occupations. I create this variable using the five-digit KLDB occupational codes in the following manner:

[18] Autor et al. (2016) emphasize that including the bite as a quadratic term is necessary: since the density of the wage distribution typically increases toward the median, a marginal increase in the minimum wage bite will affect a disproportionately larger number of workers as the bite moves further up along the distribution, implying a non-linear effect.

I begin by restricting my sample to native workers ages 18 to 64 who have a final-digit KLDB occupation code of 3 or 4, implying either employment in tasks requiring extensive specialized training or in tasks requiring a university degree. For each broad occupational category defined by the first digit of the KLDB code, I would ideally calculate by region-year cell the proportion of skilled workers who earned some kind of vocational degree. However, it is possible that refugee migration alters occupational structures in specific regions, implying that the vocational degree intensity of local occupations may be endogenous to refugee labor market outcomes.

I instead create a Bartik-style measure as a proxy for vocational requirement intensity among highly skilled workers. Specifically, for each region-year cell ct, I calculate the share of highly skilled native workers in each region in survey year 2013:[19]

$$Share_{co} = \frac{HSkill_{co}}{\sum_o HSkill_{co}}$$

$HSkill_{co}$ denotes the number of highly skilled native workers employed in occupation o in region c during 2013. Next, for each occupation-year cell from 2017 through 2024, I calculate vocational degree intensity among highly skilled workers:

$$Shift_{oct} = \frac{VOC_{ot}^{-c}}{HSkill_{ot}^{-c}}$$

VOC is an intensity measure denoting the proportion of highly skilled workers who have a vocational degree. VOC_{ot}^{-c} and $HSkill_{ot}^{-c}$ are calculated excluding workers residing in region c to ensure that the occupational intensity measure for each region is not mechanically influenced by its own high-skilled labor composition.

I finally combine the two latter terms into a Bartik-style variable:

$$HSVOC_{ct} = \sum_o Shift_{oct} \times Share_{co}$$

Regions with higher values of $HSVOC$ will have high-skill occupations that are more likely to require vocational qualifications as opposed to only college degrees.[20] If German vocational credentials constitute a barrier to highly educated refugees, then regions with higher vocational degree intensity may have larger residual wage and employment gaps.

All three of my independent variables of interest are generated using the SOEP survey data. This leads to a trade-off in choosing the level of region for aggregation: while aggregating to the NUTS2 level leads to fewer aggregate observations and larger standard errors, aggregating to the spatial planning level yields less precisely estimated independent variables, risking greater attenuation bias. I therefore run my estimations using both regional

[19] I choose 2013 since that is just before the large influx of refugees, yielding a plausibly exogenous baseline.

[20] It should be cautioned that this measure is only exogenous as long as refugees do not alter the high-skill occupational structure across all of Germany.

approaches.

As a robustness check for my primary approach in estimating the effect of prejudice, I also exploit an SOEP survey question on political affiliation and include a measure for the average support for the Alternative for Germany (AfD) Party in each region. This party first gained popularity based on its anti-refugee platform and thus serves as a viable alternative proxy for attitudes against refugees. I later show that this alternative measure is strongly correlated with my primary measure for individual-level prejudice. I decide against using this variable as my primary prejudice specification due to secular increases in the party's popularity over time that may not be directly attributable to increased prejudice itself.

Addressing Potential Concerns

There are multiple potential threats to interpreting the results from my primary specifications as causal. First, attitudes toward refugees may be influenced by the number of refugees entering a given region, the economic success of refugees, or the level of everyday interaction between natives and refugees.[21] Suppose, for instance, that native attitudes toward refugees are influenced by their labor market performance within specific regions. This would introduce reverse causality in the estimates of the effect of prejudice. I address this concern by incorporating nine-year lags for prejudice, $Prej_{c(t-9)}$, as a proxy for current prejudice. This lagged index only uses prejudice measures between 2007 and 2014, meaning that it only captures attitudes in the years leading up to the large inflow of refugees.

Since refugee-specific questions are not asked before 2016, I rely on a smaller set of two general immigration attitude questions. The first asks how worried natives are about immigration into Germany, and the second asks how worried they are about hostility toward foreigners. Note that these two questions are only scaled from 1 to 3 instead of from 1 to 10. This limited response range, combined with the limited set of questions, not only reduces variation from the resulting index but also may add significantly more noise to the estimated level of prejudice. Nevertheless, a strong correlation between lagged prejudice and current prejudice indicates that the two approaches capture similar attitudes.[22]

Second, it is possible that refugees selectively migrate out of their initially assigned districts after their required period of residence expires. Even before the end of those three years, refugees may seek employment-based exemptions from residence restrictions, may move between regions within a given state, may live close enough to other regions to commute to work outside their region of residence, or may ignore residence restrictions entirely. Selective migration in response to local conditions is an especially pertinent concern in this setting: despite being quasi-randomly settled into given regions upon arrival, many refugees in Germany can migrate within their state. Katz, Noring, and Garrelt (2016) find that refugees in Germany tend to move into urban areas, sometimes outside of their original district of residence, and live in segregated neighborhoods. It is possible that refugees who

[21] There can be nuance in how exposure to migration affects local attitudes: more direct exposure can in some cases improve sentiments toward migrants. See Albrecht et al. (2020) or Lebow et al. (2024) for a discussion on how exposure to migrants can affect sentiment in various countries.

[22] A regression of current individual prejudice on lagged prejudice yields a t-score of about 65.

remain in more prejudiced areas or in places with higher wage levels are positively selected, as those unable to find employment may move elsewhere. If this occurs, the estimated wage and employment gaps in such regions would be biased toward zero. Such selective migration within countries has been documented for immigrants in Europe before: Waisman and Larsen (2008) find that immigrants in Sweden move towards less prejudiced areas and away from more prejudiced areas. Still, this may only be a mild concern if relatively few refugees move.

To evaluate this concern, I exploit the panel structure of the SOEP to estimate the relationship between my variables of interest and the probability that a given refugee moves between regions: I first generate a binary variable for all refugees surveyed in consecutive years that is equal to one if the refugee's residence changed to a new NUTS2 region between surveys. The mean of this variable is only 0.022, indicating that relatively few refugees move between regions between consecutive years. I then regress this binary variable on one-year lags of the region-year covariates listed in equation (7). I also include a variable for the average surveyed support of the AfD political party to roughly proxy variations in prejudice by region-year. The resulting equation tests whether any of these covariates affects the probability of moving out of a given region:

$$P(Move_{ict}) = \lambda_0 + \lambda_1 bite_{ct-1} + \lambda_2 SQbite_{ct-1} + \lambda_3 HSVOC_{ct-1} + \lambda_4 Union_{ct-1} + \lambda_5 AfD_{ct-1} + \lambda_t + \epsilon_{ict} \quad (6)$$

Given the low baseline probability of moving, I use a probit in addition to a linear probability model to account for potential nonlinearity when probabilities are close to zero. The results for these specifications can be found in Appendix Table A4, but overall, I do not find evidence that any of my variables of interest are correlated with the probability of moving out of a given region.

A final concern is that both the minimum wage bite and the residual wage gap are linked to the underlying wage distribution. Because the minimum wage bite is defined relative to the regional median wage, an unobserved regional economic shock that affects wages could simultaneously influence both the bite and the refugee-native gap. While I cannot completely rule out this possibility, I ran a brief robustness check in which I included in the specification for equation (5) a conventional Bartik measure for labor demand shocks.[23] The inclusion of this measure did not meaningfully alter the estimated bite coefficients, indicating that the results are not driven by regional variation in labor demand over time.[24]

[23]This measure is similar to the vocational degree Bartik measure described in my empirical strategy, except the share portion is the share of native workers in each occupation and region, and the shift is the national growth rate of the number of native workers in each occupation.

[24]Specifically, I ran the same specifications from Table 8 and found very similar estimated coefficients. Full results for all tables with this Bartik control are forthcoming.

V. Descriptive Statistics and Basic Regressions

Gaps and Other Statistics

I begin my analysis by documenting the size and persistence of the wage and employment gaps between refugees and natives over years since migration (YSM). The top section of Figure 1 displays both the overall log wage gap and residual wage gap by years since migration between natives and refugees who entered Germany in 2014 or later, using survey years 2017 to 2024. The bottom section displays analogous results for the employment gap. To generate the overall gaps by YSM, I regress all wages and employment on year fixed effects and an interaction of refugee status with YSM. Each refugee-by-YSM coefficient is my estimate of the overall gap for that YSM cell. I use this procedure instead of calculating average outcomes by YSM because refugees in the same YSM cell may be surveyed in different years, and refugees who have been in Germany longer are more likely to be surveyed in a later year. I compute the residual gap by years since migration by estimating equation (1), but with an interaction of refugee status with YSM instead of just refugee status.[25] Doing so produces an estimated refugee penalty for each YSM cell, which I use as the residual gap.

Notably, refugees one year after migration have a large initial overall gap of 0.437 log points (about 44 percent), and this value increases to 0.742 log points by year three before declining back towards 0.4 log points in later years. The initial increase is likely due to selection into the labor force: refugees with unobserved high skills are more likely to find employment sooner after migration. This possibility is backed up by trends in the employment gap: the overall employment gap is 62.1 percentage points one year since migration and steadily declines over time spent in Germany, although a 7.8 percentage point gap exists ten years after migration.[26]

While the results for the overall gaps show that a large wage gap persists over time and that employment gaps narrow only gradually, significant portions of these gaps may be attributed to differences in observable characteristics between refugees and natives. Indeed, when I control for characteristics and calculate the residual gaps, the initial wage gap one year after migration shrinks to 0.343 log points, and it gradually declines over time until it is nearly zero by year ten. The residual employment gap, however, persists even ten years after migration, although it is consistently lower than the overall employment gap. The trends in the residual gaps imply that similar refugees and natives converge in their wage outcomes, albeit very gradually.

These overall trends mask important differences by education. Recall that initial occupational downgrading, along with vocational training requirements and other labor market barriers, may be of particular importance to refugees in Germany. Such obstacles may dis-

[25] A summary of the means of variables used, for natives and refugees separately, can be found in Appendix Table A1. Notably, refugees are significantly less educated than natives, as only 40.5 percent had at least a secondary education.

[26] These trends are very similar if I further restrict the sample to immigrants who migrated between 2014 and 2017, indicating that the results are not influenced by more recent refugees from Ukraine entering the sample in the most recent survey years.

proportionately affect highly educated refugees, as they would have greater trouble finding jobs that match their home-country educational qualifications.

There are too few highly educated refugees in my sample to investigate regional variation in the residual gap among highly educated workers. Luckily, there are more than enough for me to analyze overall trends by education across all of Germany. Figure 2 displays the same set of results as Figure 1, but only including observations who have at least some post-secondary education. Similarly, Figure 3 displays the same results for observations with less than a post-secondary education. As is shown, the residual wage gap for highly educated refugees not only persists over time, but is very large: even ten years after migration, there is a 0.345 log point residual gap for this group compared to highly educated Germans. A roughly 20 percentage point employment gap also persists after an initial decline. By comparison, Figure 3 shows that both the residual wage and employment gaps for low-educated refugees gradually converge toward zero. These figures reveal that the overall residual wage gaps are largely driven by lower returns to education among highly educated refugees.

To quantify the extent of these lower returns, I estimate equation (1) to calculate the overall residual wage gap, and also include a specification with refugee-by-education group interactions. The results of these regressions are displayed in Table 1, and all standard errors are clustered at the regional level.

As shown, there is, on average across the pooled sample, a residual wage gap of 0.192 log points and a residual employment gap of 28.2 percentage points, as represented by the refugee penalty coefficient at the top of columns 1 and 3. However, this coefficient for wages declines to only 0.031 after including interactions with refugee status and education, while the employment coefficient declines to 0.214. A comparison of the estimated education coefficients with the estimated refugee-education interaction coefficients reveals that refugees receive little return to having completed secondary or post-secondary schooling. For instance, the specification in the second column implies a 77.6 percent return to post-secondary education for natives, but the refugee-post-secondary interaction term is -0.597, implying that refugees receive only a 17.9 percent return to higher education. Thus, as implied in Figures 1 through 3, the residual wage gap can be largely attributed to lower returns to refugee education. Note that this finding is descriptive, as it does not explain why refugees have such lower returns. Still, these results indicate a significant lack of human capital transferability for refugees in Germany. This may be caused by a variety of factors, such as disproportionate discrimination and language barriers among high-skill occupations or occupational licensing restrictions. Large gaps persist, especially for highly educated refugees, that cannot be fully explained by differences in observable characteristics.

Regional Variations in Prejudice

Before estimating the effect of prejudice, I provide evidence that my prejudice measure captures meaningful variation in prejudice against refugees. After constructing the individual-level prejudice measure as described above, I regress it on a quadratic in age, education, gender, marital status, number of children, and a binary indicator of whether the respondent supports the AfD. The results can be found in Table 2 and are largely in line with those of Charles and Guryan (2008): more prejudiced attitudes are negatively associated with higher education, positively associated with age, and are more prevalent among males than females. Furthermore, higher measured prejudice is very strongly associated with support for the AfD. These results strongly indicate that the measure captures meaningful variation in attitudes toward refugees.

Next, I provide an overview of the regional variation in prejudice, along with variation in the residual gaps. Figures 4, 5, and 6 display heat maps for the average residual wage and employment gaps (as estimated in equation (2)), along with the average prejudice level across the German NUTS2 regions.[27] Appendix Table A3 reports the exact means by region.

These figures reveal significant variation in prejudice, wage gaps, and employment gaps by region. In particular, there appears to be a relationship between prejudice, urbanization, and geographic location: densely populated states like Berlin and Hamburg have relatively low levels of prejudice against refugees, whereas less densely populated areas like Thuringia have higher levels of prejudice. Many of the more prejudiced regions are also located in eastern Germany. It is unclear from the descriptive statistics alone that the residual wage gaps are correlated with NUTS2-level prejudice, although there appears to be a visual positive relationship between prejudice and residual employment gaps.

The sample statistics of the various aggregated prejudice measures are reported in Table 3. While my primary prejudice percentiles have a consistent standard deviation between 0.154 and 0.224, the lagged measures have very little variation for the most extreme percentiles. For instance, the 50th percentile in the lagged prejudice measure only has a standard deviation of 0.013, while the 5th percentile's standard deviation is 0.287. It is clear from this table that the primary measure has much richer variation by region, which is to be expected given the larger set of survey questions used and the wider ordinal range of possible survey responses.

Regional Variations in Labor Market Structures

I next analyze the descriptive variation in labor market structures across regions and time. Table 4 reports descriptive statistics for the second-stage variables used in equation (5), aggregated across region-year cells from 2017 to 2024, along with the means of the estimated overall and residual gaps across all region-year cells. I also include summary statistics on average AfD support across cells.

As shown in the table, there is a 0.548 overall log wage gap and 38.7 percentage point gap for employment across region-year cells, along with a residual gap of 0.259 log points for wages and 29.4 percentage points for employment. Furthermore, 51.6 percent of native workers in an average region-year cell are represented by a collective bargaining agreement. This estimate is consistent with OECD estimates indicating that collective bargaining coverage declined from 56 to 49 percent in Germany between 2016 and 2023.[28] There is not much variation by cell, as the standard deviation is only 0.065. The high-skill vocational index

[27] All heat maps in this paper are created using templates available at Datawrapper.

[28] See the OECD Data Explorer for more details.

also exhibits relatively little variation across region-year cells. That said, significant variation does exist for the minimum wage bite and support for the AfD, as well as for the various wage and employment gaps.

VI. Results

Prejudice

I begin by estimating the relationship between prejudice and the residual wage gaps by region as described in equations (2) and (3). The results for the residual wage and employment gaps, using both the primary and lagged prejudice measures, are displayed in Table 5 and Table 6.

As shown, none of the prejudice percentiles I use are consistently positively correlated with either the residual wage or residual employment gap.[29] There is a slight indication that prejudice at the median and 90th percentile increases the employment gap, but this result is not robust to using the lagged prejudice measure, nor is it robust to using spatial planning regions instead of NUTS2 regions.[30] Overall, I find no strong evidence that prejudice is meaningfully associated with the residual wage gap.

These results do not provide sufficient evidence that prejudice against refugees in Germany is a meaningful determinant of residual wage and employment gaps. This finding contrasts with both Charles and Guryan (2008) and Carlsson and Roof (2016), although this is a very different setting and very different group being analyzed. As previously mentioned, Jaschke et al. (2022) create anti-refugee threat indices and find that refugees living in threatening areas invest more in integration, so it is possible that competing mechanisms negate the overall effect of prejudice on the residual gaps. This may explain why I do not find robust evidence for a meaningful effect. Taken together, these results suggest that differences in local prejudice do not explain regional variation in residual refugee-native gaps.

Minimum Wages and Labor Market Structures

I next turn to regional variation in labor market structures. I am primarily interested in (1) whether minimum wages and more centralized wage-setting structures lower the residual wage gap, and (2) whether high-skilled vocational requirements can slow refugee integration.

The results of regressions on the overall wage and employment gaps based on equation (5) are presented in Table 7, with corresponding results for the residual gaps in Table 8. In both tables, the first four columns display the wage gap results, while the latter four display

[29] I also ran these regressions with the 2nd, 20th, and 80th percentiles. None of these percentiles consistently produce statistically significant results.

[30] Interestingly, all estimated percentiles of the main prejudice measure and lagged prejudice measure, when aggregated at the spatial planning region level, are strongly negatively associated with the residual wage gap, although including all percentiles jointly in the regression does not yield similar results. See Appendix Table A5 for more details.

the employment gap results. The odd numbered columns exclude the union coverage variable (and therefore include more region-year cells since data on union coverage is unavailable for 2020 and 2022). Columns 1, 2, 5, and 6 exclude the Bartik-style vocational degree index. Since these variables have a wide range of means and standard deviations, Appendix Tables A7 and A8 display the results in terms of a one SD increase of each variable of interest. As an alternative approach, Appendix Tables A9 through A12 report the same set of results at the spatial planning region level.

Across all the overall wage gap specifications in Table 7, the minimum wage bite is associated with a lower gap.[31] This set of results is robust to using spatial planning regions instead of NUTS2 and is statistically significant at the five percent level in those specifications.[32] The magnitude is also of economic significance: as shown in the first four columns of Appendix Table A7, a one standard deviation increase in the bite is associated with a 0.078 to 0.096 log point decrease in the overall wage gap. The effects on employment gaps, meanwhile, are small and statistically insignificant across all specifications, suggesting that increased minimum wage bites lift refugees up relative to natives without affecting their relative employment prospects.

These results also hold for the residual wage gap. The first four columns in Table 8 show that a 0.1 log point increase in the bite results in a 0.079 to 0.110 log point decline in the residual wage gap. Alternatively, a one standard deviation increase in the bite from the mean decreases the residual wage gap by 0.108 to 0.149 log points.[33] Such a noticeable effect size for the residual gap reflects that even highly educated refugees are near the bottom of the wage distribution and are lifted up by minimum wages relatively more than similar natives.

While it does not appear that increased union coverage reduces residual wage gaps nor any employment gap, the results in columns 2 and 4 from Table 7 suggest that a ten percentage point increase in coverage in a given region-year cell decreases the overall gap by about 0.08 log points. Alternatively in Table A7, a one standard deviation increase in coverage lowers the overall gap by 0.05 log points. However, this result is not robust to aggregating at the spatial planning region level, as the estimated coefficients are smaller in magnitude and not significant at the ten percent level, although the sign is still negative. I therefore find only suggestive evidence that increased union coverage reduces the overall wage gap, and I find no indication that the residual gap is affected. A possible explanation is that while union coverage compresses the overall wage distribution, refugees may be less likely to work in occupations covered by collective bargaining agreements, meaning that natives on the lower tail of the wage distribution may benefit more from unions than similarly situated refugees. It could also be the case that unions keep new labor market entrants such as recent refugees out of employment. However, in none of my specifications is greater union representation associated with a higher overall or residual employment gap. It appears that union representation does not worsen relative refugee outcomes, and if anything, lowers the

[31]Since the minimum wage bite enters these regressions as a quadratic term, in all of these tables, the displayed effect of the minimum wage bite is the estimated marginal effect at the mean.

[32]See Appendix Table A9

[33]See Appendix Table A8. Slightly smaller but still considerable effect sizes for spatial planning regions are shown in Appendix Table A12.

overall wage gap.

Finally, there is some indication that my Bartik-style high-skill vocational degree index, designed to capture exogenous variation in vocational degree requirements among highly skilled occupations, is associated with a larger residual wage gap. That said, the estimated coefficients are very sensitive to the level of geographic aggregation, and some coefficients seem too large.[34]. Both this measure and the union coverage variable have relatively little variation between region-year cells and even less variation between regions in the same year, making the estimates sensitive to the level of aggregation and rendering it difficult to estimate a precise effect. Still, these results do provide tentative evidence that refugees are more likely to find employment in regions with fewer barriers to high-skilled professions.

Combined, the results from Tables 7 and 8 and the various robustness checks in Tables A7 to A12 indicate that more compressed wage distributions from minimum wage bites lower both the overall and residual wage gap without affecting employment gaps. Furthermore, there are indications that union coverage produces a similar effect, and regions in which more highly skilled occupations do not require vocational training may also relatively benefit refugees. Regional variation in labor market structures, and policies that compress the wage distribution, appear to play a central role in shaping relative refugee wage outcomes.

VII. Conclusion

In this paper, I explore how policies, market structures, and prejudice affect refugee labor market outcomes relative to natives. I show that highly educated refugees face particularly persistent labor market disadvantages relative to natives. In fact, the residual wage gap is almost entirely driven by low returns to education among refugees, and the gap among highly educated workers remains large even a decade after migration. Such persistence suggests that policies or market structures affecting human capital transferability may affect the gap. I find very little evidence that prejudice produces any effect on wage and employment gaps, but I do demonstrate that labor market structures play an important role: refugees seem to have relatively better wage outcomes in regions with more binding minimum wages. I also find suggestive indications that greater union representation reduces the overall wage gap. These results make sense given that refugees are disproportionately on the left tail of the wage distribution, meaning policies or institutions that compress the distribution will lower the gap. Furthermore, I find suggestive evidence that refugees do relatively better in regions with lower vocational training requirements in highly skilled occupations, providing greater indications that human capital transferability plays a key role in the wage gap. All told, it appears that market structures, policies, and human capital transferability rather than prejudice are primary factors in determining relative refugee outcomes.

[34] Specifically, a one standard deviation increase in this measure is associated with a 0.385 to 0.549 log point increase in the residual gap. See columns 3 and 4 of Table A8 for more details, and Tables A9 through A12 for corresponding spatial planning region results.

Tables and Figures

Table 1: Refugee Penalty and Returns to Education

	Log Wage		Employment	
	(1)	(2)	(3)	(4)
Refugee	-0.192***	0.031	-0.282***	-0.214***
	(0.028)	(0.039)	(0.013)	(0.018)
Secondary Education	0.408***	0.426***	0.123***	0.132***
	(0.035)	(0.035)	(0.014)	(0.015)
Refugee × Secondary		-0.334***		-0.022
		(0.049)		(0.035)
Post-Secondary Education	0.755***	0.776***	0.175***	0.187***
	(0.033)	(0.034)	(0.015)	(0.015)
Refugee × Post-Secondary		-0.597***		-0.226***
		(0.061)		(0.024)
Obs.	88,466	88,466	129,019	129,019

Notes: The table reports estimates from 2017-2024 pooled regressions of log hourly wages and employment on refugee status, education, and interactions between refugee status and education. Also included are controls for age, gender, marital status, number of children, an interaction of gender with the latter two terms, and NUTS2 region and year fixed effects. No region-year cell with fewer than five refugee wage observations is included. "Secondary Education" and "Post-Secondary Education" are binary indicators. All specifications use survey weights and are clustered at the NUTS2 region level. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Associations with Individual Prejudice

	(1)	(2)
Female	-0.070***	-0.069***
	(0.015)	(0.015)
Age	0.038***	0.038***
	(0.006)	(0.005)
Age Squared	-0.000***	-0.000***
	(0.000)	(0.000)
Secondary Education	-0.257***	-0.272***
	(0.034)	(0.034)
Post-Secondary Education	-0.771***	-0.775***
	(0.034)	(0.034)
Married	0.007	0.022
	(0.020)	(0.018)
# of Children in Household	-0.008	-0.014
	(0.013)	(0.012)
AfD Support		1.467***
		(0.172)
Obs.	52,137	52,137

Notes: The dependent variable is the individual prejudice index. The sample consists of native Germans ages 18 to 64 from all survey years in which 2016 refugee attitude questions were recorded (2016, 2018, 2020, 2023). Only respondents who answered all five questions are included. Standard errors are reported in parentheses and are clustered at the NUTS2 regional level. Secondary Education and Post-Secondary Education are measured relative to the omitted category of less than secondary education. AfD is a binary indicator of whether the respondent supports the Alternative for Germany party. Both specifications use survey weights. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Descriptive Statistics: Prejudice Percentiles

Percentile	Mean	SD	Min.	Max.
Main Prejudice Measures				
5th	-1.416	0.158	-1.772	-1.031
10th	-1.105	0.154	-1.432	-0.744
50th	-0.090	0.206	-0.519	0.391
90th	1.206	0.224	0.547	1.574
Lagged Prejudice Measures				
5th	-0.985	0.287	-1.356	-0.719
10th	-0.684	0.013	-0.719	-0.667
50th	0.026	0.013	0.006	0.051
90th	0.744	0.019	0.679	0.787

Notes: The table reports descriptive statistics for the weighted prejudice distribution across the 38 NUTS2 regions. The main contemporary prejudice measures in the top panel are calculated using the five refugee attitude questions from the 2016, 2018, 2020, and 2023 surveys. The bottom panel reports lagged prejudice measures using two immigration-related question from 2007 to 2014. All surveyed respondents are native Germans ages 18 to 64 who answered all related questions.

Table 4: Descriptive Statistics: Second-Stage Variables

Variable	Mean	Std. Dev.	Obs.
Overall Wage Gap	0.548	0.311	280
Overall Employment Gap	0.387	0.170	280
Residual Wage Gap	0.259	0.338	280
Residual Employment Gap	0.294	0.186	280
Minimum Wage Bite	-0.659	0.133	280
High-Skill Vocational Index	0.501	0.053	280
Union Coverage	0.516	0.065	210
Average AfD Support	0.095	0.074	280

Notes: The unit of observation is a NUTS2 region-year cell. The residual wage gap and residual employment gap are estimated from first-stage regressions comparing refugees and natives within region-year cells after controlling for observable characteristics. "High-Skill Voc. Index" is the Bartik-style measure calculated as described from equation (5), and "AfD" refers to the Alternative for Germany political party.

Table 5: Effect of Prejudice on the Residual Wage Gap

	(1)	(2)	(3)	(4)	(5)
Main Measure					
5th Percentile	-0.231				0.893
	(0.237)				(1.093)
10th Percentile		-0.226			-1.943
		(0.241)			(1.342)
50th Percentile			0.039		1.326**
			(0.183)		(0.598)
90th Percentile				-0.016	-0.631
				(0.170)	(0.400)
Lagged Measure					
5th Percentile	0.006				0.025
	(0.131)				(0.154)
10th Percentile		-0.155			3.258
		(2.830)			(3.658)
50th Percentile			-2.871		-0.939
			(2.728)		(4.018)
90th Percentile				-3.380*	-4.190
				(1.859)	(2.649)
Obs.	38	38	38	38	38

Notes: The dependent variable is the residual wage gap by NUTS2 region as estimated in equation (4). All regressions are weighted by the inverse variance of the estimated residual employment gap. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of Prejudice on the Residual Employment Gap

	(1)	(2)	(3)	(4)	(5)
Main Measure					
5th Percentile	-0.045				0.396
	(0.070)				(0.260)
10th Percentile		-0.024			-0.870**
		(0.073)			(0.318)
50th Percentile			0.124**		0.540***
			(0.051)		(0.138)
90th Percentile				0.112**	-0.116
				(0.046)	(0.092)
Lagged Measure					
5th Percentile	-0.011				-0.006
	(0.039)				(0.047)
10th Percentile		-0.809			-1.560
		(0.818)			(1.098)
50th Percentile			0.484		1.344
			(0.840)		(1.274)
90th Percentile				0.109	0.091
				(0.573)	(0.814)
Obs.	38	38	38	38	38

Notes: The dependent variable is the residual employment gap by NUTS2 region as estimated in equation (4). All regressions are weighted by the inverse variance of the estimated residual employment gap. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Overall Gap Results, NUTS2 Regions

	Overall Wage Gap				Overall Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.701	-0.579	-0.701	-0.572	-0.045	-0.170	-0.046	-0.171
	(0.554)	(0.595)	(0.553)	(0.597)	(0.169)	(0.237)	(0.166)	(0.238)
Union Coverage		-0.763*		-0.837*		0.023		0.025
		(0.405)		(0.441)		(0.227)		(0.234)
High-Skill Voc. Index			2.404	5.187			1.355	-0.165
			(4.391)	(5.400)			(2.522)	(2.732)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	280	210	280	210	280	210	280	210

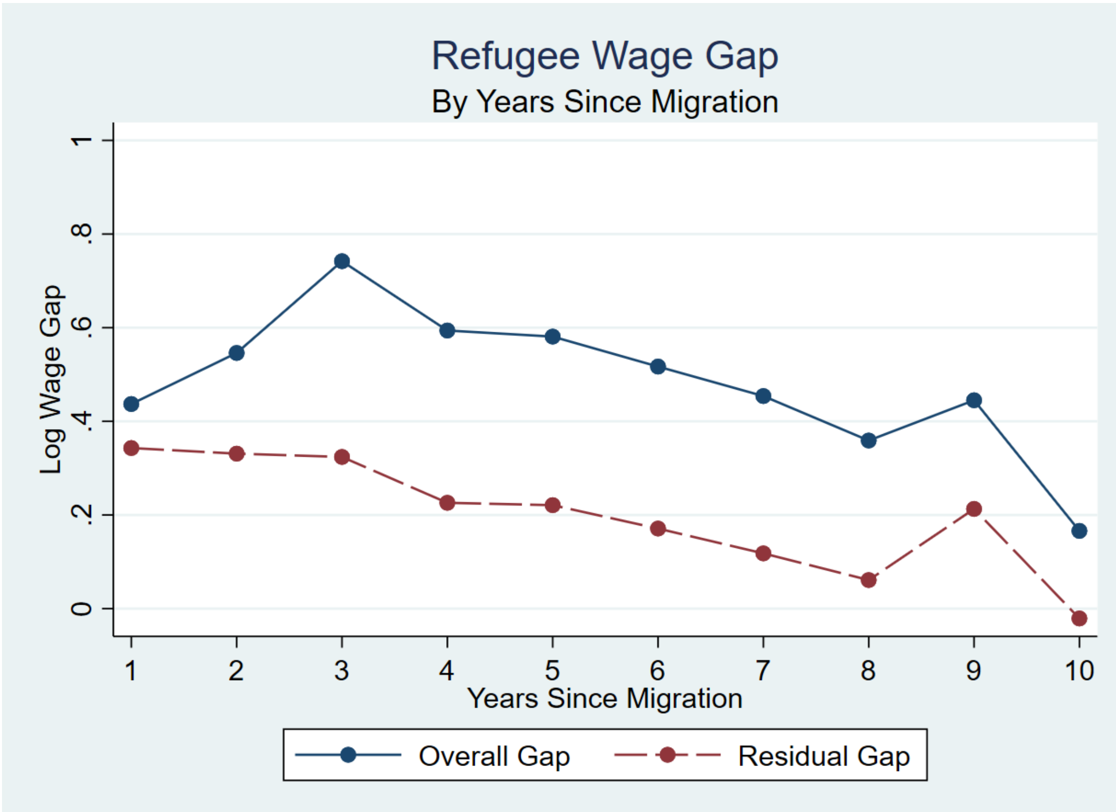
Notes: The table reports results from estimating equation (5) using raw refugee-native gaps. The reported coefficient for the minimum wage bite is the marginal effect evaluated at the sample mean of the bite. Standard errors are clustered at the NUTS2 region level and are reported in parentheses. Specifications including union coverage omit survey years 2020 and 2022. All regressions are weighted by the inverse variance of the estimated gaps by region, and no regions with fewer than five refugee wage observations are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Residual Gap Results, NUTS2 Regions

	Residual Wage Gap				Residual Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.794	-0.970	-0.876	-1.096	0.229	0.227	0.214	0.218
	(0.594)	(0.684)	(0.596)	(0.700)	(0.259)	(0.323)	(0.256)	(0.320)
Union Coverage		0.157		-0.013		0.177		0.144
		(0.403)		(0.438)		(0.304)		(0.319)
High-Skill Voc. Index			6.796*	9.685**			2.971	2.487
			(3.925)	(4.743)			(3.633)	(4.323)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	280	210	280	210	280	210	280	210

Notes: The table reports results from estimating equation (5). The reported coefficient for the minimum wage bite is the marginal effect evaluated at the sample mean of the bite. Standard errors are clustered at the NUTS2 region level and are reported in parentheses. Specifications including union coverage omit survey years 2020 and 2022. All regressions are weighted by the inverse variance of the estimated residual gaps by region, and no regions with fewer than five refugee wage observations are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Refugee-Native Gaps by Years Since Migration



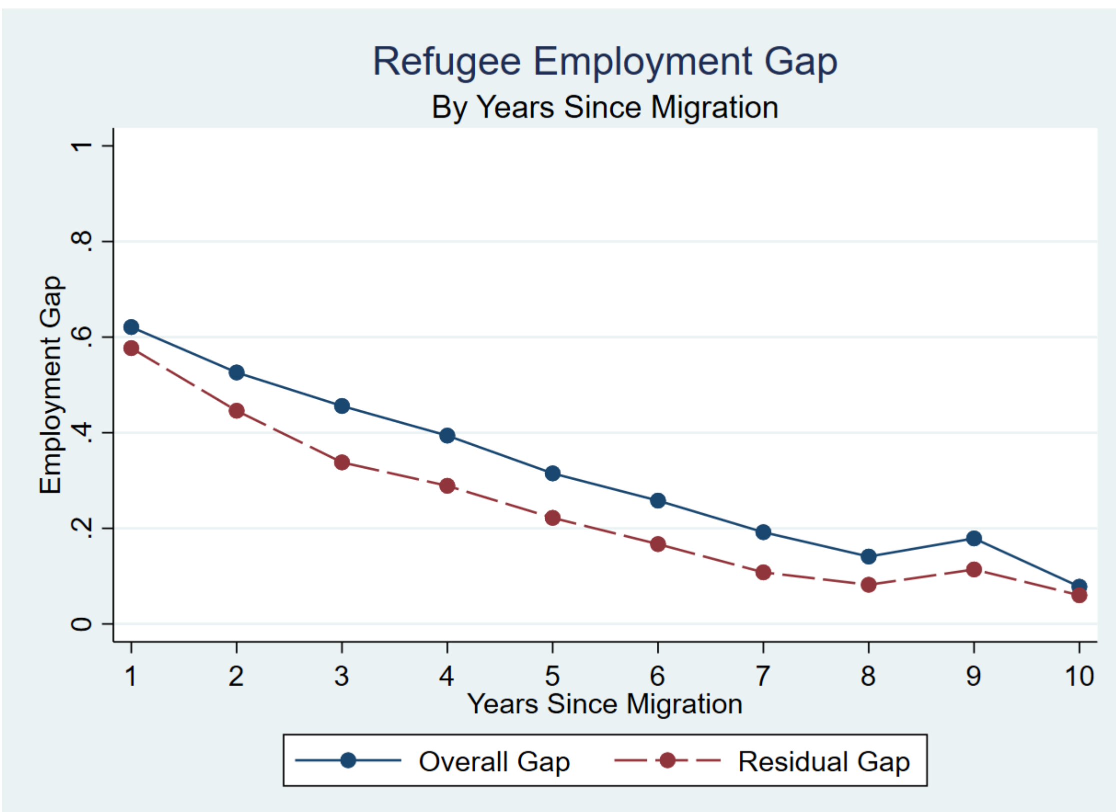


Figure 2: Refugee-Native Gaps by Years Since Migration, Post-Secondary Education

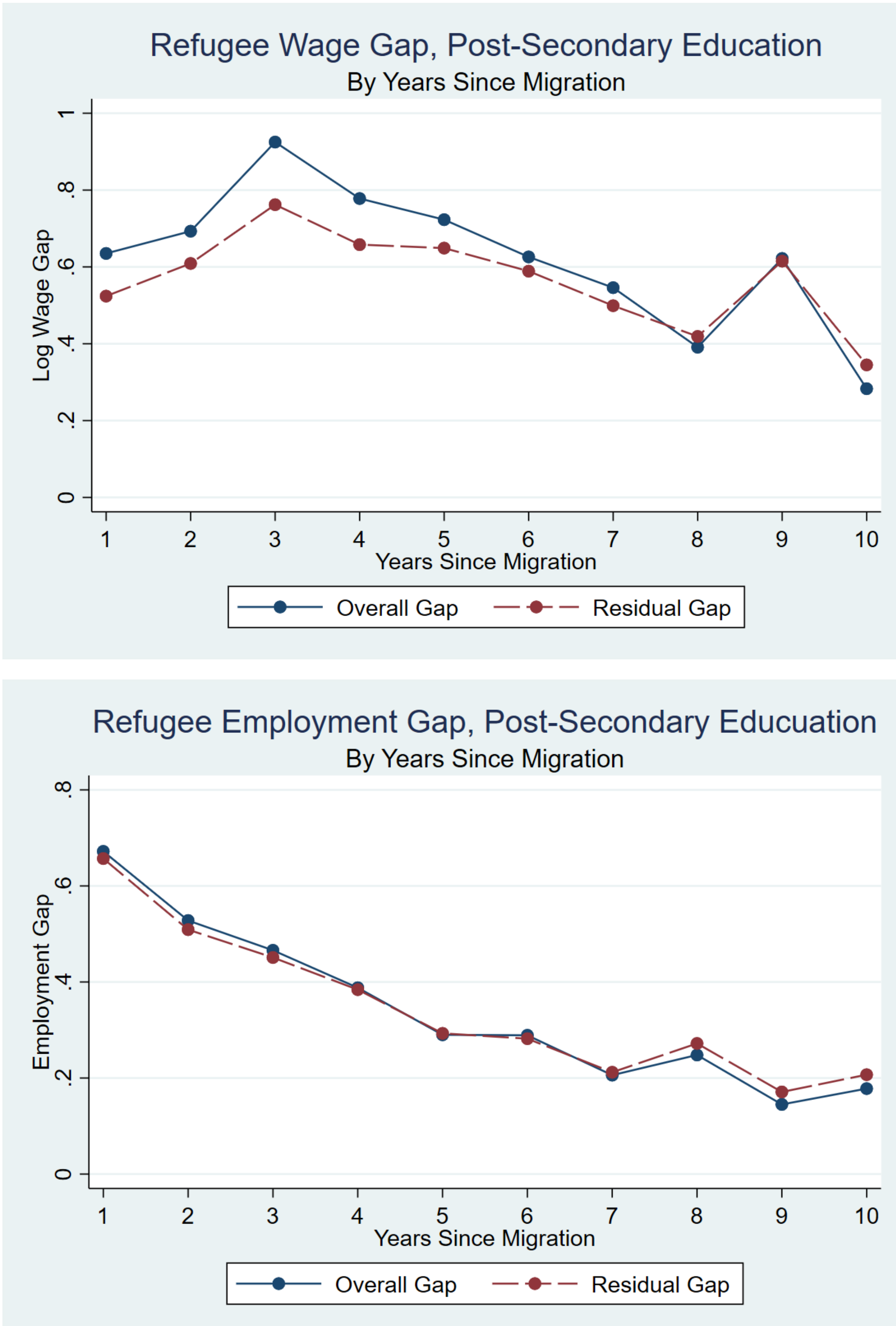


Figure 3: Refugee-Native Gaps by Years Since Migration, No Post-Secondary Education

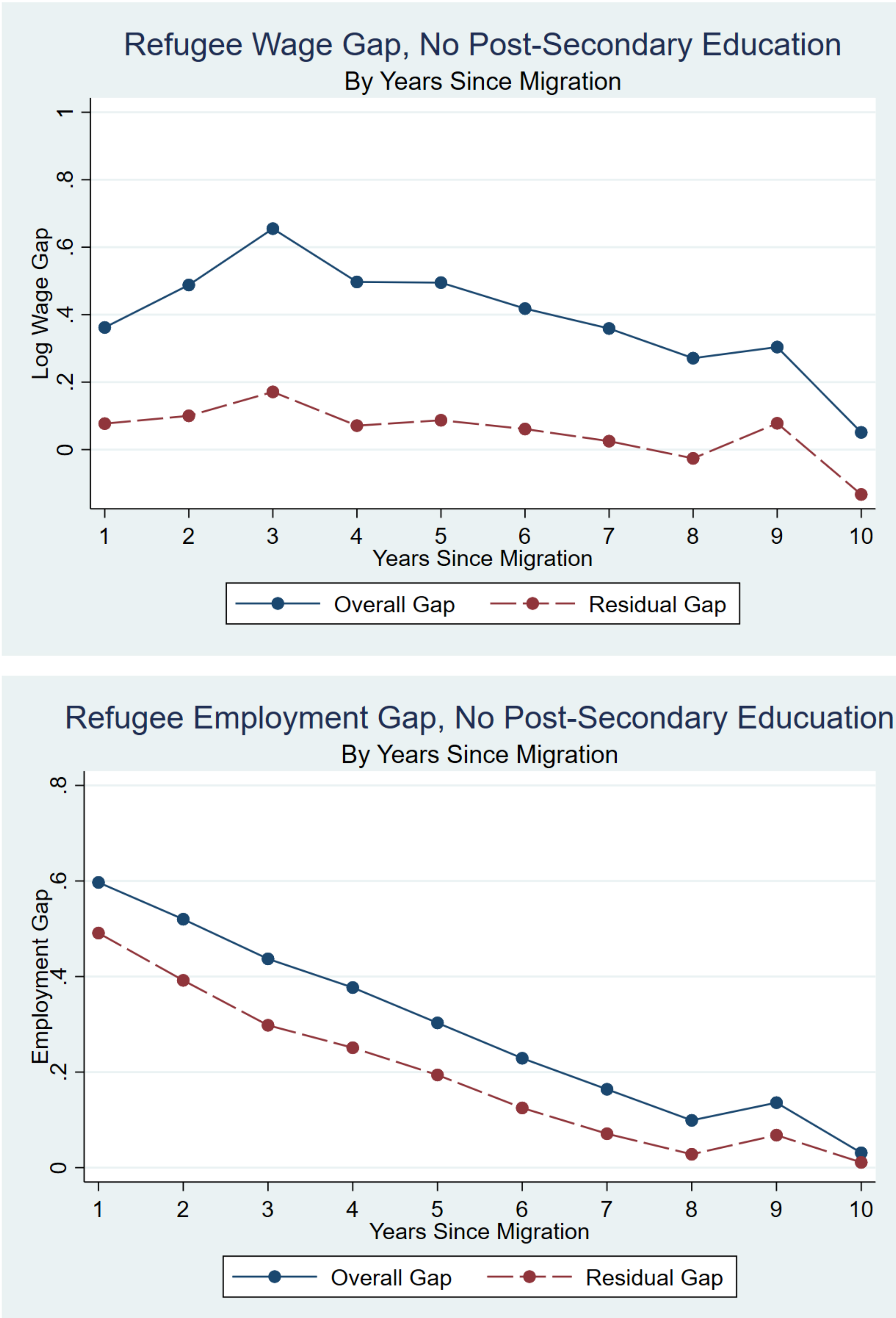


Figure 4

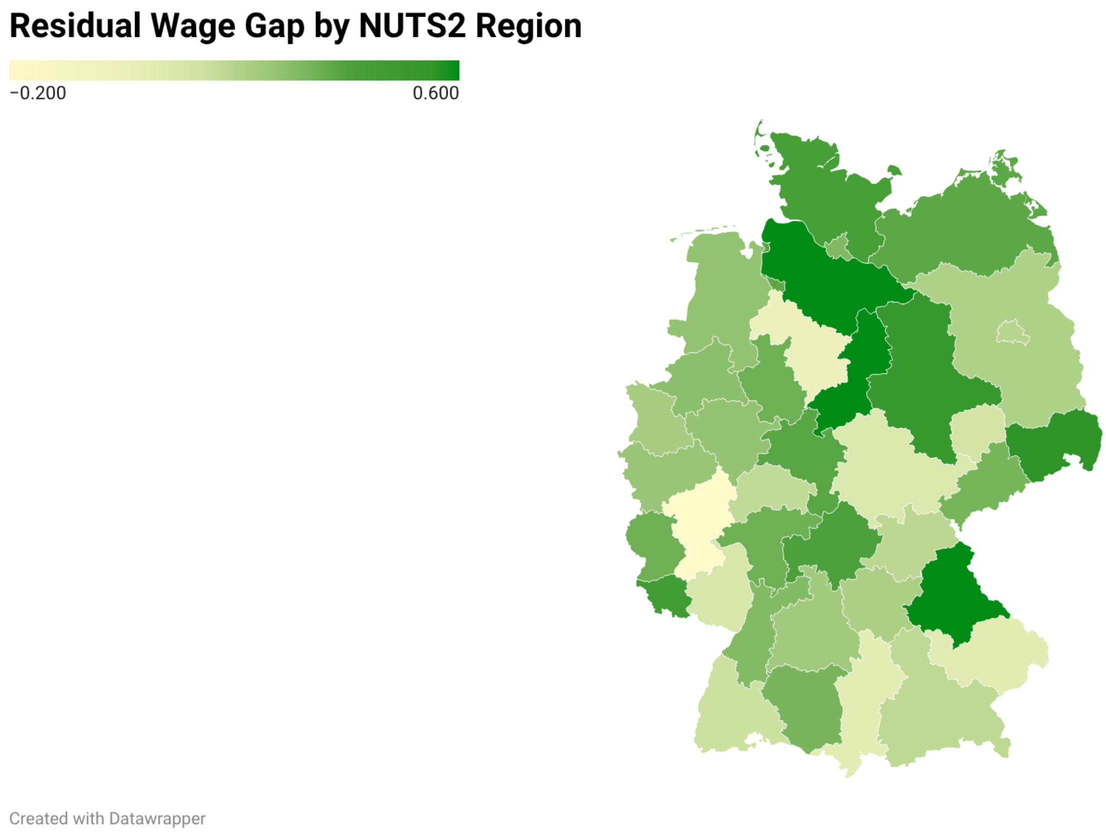

Residual Wage Gap by NUTS2 Region
−0.200
0.600
Created with Datawrapper

Figure 5

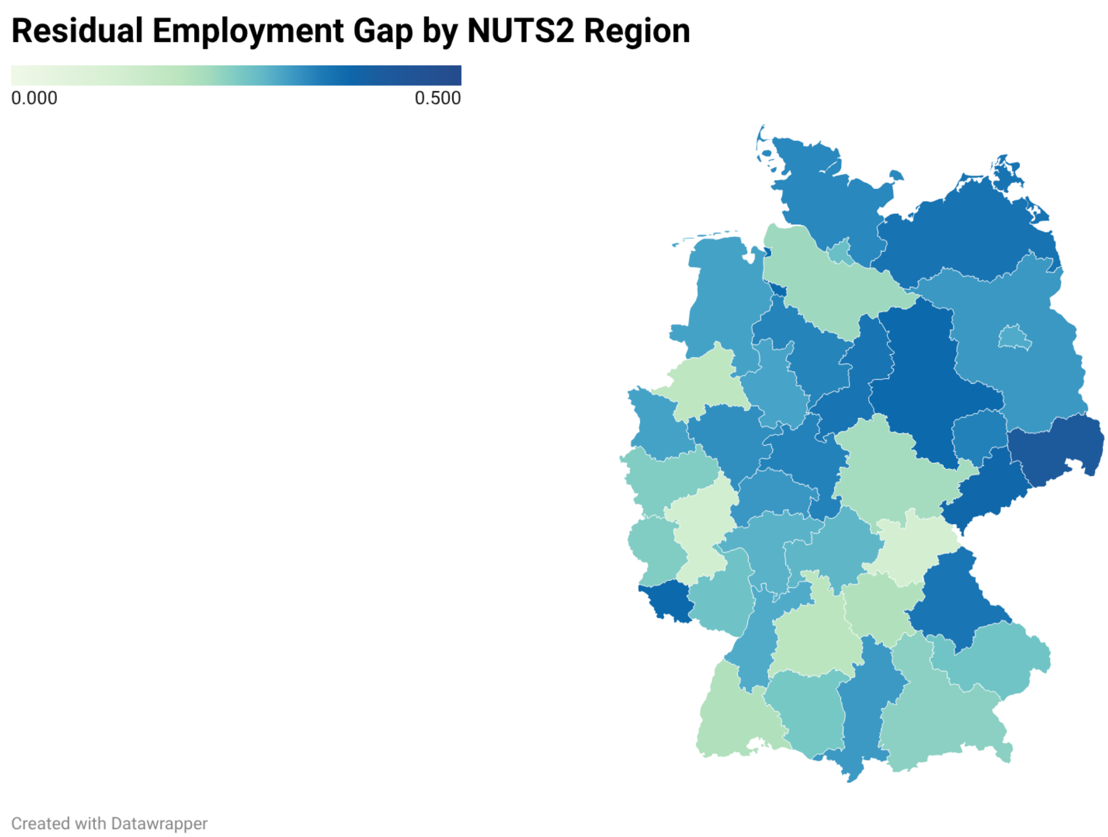
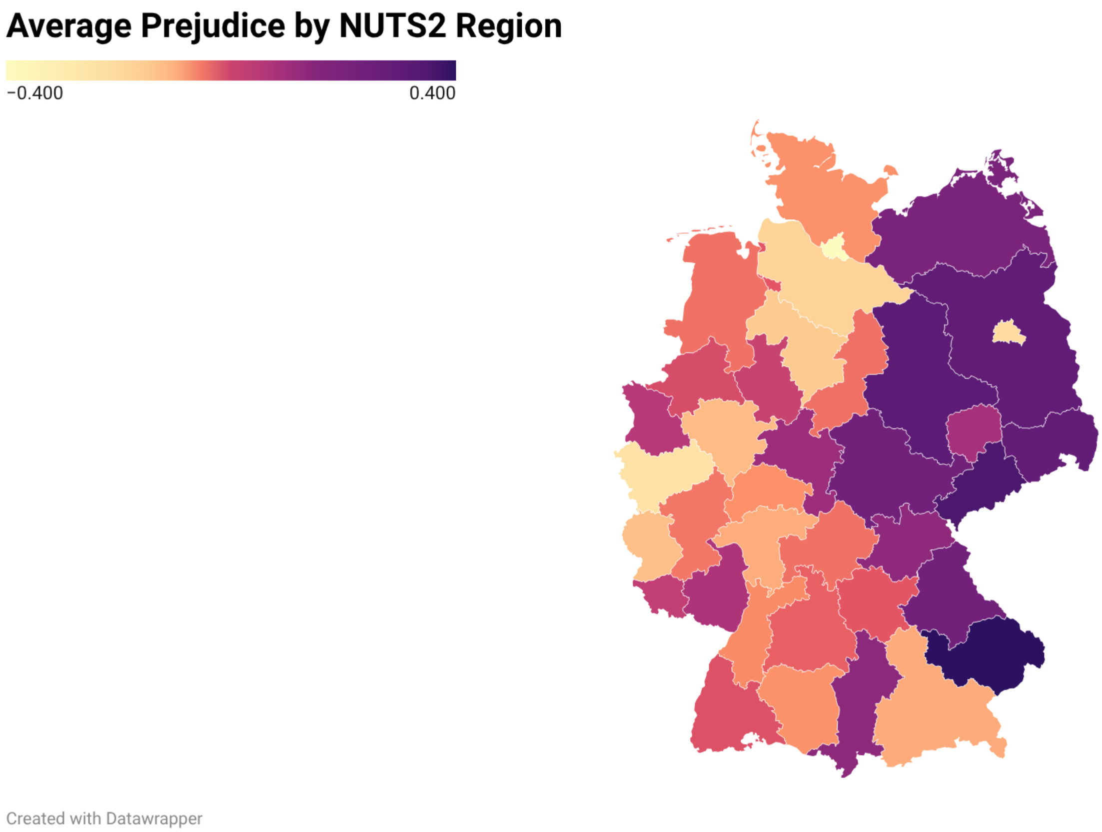

Residual Employment Gap by NUTS2 Region
0.000
0.500
Created with Datawrapper

Figure 6


Average Prejudice by NUTS2 Region
−0.400
0.400
Created with Datawrapper

Appendix

A. Supplementary Tables

Table A1: Descriptive Statistics: Refugees vs. Natives

	Refugees		Natives	
Variable	Mean	Obs.	Mean	Obs.
Hourly Wage	14.243	7,708	20.443	80,758
Employed	0.458	27,773	0.821	101,246
Age	33.629	27,773	43.473	101,246
Female	0.357	27,773	0.493	101,246
Secondary Education	0.139	27,773	0.616	101,246
Post-Secondary Education	0.266	27,773	0.298	101,246
Married	0.416	27,773	0.467	101,246
# of Children in Household	0.978	27,773	0.461	101,246

Notes: The table includes natives and refugees from the 2017-2024 survey years. Refugees who immigrated before 2014 are excluded. "Employed," "Female," "Married," and the education variables are all binary variables. All descriptive statistics are weighted by survey weights. Only observations in NUTS2 region-year cells with at least five refugee wage observations are included. Wages are reported in 2012 Euro.

Table A2: Blinder-Oaxaca Decomposition of Refugee-Native Gaps

	Wage Gap	Employment Gap
Overall Gap	0.479***	0.362***
	(0.022)	(0.011)
Explained	0.323***	0.085***
	(0.025)	(0.008)
Unexplained	0.156***	0.277***
	(0.030)	(0.013)
Explained		
Education	0.238	0.069
Other Factors	0.085	0.016
Unexplained		
Education	0.213	0.049
Other Factors	-0.057	0.228

Notes: The table reports two-fold Blinder-Oaxaca decompositions of refugee-native wage and employment gaps. The explained component reflects differences in observable characteristics between refugees and natives. The unexplained component reflects differences in estimated returns to those characteristics. "Education" combines secondary and post-secondary education indicators. The covariates in "Other Factors" include sex, a quadratic in age, marital status, number of children, and the interaction between sex and the latter two terms. Standard errors are reported in parentheses for the aggregate decomposition components.

Table A3: Descriptive Statistics by Region

NUTS2 District	Average Prejudice	Residual Wage Gap	Residual Employment Gap
Arnsberg	-0.111	0.281	0.322
Berlin	-0.204	0.195	0.298
Brandenburg	0.296	0.217	0.314
Braunschweig	-0.044	0.647	0.354
Bremen	-0.018	0.374	0.368
Chemnitz	0.367	0.335	0.377
Darmstadt	-0.092	0.351	0.288
Detmold	0.002	0.351	0.305
Dresden	0.287	0.589	0.414
Düsseldorf	0.055	0.239	0.306
Freiburg	-0.013	0.161	0.206
Gießen	-0.072	0.183	0.315
Hamburg	-0.481	0.319	0.270
Hannover	-0.141	-0.004	0.334
Karlsruhe	-0.069	0.314	0.297
Kassel	0.105	0.382	0.336
Koblenz	-0.050	-0.785	0.124
Köln	-0.236	0.271	0.248
Leipzig	0.092	0.132	0.337
Lüneburg	-0.179	0.647	0.226
Mecklenburg-Vorpommern	0.202	0.373	0.355
Mittelfranken	-0.018	0.224	0.205
Münster	-0.008	0.296	0.178
Niederbayern	0.413	0.059	0.262
Oberbayern	-0.088	0.187	0.241
Oberfranken	0.119	0.190	0.121
Oberpfalz	0.231	0.732	0.352
Rheinhessen-Pfalz	0.080	0.112	0.263
Saarland	0.024	0.452	0.371
Sachsen-Anhalt	0.310	0.531	0.372
Schleswig-Holstein	-0.073	0.422	0.329
Schwaben	0.122	0.053	0.313
Stuttgart	-0.026	0.250	0.186
Thüringen	0.229	0.093	0.218
Trier	-0.118	0.349	0.248
Tübingen	-0.074	0.332	0.255
Unterfranken	-0.045	0.408	0.282
Weser-Ems	-0.045	0.283	0.306

Table A4: Associations with Refugee Mobility

	LPM		Probit	
	(1)	(2)	(3)	(4)
Lagged Minimum Wage Bite	0.030	0.046	0.028	0.043
	(0.050)	(0.059)	(0.046)	(0.051)
Lagged High-Skill Vocational Index	0.469	0.536	0.375	0.436
	(0.393)	(0.465)	(0.316)	(0.374)
Lagged Average AfD Support	-0.092	-0.097	-0.093	-0.094
	(0.067)	(0.074)	(0.074)	(0.081)
Lagged Union Coverage		-0.008		-0.007
		(0.062)		(0.057)
N	15,586	13,431	15,586	13,431

Notes: The dependent variable equals one if a refugee changed their NUTS2 region of residence between consecutive survey waves. Only refugees surveyed in consecutive years between 2016 and 2024 are included. Columns (1) and (2) report linear probability models. Columns (3) and (4) report average marginal effects from probit models. The reported minimum wage bite estimates for the LPM are linear combinations evaluating the marginal effect of the bite at its sample mean. All independent variables are lagged by one year and therefore correspond to characteristics of the origin region from which a refugee may move. Standard errors clustered at the NUTS2 level are reported in parentheses. Survey weights and year fixed effects are included in all specifications.

Table A5: Effect of Prejudice on the Residual Wage Gap, Spatial Planning Regions

	(1)	(2)	(3)	(4)	(5)
Main Measure					
5th Percentile	-0.472***				-0.649
	(0.146)				(0.477)
10th Percentile		-0.510***			0.611
		(0.159)			(0.617)
50th Percentile			-0.443***		-0.276
			(0.121)		(0.288)
90th Percentile				-0.421***	-0.195
				(0.121)	(0.233)
Lagged Measure					
5th Percentile	-0.295***				-0.117
	(0.103)				(0.155)
10th Percentile		-4.810***			-2.874
		(1.454)			(2.523)
50th Percentile			-4.367**		0.971
			(1.804)		(2.545)
90th Percentile				-0.544***	-0.395*
				(0.187)	(0.215)
Obs.	93	93	93	93	93

Notes: The dependent variable is the residual wage gap by spatial planning region as estimated in equation (5). All regressions are weighted by the inverse variance of the estimated residual employment gap. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effect of Prejudice on the Residual Employment Gap, Spatial Planning Regions

	(1)	(2)	(3)	(4)	(5)
Main Measure					
5th Percentile	-0.069				-0.093
	(0.055)				(0.178)
10th Percentile		-0.056			-0.070
		(0.058)			(0.220)
50th Percentile			0.011		0.085
			(0.045)		(0.104)
90th Percentile				0.024	0.024
				(0.045)	(0.083)
Lagged Measure					
5th Percentile	-0.066*				-0.083
	(0.036)				(0.052)
10th Percentile		-0.619			-0.311
		(0.532)			(0.876)
50th Percentile			0.038		1.326
			(0.622)		(0.887)
90th Percentile				-0.048	-0.071
				(0.070)	(0.080)
Obs.	93	93	93	93	93

Notes: The dependent variable is the residual employment gap by spatial planning region as estimated in equation (4). All regressions are weighted by the inverse variance of the estimated residual employment gap. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effects of SD Increase on Overall Gaps, NUTS2 Regions

	Overall Wage Gap				Overall Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.096	-0.079	-0.096	-0.078	-0.006	-0.023	-0.006	-0.023
	(0.076)	(0.081)	(0.075)	(0.081)	(0.023)	(0.032)	(0.023)	(0.032)
Union Coverage		-0.049*		-0.053*		0.001		0.002
		(0.026)		(0.028)		(0.015)		(0.015)
High-Skill Voc. Index			0.125	0.269			0.070	-0.009
			(0.228)	(0.280)			(0.131)	(0.142)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	280	210	280	210	280	210	280	210

Notes: This table reports the estimated coefficients and standard errors from Table 7 multiplied by the precision-weighted standard deviation of each explanatory variable.

Table A8: Effects of SD Increase on Residual Gaps, NUTS2 Regions

	Residual Wage Gap				Residual Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.108	-0.132	-0.119	-0.149	0.031	0.031	0.029	0.030
	(0.081)	(0.093)	(0.081)	(0.095)	(0.035)	(0.044)	(0.035)	(0.044)
Union Coverage		0.009		-0.001		0.010		0.008
		(0.023)		(0.025)		(0.018)		(0.018)
High-Skill Voc. Index			0.385*	0.549**			0.168	0.141
			(0.223)	(0.269)			(0.206)	(0.245)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	280	210	280	210	280	210	280	210

Notes: This table reports the estimated coefficients and standard errors from Table 8 multiplied by the precision-weighted standard deviation of each explanatory variable.

Table A9: Overall Gap Results, Spatial Planning Regions

	Overall Wage Gap				Overall Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.983**	-0.907**	-0.978**	-0.897**	-0.111	-0.157	-0.112	-0.160
	(0.388)	(0.351)	(0.388)	(0.347)	(0.150)	(0.182)	(0.152)	(0.182)
Union Coverage		-0.212		-0.234		0.119		0.139
		(0.300)		(0.299)		(0.171)		(0.171)
High-Skill Voc. Index			2.046	4.447			-1.818	-2.883
			(4.018)	(5.118)			(2.315)	(2.695)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	469	469	361	361	469	469	361	361

Notes: The table reports results from estimating equation (5) using spatial planning regions. The dependent variables are the overall refugee-native wage and employment gaps. Since a quadratic in the minimum wage bite is included, the reported coefficient for the minimum wage bite is the marginal effect evaluated at the sample mean of the bite. Standard errors are clustered at the spatial planning region level and are reported in parentheses. Specifications including union coverage omit survey years 2020 and 2022. All regressions are weighted by the inverse variance of the estimated gaps by region, and no region with fewer than five refugee wage observations is included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Residual Gap Results, Spatial Planning Regions

	Residual Wage Gap				Residual Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.469	-0.714	-0.470	-0.719	0.155	0.114	0.155	0.114
	(0.464)	(0.531)	(0.469)	(0.537)	(0.253)	(0.289)	(0.253)	(0.289)
Union Coverage		0.209		0.172		0.045		0.045
		(0.493)		(0.479)		(0.227)		(0.227)
High-Skill Voc. Index			0.529	3.494			-2.726	-3.793
			(6.545)	(7.147)			(3.219)	(3.878)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	469	361	469	361	469	361	469	361

Notes: The table reports results from estimating equation (5) using spatial planning regions. The reported coefficient for the minimum wage bite is the marginal effect evaluated at the sample mean of the bite. Standard errors are clustered at the spatial planning region level and are reported in parentheses. Specifications including union coverage omit survey years 2020 and 2022. All regressions are weighted by the inverse variance of the estimated residual gaps by region, and no region with fewer than five refugee wage observations is included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Effects of SD Increase on Overall Gaps, Spatial Planning Regions

	Overall Wage Gap				Overall Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.139**	-0.128**	-0.138**	-0.126**	-0.016	-0.022	-0.016	-0.023
	(0.055)	(0.049)	(0.055)	(0.049)	(0.021)	(0.026)	(0.021)	(0.026)
Union Coverage		-0.020		-0.022		0.011		0.013
		(0.029)		(0.029)		(0.016)		(0.016)
High-Skill Voc. Index			0.116	0.252			-0.103	-0.163
			(0.228)	(0.290)			(0.131)	(0.153)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	469	469	361	361	469	469	361	361

Notes: This table reports the estimated coefficients and standard errors from Table A9 multiplied by the precision-weighted standard deviation of each explanatory variable.

Table A12: Effects of SD Increase on Residual Gaps, Spatial Planning Regions

	Residual Wage Gap				Residual Employment Gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum Wage Bite	-0.064	-0.097	-0.064	-0.098	0.021	0.015	0.021	0.015
	(0.063)	(0.072)	(0.064)	(0.073)	(0.034)	(0.039)	(0.034)	(0.039)
Union Coverage		0.018		0.015		0.004		0.004
		(0.043)		(0.042)		(0.020)		(0.020)
High-Skill Voc. Index			0.032	0.208			-0.163	-0.226
			(0.391)	(0.426)			(0.192)	(0.231)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	469	361	469	361	469	361	469	361

Notes: This table reports the estimated coefficients and standard errors from Table A10 multiplied by the precision-weighted standard deviation of each explanatory variable.

B. Supplementary Discussions

B.1. Alternative Prejudice Models

It should be noted that the predictions of Becker's (1957) model for employer prejudice would not hold if labor market discrimination were instead driven by consumers. Suppose a customer i has a reservation price p for some good or service and that the product happens to be set at this price. Suppose also that the customer incurs an additional cost $\lambda(prej_i)$ to purchasing the product if the employer hires refugees, where λ is an increasing function of prejudice $prej_i$. Thus, refugees in regions with more prejudiced consumers would be less "productive" to employers and would have to accept lower wages. In this case, the relevant level of prejudice in a given region would not necessarily correspond to the proportion of discriminated workers in the labor force. Instead, the relevant level would depend on the second derivative of the function $\lambda(prej_i)$: for instance, if the second derivative were strictly positive, then an increase in prejudice on the right side of the distribution would have a larger marginal effect and would more strongly impact refugee wages than an increase in the average level of prejudice. Consumer prejudice is also but one alternative model: if, for example, prejudice limits social networks between refugees and natives, or if refugees have imperfect knowledge of discriminatory firms, there may be lower refugee reservation wages during the job search process in more prejudiced regions, and it is again unclear that Becker's (1957) predictions apply.

B.2. Blinder-Oaxaca Decomposition

For the Blinder-Oaxaca Decomposition found in Appendix Table A2, I run separate regressions on refugee and native outcomes using the same covariates as in equation (1), but without year and region fixed effects. After computing the estimated coefficients, the total gap between refugees and natives can be decomposed into two portions:

$$\bar{\mathbf{Y}}_{\mathbf{nat}} - \bar{\mathbf{Y}}_{\mathbf{ref}} = \hat{\alpha}_{\mathbf{nat}}(\bar{\mathbf{X}}_{\mathbf{nat}} - \bar{\mathbf{X}}_{\mathbf{ref}}) + \bar{\mathbf{X}}_{\mathbf{ref}}(\hat{\alpha}_{\mathbf{nat}} - \hat{\alpha}_{\mathbf{ref}})$$

The first term represents the portion of the gap explained by differences in characteristics between refugees and natives, with native returns used as the baseline coefficients. The second portion represents the portion of the gap driven by differences in returns to those characteristics and is often called the "unexplained gap." As shown in Appendix Table A2, the overall wage gap is 0.479, and it is decomposed into 0.323 and 0.156 between the explained and unexplained portions, respectively. Likewise, the employment gap is 0.362, of which 0.085 is explained by differences in characteristics and 0.277 is unexplained.

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