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# The Mediterranean Boatlift: Effects of the Refugee Crisis on Existing Immigrants in Germany

Tom Forntheil (42436)

**Abstract.** This paper examines the effects of the 2015/16 refugee crisis on existing immigrants in Germany. I apply a difference-in-difference regression with individual microdata from the German Socio-Economic-Panel to test multiple channels. My analysis confirms differential treatment effects among immigrants. Depending on the educational level or the country of origin, results differ substantially. Especially low educated refugees are impacted by the crisis. In particular, they experience a significant increase in unemployment and welfare dependency. My results suggest that immigrants from other origins were unaffected by the crisis. Hence, it is likely that a discriminatory behavior towards refugees, which began with the offspring of the Syrian Civil War and intensified during the refugee crisis, caused the dynamics.

**Keywords:** Refugee crisis, immigration, diff-in-diff, welfare dependency, unemployment

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| **Discussant:** | Ellen Malm |
| **Examiner:** | Magnus Johannesson |

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# List of Abbreviations

| | |
|---|---|
| DART | Data Access Research Tool |
| DiD | Difference-in-Difference |
| DIW | The German Institute for Economic Research |
| EASY | System zur Erstverteilung von Asylsuchenden |
| E.G. | For example |
| ETC. | Et cetera |
| EU | European Union |
| EUR | Euro |
| GDP | Gross domestic product |
| HAC | Heteroscedasticity and autocorrelation |
| ISCDE | International Standard Classification of Education |
| LIS | Luxembourg Income Study |
| SOEP | Socio-Economic Panel |
| US | United States |

# 1 Introduction

Over 281 million people now reside in countries different from their country of birth[1] (*World Migration Report*, 2022). This number increased over the past five decades and led many researchers to investigate the impacts of immigrants on host countries. Especially since the beginning of the "European Refugee Crisis" in 2015, this topic has received much attention. In 2015 alone, more than 1.2 million immigrants filed asylum applications in the EU due to ongoing armed conflicts in their countries of origin (Eurostat, 2016). With climate change, increasing inequality, and political extremism in many countries, we face challenges that will evidently lead to similar migrant flows in the future. Hence, a clear understanding of successful labor market integration is important for the future of European economies and welfare systems.

I exploit the episode of the 2015/16 refugee crisis to study how newly arriving refugees impact existing immigrants in Germany. Germany registered the highest number of first time asylum applicants in the EU during the crisis (Eurostat, 2016) and is therefore an interesting case to investigate. Furthermore, Germany already had big Afghan and Syrian communities before the refugee crisis (Engler and Schneider, 2016). This allows me to identify the effects specifically for co-nationals of the arriving refugees. The impact of the refugee crisis most likely differed depending on skill level and origin of the immigrant. Hence, it is important to identify these differences for better policy making. Moreover, looking at the impact on existing immigrants is important as immigrant employment may be more sensitive to changes in local labor market conditions than native employment, as they are overrepresented in low-skilled jobs, employers may discriminate immigrant applicants, in many countries employers use the last-in-first-out principle, and job referral networks of recent immigrant cohorts are ethnically stratified (Azlor et al., 2020).

[1]The United Nations defines an international migrant as someone who changes his/her usual country of residence (irrespective of the reason for migration or legal status) to live temporarily or permanently in a country where he/she was not born. As defined by the United Nations, "short-term or temporary migration covers movements with a duration between 3 and 12 months, whereas long-term or permanent migration refers to a change of country of residence for a duration of one year or more."

As the labor supply shock was largely exogenous, the refugee crisis offers a quasi-experimental setting to investigate how the impact differs among existing immigrants. By using individual microdata from the German Socio-Economic Panel (SOEP), I determine the effect of the refugee crisis with a difference-in-difference (DiD) approach. I split the sample into control and treatment group by the immigrants' educational level and country of origin and run two separate difference-in-difference estimations. This allows me to investigate the underlying mechanism.

I show that the refugee crisis impacted unemployment and welfare dependency among low educated immigrants already residing in Germany. They are more likely to be unemployed and receive higher welfare benefits on average. Wages earned and hours worked do not differ in the aftermath of the refugee crisis. While there is supporting evidence that increased competition in the labor market induced these observations, intensified discriminatory attitudes in the labor market might be the underlying cause for these dynamics. I am observing higher welfare dependency among refugees but do not find statistically significant treatment effects on unemployment. When restricting the sample to low educated immigrants, especially refugees experience higher unemployment and welfare dependency. Both measures increase by over 20 percentage points for low educated refugees. Further support for the channel comes from the robustness checks in which I use low educated natives as a control group. When using low educated refugees as the treatment group, the estimated treatment effects is similar to the baseline results. However, there are no statistically significant effects on EU and non-EU immigrants. Regardless, as previous low educated refugee cohorts are the closest substitutes to the newly arriving refugees, the labor supply channel cannot be discarded completely and further research is needed to distinguish the effects of both channels.

Previous studies have investigated the welfare dependency among immigrants (Baker and Benjamin, 1995; G. Borjas and Hilton, 1996; G. Borjas and Trejo, 1991; Riphahn, 2004) and highlighted the differences between ethnic groups in terms of take up rates. Furthermore, immigrant inflows impact welfare dependency by exposing workers to higher competition in the labor market (Azlor et al., 2020); Blume and Verner, 2007). However, the effect differs substantially depending on individual characteristics (Francesco Fasani, 2018). Refugees are 11.6% less likely to have a job and 22.1% more likely to be unemployed than migrants with similar characteristics. Immigration shocks are regularly used to analyze the effects on existing immigrants (Card, 1990; G. J. Borjas, 2017; Deole and Huang, 2020; Tumen, 2016). Generally, no effects on natives can be identified, whereas other groups of residents experience hardships due to the inflow of workers. This emphasizes the importance of identifying the correct treatment group.

My study contributes to the literature in the following ways. First, I show that immigrant inflows affect the labor market conditions in host countries. Nevertheless, not all individuals are affected equally. I contribute by showing that low educated immigrants and refugees experience the most severe difficulties. Moreover, I demonstrate that the impact on refugees among the low educated immigrants is likely to be the main driver behind the observation of higher unemployment among immigrants. My results differ from the ones Deole and Huang (2020) observe, as they are focusing primarily on the impact of the refugee crisis on social aspects. Moreover, their treatment group includes immigrants from culturally similar countries instead of limiting it to refugees. I am further distinguishing it to have more clarity behind the effects. Besides, I go one step further and show that refugees among the low educated immigrants are most likely behind the dynamics. Nevertheless, it is reassuring to have estimates that point into the same direction.

The paper is organized in the following way. Section 2 provides a brief overview of the current state of research, while Section 3 highlights the main aspects of the German immigration policy and the refugee crisis. The underlying theory is outlined in Section 4. Section 5 and Section 6 explain the data and the empirical strategy, respectively. Section 7 then presents the results and robustness checks. Finally, Section 8 discusses the results and acknowledges limitations before a conclusion is drawn in Section 9.

# 2 Literature Review

The effects of immigration on host countries has been a topic in the literature for some time as policy makers are interested in solutions to the growing concerns about the negative impact on welfare sectors of the population (Ruist, 2015). Many studies have focused on the performance of immigrants in the host country's economy. Especially the use of social benefits has been investigated, as there is the common claim that immigrants are "living off the welfare state". Borjas (1999) identifies that immigrants are attracted by higher welfare rates, also known as welfare magnets, as immigrant welfare recipients are clustered more heavily in high welfare states in the US, for example. Furthermore, their welfare participation rate is much more sensitive to changes in welfare benefits than that of natives. Regardless, welfare reliance is on average higher for immigrants than for their native counterparts at the beginning of their stay (Castronova et al., 2001; Hansen and Lofstrom, 2003; G. Borjas and Trejo, 1991). Over time, welfare dependency could increase, due to better knowledge of the institutional setting or decrease, due to better employment opportunities. When looking at the process of assimilation of immigrants after arriving in host countries, researchers find that there is an assimilation into welfare dependency in host countries such as the USA, Canada and Germany (Baker and Benjamin, 1995; G. Borjas and Hilton, 1996; G. Borjas and Trejo, 1991; Riphahn, 2004). However, in the case of Germany, this can be explained by the characteristics of immigrant households like income or family structures, instead of an "immigrant premium". Contrarily, researchers find an assimilation out of welfare dependency in Denmark (Blume and Verner, 2007) and Sweden (Hammarstedt, 2000; Hansen and Lofstrom, 2003). Sweden has a very unique welfare state, as it is described to be universal in character and is known for the degree of income security that it provides for the country's population (Hammarstedt, 2008). In general, there are several reasons for the higher welfare dependency of immigrants, such as language problems, discrimination, or network effects (Brücker et al., 2002). Overall, assimilation is conceived as something positive, since it is associated with higher wages for both male and female, is strongly correlated with the formation of networks, and language proficiency is positively associated with being employed for males (Piracha et al., 2023). This exemplifies the importance of a successful immigration policy, since it not only creates better opportunities for immigrants but can substantially benefit the host country's economy.

Initial local conditions and policies substantially effect the assimilation process of immigrants. Being exposed to a dispersal policy without choice of destination or to high initial unemployment in a municipality negatively affects the economic and social integration of refugees and worsens their labor market outcomes (Francesco Fasani, 2018; Aksoy et al., 2020). In addition, stricter integration policies, such as limited family reunification possibilities and lower welfare benefits for immigrants, do not appear to result in the intended higher employment or earnings among non-western immigrants (Jakobsen et al., 2019). However, these restrictions can lead to unintended side effects, as they induce a strong withdrawal from the labor force among women and a large drop in disposable income for most households (Andersen et al., 2019).

Achieving higher employment rates among immigrants is one key goal of almost all labor market policies. The Swedish Establishment Reform from 2010 provided treatment families with individual coaching to facilitate faster integration. Joona et al. (2016) show that the reform led to higher probability of employment. Although early entry into the labor market may seem favorable (Andrén and Andrén, 2013), long-term goals should not be overlooked. Receiving on-the-job training instead of language courses, for example, increases the probability of being employed in the second year after immigration. However, as language skills become more important for further labor market success, this effect disappears three and four years after immigration (Arendt and Bolvig, 2020). When comparing European countries, Büchel and Frick (2005) find that the optimal immigration policy, a policy that results in a nonsignificant difference between the economic performance of immigrants and that of the native population, is not achieved. Particularly in Germany and Denmark, the economic performance of immigrants is substantially lower. However, immigrants improve their economic situation rapidly with increasing duration of their stay, which suggests that these countries' policies do fairly well in fostering economic integration. Economic integration is important for assimilation and self-sufficiency of immigrants. Nonetheless, it also affects the native and immigrant population in the host country as they face more competition in the labor and housing market, and for social subsidies.

There is a large body of literature investigating the effects of immigration on native employment and wages. The studies indicate that the impact of immigration on natives is on average null or slightly positive (Brücker et al., 2014; Edo and Toubal, 2015). Wages of low educated natives in the US are only slightly affected by immigration (between 0.6% and +1.7%) as there is imperfect interchangeability between natives and immigrants. Card (1990) observed no effect from the Mariel Boatlift on the wages and unemployment rates of less-skilled workers. Even though the immigrants increased the labor supply of low skilled individuals substantially, no effect was identified among natives nor Cubans who had immigrated to Miami earlier. Borjas (2017) reassessed the question of wage impacts from the Mariel Boatlift and highlighted the importance of skill matching between the immigrants and the existing workforce. He examines the impact on high school dropouts as 60% of the Marielitos were high school dropouts. The wage of this low-skill group dropped dramatically by 10 to 30%. As adjustments in the labor market take time, the immediate and longer run impacts of immigration can differ. Nevertheless, immigration can create winners and losers among the population by changing the skill composition in the receiving economies. The reaction of a country's labor market to immigration depends on its institutional features. Ottaviano et al. (2012) assess the effect of immigration on wages in the US. They find a decrease of 6.7% for previous immigrants in the long-run. Due to generous welfare state benefits, high levels of minimum wage, and employment protections in European countries, wages cannot adjust downwards and immigration leads to higher unemployment of similarly skilled natives (Glitz, 2012). Glitz uses the fall of the Berlin Wall as a quasi-experiment of immigration. Similarly, Tumen (2016) uses the arrival of refugees in Turkey as a result of the Syrian conflict for a natural experiment to study the economic impact of immigration. He documents moderate employment losses among native informal workers, which suggests that they are partly replaced by refugees, and lower consumer prices of items produced in informal labor intensive sectors due to labor cost advantages generated by refugee inflows. The effects of the refugee crisis is also investigated by Deole and Huang (2020), who look at several outcomes on immigrants from Turkey and the Middle East (TMENA) in Germany. The refugee crisis led to an increase in employment due to an increase in demand of culturally similar consumer goods. Moreover, worries about immigration increased among all respondents.

# 3 Background

The refugee crisis is a possibility to study the effect of immigration, as it was an unexpected event to which the labor market was not prepared. It offers a great opportunity to investigate short term effects of immigrant shocks to the labor market and the adjustment dynamics in the following years.

## 3.1 Immigration Policy

Germany's immigration and asylum policy has been very generous since the end of the Second World War and has been centered around the understanding that every politically persecuted person is entitled for asylum. This was stipulated in the German constitution, however, due to large migration movements during the 1970s and 1980s and unsuccessful control mechanism, first initiatives were taken in 1993 to make Germany less attractive for immigrants. Meanwhile, German politicians were pushing forward in centralizing the asylum law on EU level, which led to stronger legislative power on EU-level in the asylum policy beginning from the mid-1990s. In the European Union, immigration policy received attention after the European Community agreed upon the Single European Market and the associated border openings, which was launched on January 1st, 1993. This would have enabled refugee seekers to cross unhindered into other member states and apply for asylum once again. Hence, the governments were interested in finding a uniform and binding structure for how to deal with asylum applications. The Dublin Convention from 1990 specified the responsibility for asylum processes (Engler and Schneider, 2015b).

Even though it has been updated multiple times, the main principle remains the same, which entitles a member state responsible for a particular asylum application process, if it is the first member state where finger prints of a refugee are stored or an asylum claim is lodged. Generally, this makes the member state, where a refugee enters the EU, responsible. Even though there was a desire for further development of standards and procedures in the EU, the member states could only agree upon minimum requirements. The fundamental principle remained the voluntary admission of migrants. Hence, each country could specify individually their own intake capacity, instead of having preassigned quotas (Engler and Schneider, 2015b). Within the European framework, individual countries have limited room for deviation and mostly differed in the extent to which they offered social assistance and integration programs.

In Germany, the immigration policy centers around the principle "support and demand". Refugees receive support through welfare benefits and courses to foster their integration. In return, they are expected to participate diligently and behave according to their entitlements. More precisely, this can mean that newly arrived refugees have to participate in the offered languages and integration courses, with possible sanctions in the case of disobedience. Courses are offered full-time and are designed to prepare each participant to have sufficient knowledge for formal conversations, as well as some background information about German history and culture. Essentially, the course prepares refugees for future work placements or apprenticeships. Nevertheless, refugees are generally eligible to access the labor market three months after official application for asylum, as long as they are not mandated to live in a admission facility. In this case, they receive eligibility after nine months, regardless of their living situation. Once refugees enter the labor market on a full-time basis, they are not longer obligated to participate in the integration course.

Since 1961, Germany has a general, national, means-tested assistance program. Social Assistance[2] remains today as the most important means-tested part of the German social welfare system. Means are tested at the household level. Social assistance comprises

[2] "Sozialhilfe".

primarily cash transfers, for which each household can apply. The standard transfer is a flat-rate that is set to cover all basic needs, including food, clothes, and household tools. The rate depends on the composition of the household and is frequently adjusted to meet the increase of expenses due to inflation trends. For an individual living in a single-person-household, the current standard rate is EUR 563 per month. For each additional household member, the household receives additional benefits. Besides the standard rate, households can also get additional assistance for housing and other extraordinary situations. Furthermore, health insurance is covered by the state. If one or more household members earn income from employment, their income will be deducted from their welfare payments. Generally, immigrants are entitled to receive the same benefits as native Germans if they possess a residence permit. Refugees instead have to apply for support during the asylum application process. They only receive benefits according to the Asylum Applicant Benefit Act[3]. Those benefits are calculated to cover costs for housing, food, clothes, as well as household goods and medical supplies. Furthermore, asylum seekers receive benefits for public transportation, phone bills, and sanitary products. In total, refugee benefits sum up to EUR 460 per month, but almost half is distributed through in-kind benefits. After a stay of 18 months, refugees are entitled to receive *Equal Benefits*[4]. Those benefits match the social assistance payments and regulations of natives and residents.

## 3.2 Refugee Crisis

The term refugee crisis is associated with the heightened inflow of refugees during the years 2015 and 2016 that affected near to all European countries. The main causes of the refugee flows were the Arab Spring and the Syrian Civil War that started around the beginning of 2011. Germany recorded 50.000 asylum applications in that year (Bundesamt für Migration und Flüchtlinge, 2016). However, from 2014 onwards, more and more immigrants embarked on their journey towards Europe. Most of the refugees took the Eastern Mediterranean Route by boat from Turkey to Greece. According to the Dublin regula-

[3] "Asylbewerberleistungsgesetz".
[4] "Analogleistungen".

tion that governs the asylum application responsibilities in the EU, the country in which the refugee first arrives in is responsible for the respective asylum application. However, many of the arriving refugees had intentions to continue further toward the middle and northern European countries, especially towards Austria, Germany, and Sweden. Those countries were particularly interesting for refugees, as they offered higher welfare benefits and better employment opportunities. With many refugees stranded in Hungary, the German government suspended the Dublin regulation in later summer 2015 and allowed all refugees, who had passed through EU countries, to file for asylum in Germany[5]. During the crisis, the newly arriving refugees were supposed to be received by the federal police at their point of entry. After a regular check-up, they would be brought to a temporary accommodation, where the refugees were supposed to stay before they were assigned to a federal state with free capacities. They were allocated according to a quota[6] that is determined by the size of the population and the GDP of each federal state, in order to allocate the costs related to housing and the processing of asylum claims evenly. However, the sudden jump in arrival rates of refugees in Germany led to a severe processing backlog of asylum applications. This forced many arriving refugees to officially apply for asylum in 2016 instead of 2015. The refugee inflow eventually dropped with the closing of the Eastern Mediterranean Route in March 2016. In total, the Federal Office for Migration and Refugees received 1.3 million asylum applications in 2015 and 2016. Refugees that arrived during the refugee crisis were mostly from Syria, Iraq, and Afghanistan (Bundesamt für Migration und Flüchtlinge, 2016), hence, they had mostly received education and degrees that were not easily transferable into the German education system. Often times, the refugees were unable to obtain certification to work in the same occupation they had before, also due to different standards in Germany and their home countries. Moreover, the language posed a difficulty to be integrated into the industry or occupation they had worked in before. Consequently, they were unable to compete with immigrants from previous cohorts that had higher education. They were often restricted to work in occupations for which no higher education was needed.

[5]The Dublin rules were partly reinstated in November 2015.
[6]"Koenigssteiner Schluessel".

# 4 Theory

How is the 2015/16 migrant crisis expected to have affected previous cohorts of immigrants in Germany? I am going to investigate two possible channels through which existing immigrants might have been impacted, the labor supply and the discriminatory channel. The main countries of origin for refugees arriving during the crisis were Syria, Afghanistan, and Iraq. Especially young individuals came, who were unfamiliar with the German language and lacked proof of their educational or professional background. Their educational composition differed substantially from the German population's (Brücker, 2016). Hence, native Germans should have not been affected by the sudden inflow of labor supply, as there was only limited interchangeability between these refugees and natives. Nevertheless, the newly arrived refugees were there to stay and had to be integrated into the labor market, which might have affected previous immigrants in the labor market because of higher competition. Moreover, the refugee crisis was an unprecedented event that had repercussions throughout the German society. Discriminatory attitudes might have worsened in the fear of welfare abuse from immigrants. In general, there are reasons to believe that especially previous immigrants were hit by the refugee crisis.

## 4.1 Labor Supply Channel

According to standard economic models, the main mechanism through which immigration can affect the labor market is the increasing number of workers. This increase mechanically reduces the level of physical capital per worker, negatively affecting labor productivity. Therefore, the average wage of workers decreases in response to an immigration-induced increase in the labor supply (G. Borjas, 2013). Indeed, the initial negative impact of immigration on wages can lead some natives to exit the labor force. However, if wages are not flexible due to labor market institutions (such as strict employment protection, a high minimum wage, or generous welfare state benefits), unemployment in the economy will rise. Edo and Rapoport (2019) find that labor market rigidity tends to prevent wage adjustments for some groups of native workers following labor supply shocks. However, this lack of flexibility tends to increase unemployment and decrease native employment.

An important assumptions underlying these preliminary results is that the capital stock in the economy is fixed. However, this assumption may not be realistic (Ottaviano and Peri, 2012). From a theoretical point of view, it is important to distinguish the impact of immigration on wages in the "short run" and the "long run", as firms are able to respond to the increased number of workers through capital accumulation in the long run. Therefore, the impact of an immigration-induced increase in labor supply on the average wage depends on the dynamic response of physical capital accumulation. The ability of firms to change their technology is an important factor as well, since capital and low-skilled labor are substitutes. Since physical capital has not the same degree of interchangeability with all skill groups, immigration can be absorbed through changes in firms' production techniques. In fact, firms can adopt new technologies that make more intensive use of those skills that have become more abundant as a result of immigrant inflow. This adjustment through changes in technology is expected to attenuate any negative wage effect by increasing the productivity of the abundant factor (Lewis, 2011; Lewis, 2013). Nevertheless, adjustment mechanisms take time, especially when unexpected shocks occur in the labor market.

Another channel through which immigration can affect the labor market is by changing the skill composition of the workforce. Immigrants can differ from the native population in terms of their characteristics such as education, health, and age. The presence of heterogeneous labor implies that the wage impact of immigration will be heterogeneous between skill groups (G. Borjas, 2003; Ottaviano and Peri, 2012). Immigration will decrease the marginal product and therefore the wages of resident workers more similar to immigrant workers (Dustmann et al., 2016). Peri and Sparber (2009) find that immigrants specialize in manual-intensive jobs for which they have a comparative advantages, while natives with similar education pursue jobs involving higher levels of communication. As a result, immigration can push some native workers with comparable education into more cognitive and communication-intensive jobs. Immigration tends to worsen the wages of competing workers, those who have skills similar to those of the migrants and improve wages of complementary workers, those who have skills that complement those of immigrants. In general, previous waves of immigrants are the closest substitutes for new immigrants, so the adverse effects in the labor market of immigration tend to be concentrated among immigrants themselves (Edo, 2019). In both Sweden and Finland, for example, immigrants enter the labor market through low-paying establishments, where their coworkers and managers are disproportionately often immigrants (Ansala et al., 2022). Hence, immigrants from previous cohorts could have been replaced by newly incoming immigrants because of working in occupation for which only little training was needed and the language barrier is not as strict as in other communication-oriented jobs. As the immigrants' total rate of participation in the income security system is determined by their rate of unemployment and their state of health (Hammarstedt, 2000), the refugee crisis possibly increased the welfare dependency of existing immigrants in Germany.

## 4.2 Discriminatory Channel

The second channel through which the refugee crisis could have led to higher unemployment and welfare dependency among immigrants is the discriminatory channel. Due to the enormous number of incoming refugees and the allocation throughout the entire country, the entire German society was impacted by the refugee crisis. The media and right-wing political parties fueled the perception of immigrants, and especially refugees, as a threat to the German society (Abbott, 2013). This channel most likely did not erupt suddenly as the inflow of refugees into Germany, but was initiated by reports about ongoing conflicts in the Middle East. However, when the number of refugee quadrupled in 2014 compared to 2013 (Bundesamt für Migration und Flüchtlinge, 2016), the public discourse intensified. There were accusations of welfare immigrants, who exploit the German welfare system by collecting benefits without participating in the repayment of the associated costs. Regardless of their skill level, immigrants, and especially those from the current refugee countries, faced increased hostility. The objection towards refugees could have further deteriorated their labor market position. Immigrants already face a heavy burden, as people might see them as competition for their jobs without acknowledging their right of residency. Even though employees are protected by law against any form of discrimination, there are indirect measures that employers can use to limit the intake of individuals from specific countries, such as language requirements, credential evaluation, and cultural fit assessments. Furthermore, finding employment can be especially hard for refugees when they are facing heightened negative sentiment[7]. In other words, refugees might have experienced more severe hardships in the (re-)integration process in the labor market due to the refugee crisis. Hence, by differentiating between EU, non-EU, and refugee immigrants, I can identify whether there were differential effects among these groups in response to the crisis.

# 5 Data

This paper uses data from the Luxembourg Income Study Database [8](LIS, May 2024), which is the largest income database of harmonised microdata collected from 53 countries in Europe, North America, Latin America, Africa, Asia, and Australasia spanning five decades. Data is made available by research institutes from each participating country to offer microdata that would otherwise be incomparable or impossible to access. Harmonised into a common framework, LIS datasets contain household- and individual-level data on labor income, capital income, pensions, public social benefits and private transfers, as well as taxes and contributions, demography, employment, and expenditures. German data is provided by the German Institute for Economic Research (DIW) and comes from their annual Socio-Economic Panel (SOEP), which is the largest and longest-running multidisciplinary household survey worldwide. The German SOEP is a large-scale household panel survey that is designed to be representative of the entire German population. All samples of SOEP are multi-stage random samples that are regionally clustered. The respondents (households) are selected by random-walk. In principle, an interviewer tries to obtain face-to-face interviews with all members of a given survey household aged 16 and above. Additionally, one person, the head of the household, is asked to complete a house-

[7]Arai et al. (2021) find that male public employment officers favor job seekers without a foreign background for participation in a labor market program in Sweden.

[8]The database is accessible to registered users via a remote-execution system known as LISSY and via DART.

hold questionnaire. This also includes some questions about children up to 16 years of age in the household (e.g. kindergarten attendance, elementary school attendance, etc.). The dataset contains wide-ranging longitudinal data of private households in Germany beginning in 1984. It includes data on respondents' demographics, living conditions, family composition, employment in annual wages, and social benefits. In 1990, it was expanded to include representative data from East Germany and in 2016, a new sample of refugees was added. The most recent version, covering 1984 until 2021, includes approximately 30,000 individuals living in 15,000 households (German Institute for Economic Research, 2023). There are many features of the SOEP that make it an attractive data source for this study. As it tracks the individual survey respondents, even if they move, the survey allows me to monitor the evolution of economic performance and dependence on social benefits of the same individuals. Furthermore, the SOEP is a very rich survey and the level of detail provided both at the individual and at the household level enables me to use a wide range of variables. Additionally, reporting errors are minimized since information on the employment status, earning, and social benefits are not gathered retrospectively but come directly from the respondents' answers.

## 5.1 Sample Selection

As I am interested in the spillover effect of the refugee crisis on immigrants that are already residing in Germany, I am restricting the sample to include only immigrants. The immigrant status refers to people whose citizenship is not the same as the country they live in. Furthermore, only individuals that arrived in Germany before 2010 are included in the sample, in order to exclude immigrants who entered Germany in response to the Syrian Civil War. There were already increased numbers in asylum applications between 2010 to 2014 (Bundesamt für Migration und Flüchtlinge, 2016). The effect that I want to identify is on those individuals that are already established in Germany and are eligible to work. Before 2014, immigrants were allowed to enter the labor market nine months after their official asylum application (Engler and Schneider, 2015a). Hence, immigrants that entered Germany in 2010 or before were entitled to work. The main focus is on individuals in the labor market as those are most likely to be the group that experiences the highest impact of the refugee crisis. Hence, I restrict the sample to only include immigrants aged 18-65 years. My sample includes people in employment, unemployment, and out of the labor market. To ensure the effects are not driven by different samples, I further restrict the sample to only include immigrants for which I have information on all variables used in the analysis. Moreover, I am only including survey years until 2019 to avoid any impact of COVID on my outcome variables. In total, I have 22.950 observations, of which 5803 are low educated immigrants and 6118 are high educated immigrants.

## 5.2 Treatment and control group

I am using the educational level of immigrants to distinguish between immigrants that were affected by the refugee crisis and those that were mainly protected from the effects. In the data, the educational level of immigrants is coded into three categories: low, medium, and high based on the International Standard Classification of Education (ISCDE) levels. A low education level corresponds to level 0, 1, and 2, which include individuals with less than primary, primary, and lower secondary education. People with a medium education level are either in level 3 or 4 on the ISCDE scale, representing those with a upper secondary and post-secondary but not tertiary education. High encompasses all individuals with short-cycle tertiary education and above. The treatment group will contain immigrants with low education who arrived before 2010. The control group includes immigrants with high level of education that arrived before 2010. As mentioned above, this group should not have experienced an effect from higher numbers of refugees coming in, since those immigrants mostly worked in different occupations. Hence, they should serve as a reliable counterfactual. The effect for medium educated immigrants is estimated separately for further insights into the ongoing dynamics.

To investigate the discriminatory channel, I am using the citizenship of immigrants to separate them into three groups: EU immigrants, refugees[9], and immigrants from neither

[9]Immigrants coming from one of the top 5 countries of origin during the refugee crisis. These are Afghanistan, Eritrea, Iran, Iraq, and Syria.

of the two sets of origin countries. I am looking again at immigrants that arrived before 2010 in Germany. The treatment group in this specification includes all immigrants from refugee countries. The control group comprises all immigrants from EU countries. The effect for non-EU immigrants is estimated separately to individually identify the effect on refugee immigrants through the discriminatory channel. EU immigrants face less obstacles than immigrants from third countries as they can generally transfer their educational certificates more easily, do not require visas, and have more liberty in choosing a job due to the European Schengen agreement.

## 5.3 Outcome variables

Due to the data structure, the household is the income unit. However, the unit of analysis is the individual with characteristics sampled in the panel survey. A household's income is defined as the annual market income plus transfers of all household members. This is the sum of cash and non-cash income from labor, income from capital, income from pensions (including both public and private pensions) and non-pension public social benefits stemming from insurance, universal or assistance schemes (including in-kind social assistance transfers), as well as cash and non-cash private transfers. Pensions consist of public non-contributory pensions, public contributory pensions, and private pensions. Those are generally monetary transfers for old-age, disability, and survivors, stemming from the public programs, which are aimed at covering the whole population or a part of the population selected based on other criteria than previous employment existence or income or assets thresholds. Nevertheless, as I am focusing on individuals in the labor market, pensions do not affect the total income of a household. Some of the social assistance benefits for immigrants are provided as in-kind transfers, however, these are denoted with a specific Euro value that is included in the total household income.

Mainly, I am focusing on two outcome variables: welfare dependency and unemployment. To avoid issues regarding the absolute amount of welfare benefits or participation rates, Blume and Verner (Blume and Verner, 2007) use the household welfare dependency rate as it can allow insights into the degree of welfare dependency more accurately. I am following their approach and calculate the welfare dependency rate accordingly:

$$\text{Welfare dependency rate}_{jt} = \frac{\text{All Public Income Transfers}_{jt}}{\text{Total Household Income}_{jt}}$$

Public income transfers fall generally in two categories: child benefits and public housing and income-replacing transfers (social assistance, unemployment benefits, etc.). I add all received benefits together to get a measure of *All Public Income Transfers* to calculate the welfare dependency rate. Market income and income transfers include labor income, income from capital and transfers. They do not include rental value for housing, nor free day care and other state-financed amenities. Income from children and household members other than the head of the household and the spouse are ignored. The measure will show the welfare dependency rate for household $j$ at time $t$. Using the welfare dependency rate will allow me to analyze whether the degree of public support is changing over time.

Unemployment is the second outcome I explore. Each individual in the sample provides information about their labor force status. Hence, unemployment is a dummy that equals the value 1 if the individual is unemployed or out of the labor force, and 0 otherwise. This helps me to identify the underlying mechanism. Descriptive statistics for the outcome variables as provided in Section 5.5.

## 5.4 Conditioning and control variables

The choice of control variables is motivated by economic theory, hence, those are variables that can reasonably be expected to influence the degree of welfare dependency and the level of unemployment. The final selection of variables is based on a screening of variables used in similar empirical studies on welfare dependency (Blume and Verner, 2007; Hansen and Lofstrom, 2003; Castronova et al., 2001; Hammarstedt, 2008).

Household, household head, and individual characteristics are included in the specifications to capture differences in the outcome variables that are not driven by the refugee crisis. The control variables include the sex, age, and living situation of the household head, total number of household members, number of household members below the age of 13. Furthermore, the individual characteristics that are considered are the number of years residing in Germany, gender and age, as well as dummy variables for being married, never married, separated, divorced, and widowed.

## 5.5 Descriptive Statistics

Table 5.1: Descriptive Statistics Labor Supply Channel

| Variable | Treated | Control | Difference | P-Value |
|---|---|---|---|---|
| Welfare Dependency | 0.323 | 0.128 | 0.195*** | 0.000 |
| Unemployment | 0.307 | 0.136 | 0.170*** | 0.000 |
| Refugee | 0.048 | 0.011 | 0.037*** | 0.000 |
| NonEU | 0.761 | 0.728 | 0.032*** | 0.000 |
| EU | 0.191 | 0.260 | -0.069*** | 0.000 |
| | | | | |
| Female Household Head | 0.416 | 0.484 | -0.068*** | 0.000 |
| Age Household Head | 42.611 | 42.999 | -0.387 | 0.037 |
| Partnered Household Head | 0.785 | 0.797 | -0.012 | 0.101 |
| Household Members | 3.947 | 3.078 | 0.869*** | 0.000 |
| Household Members below 13 | 1.079 | 0.878 | 0.201*** | 0.000 |
| | | | | |
| Years of Residency | 18.838 | 17.332 | 1.506*** | 0.000 |
| Female | 0.496 | 0.545 | -0.048*** | 0.000 |
| Age | 40.225 | 42.801 | -2.577*** | 0.000 |
| Married | 0.657 | 0.713 | -0.056*** | 0.000 |
| Never Married | 0.201 | 0.141 | 0.060*** | 0.000 |
| Separated | 0.039 | 0.049 | -0.009** | 0.014 |
| Divorced | 0.083 | 0.088 | -0.004 | 0.412 |
| Widowed | 0.019 | 0.010 | 0.009*** | 0.000 |
| Observations | 5803 | 6118 | 315 | |

*Note:* This table presents means and mean differences for the set of outcome and control variables in my labor supply channel analysis. All variables are measured on a pooled sample of immigrants in my dataset for the period 2012-2019. Treated are all low educated immigrants. Control are all high educated immigrants. The last column displays p-values for the t-test. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

In Table 5.1, descriptive statistics are reported for the outcome variables, as well as all control variables included in the estimations. Treated observations are those belonging to the low educated immigrant group and the control observations represent high educated immigrants. Several things are worth noting from this table. Firstly, low educated and high educated immigrants have a significant difference in both of the outcomes variables, welfare dependency and unemployment. Secondly, in the low educated immigrant group, the share of refugees is more than four times higher than in the high educated immigrant group. Lastly, low educated immigrants have resided on average longer in Germany than high educated immigrants. Descriptive statistics for the discriminatory channel are provided in Table A.1.

# 6 Empirical Strategy

Determining if and to what extent newly arriving immigrants affect existing immigrants in Germany is challenging. Estimating the causal effects of this requires comparing immigrants who experience an impact with individuals that do not. The refugee crisis offers a great opportunity to study the effects on existing immigrant cohorts, as it was an unexpected event that induced a labor market shock of mainly low educated refugees. Previous research has used immigrant inflows as an exogenous shock to identify the effects on labor market outcomes, wages, and consumer prices (Friedberg, 2001; Foged and Peri, 2016; Tumen, 2016). In the following sections, I will develop the empirical strategy to estimate the effect of the refugee crisis on existing immigrants in Germany.

Since the refugee crisis affected the entire German society, there are no immigrants that can represent the true counterfactual outcome. Instead, I am evaluating the impact on immigrants with different educational levels and with different citizenship. Labor market outcomes of immigrants and immigrant inflows are however correlated with unobserved factors, such as the perceived social stigma associated with receiving welfare benefits. Hence, changes in the welfare dependency are not inherently random and using OLS for identification would lead to endogeneity. Omitting the perceived social stigma would lead to an underestimation of the effect of the refugee crisis on existing immigrants. To account for this omitted variable bias, I am using a difference-in-difference (DiD) approach. This has been a popular approach to estimate the effects of macro-level shocks on individual level outcomes (Card, 1990; G. J. Borjas, 2017; Deole and Huang, 2020).

To estimate the causal effect of the refugee crisis on existing immigrants, I estimate the following regression:

$$Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst} \tag{1}$$

$Y_{ijst}$ represents one of the outcome variables for individual $i$ in household $j$ in region $s$ at time $t$. $\beta_0$ is the intercept. The variable $Treat_i$ represents the educational level of the respondent. If an individual has a low education level, they belong to the treatment group. The treatment effect is captured by $\beta_3$, showing the different impact on the treatment group compared to the high educated control group. $Post_t$ is equal to 1 if the year is 2017 or later. $X_{ijt}$ is a vector of individual and household characteristics. $\lambda_s$ are region fixed effects to account for differences in state-level time invariant (un-)observable factors that influence the outcomes.

To evaluate the discriminatory channel, I estimate Equation (1) and define the variable $Treat_i$ by citizenship. In this case, being treated are those immigrants from one of the refugee countries. $Post_t$ is equal to 1 if the year is 2014 or later, as the discriminatory channel most likely affected immigrants already with the start of higher refugee inflow numbers in Germany.

The most critical assumption when using a difference-in-difference specification is the parallel trends assumption that must hold. Treatment and control group need to have similar trajectories before the reform in order to be able to attribute the change in the treatment group to the event. Following the parallel trends reasoning, in the absence of the event, there would not have been a change in the difference. In order to identify any causal treatment effect of the refugee crisis on low educated immigrants that arrived before 2010 in Germany, the parallel trend assumption has to be investigated. In this study, the treatment group are all immigrants with a low education level. The control group contains immigrants with a high education level. Estimates for medium educated immigrants are shown as a robustness check.

Even though the parallel trend assumption is of fundamental importance, there is no possibility to directly test whether the assumption holds. Hence, I will apply an event study approach to investigate whether there are similar trends in treatment and control group before the event of interest. Such an analysis can be helpful in determining whether parallel trends is a plausible assumption. For the event study, I run the following specification:

$$Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum_{t=2012, t \neq 2016}^{2019} \gamma_t Year_t + \sum_{t=2012, t \neq 2016}^{2019} \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst} \quad (2)$$

$Y_{ijst}$ represents one of the outcome variables for individual $i$ in household $j$ in region $s$ at time $t$. $\beta_0$ is the intercept. Treatment is defined as before. The baseline year is 2016. $\sum_{t=2012, t\neq 2016}^{2019} Year_t$ is a set of year dummy variables. The treatment effect is captured by the interaction term between $Year_t$ and $Treat_i$. For the parallel trends assumption to be plausible, all $\delta_{tj}$ before 2016 should be indistinguishable from zero. $X_{ijt}$ is a vector of individual and household characteristics. $\lambda_s$ are region fixed effects to account for differences in state-level time invariant (un-)observable factors that influence the outcomes. I am running specification with and without controls. The control variables include a dummy variable for female household heads, the age of the household head, a dummy variable specifying whether the household head lives together with their partner, the number of household members, the number of household members below the age of 13, a dummy variable for being female for the individual, the individual age, years of residence in Germany, a dummy for being married, a dummy for never being married, a dummy for being separated, a dummy for being divorced, and a dummy for being widowed.

I run a similar regression for the discriminatory channel with slight changes. Primarily, the event year is set to represent the start of increased discriminatory attitudes towards refugees. Hence, the baseline year is 2014 in this specification. Furthermore, the treatment and control group in this case are EU immigrants and refugee immigrants. This event study is used as well to show suggestive evidence that in the absence of the refugee crisis, the treatment and control group would have followed the same trends.

In all specification, I include region fixed effects. Region fixed effects are important to control for baseline differences in time-invariant (un-)observable factors at the state-level. The regional level is the federal state in Germany. Given the survey nature of the data, the SOEP survey weights are used as base weights both for the treatment and control units in order ensure proper representation of the German population. To avoid any residual bias due to unobserved characteristics, I am using cluster robust standard errors. According to Cameron and Miller (2015), you should choose the broadest feasible clustering level, however, there should be at least 50 clusters to ensure reliable calculations. Using household clusters solves this problem and allows me to avoid an autoregressive bias.

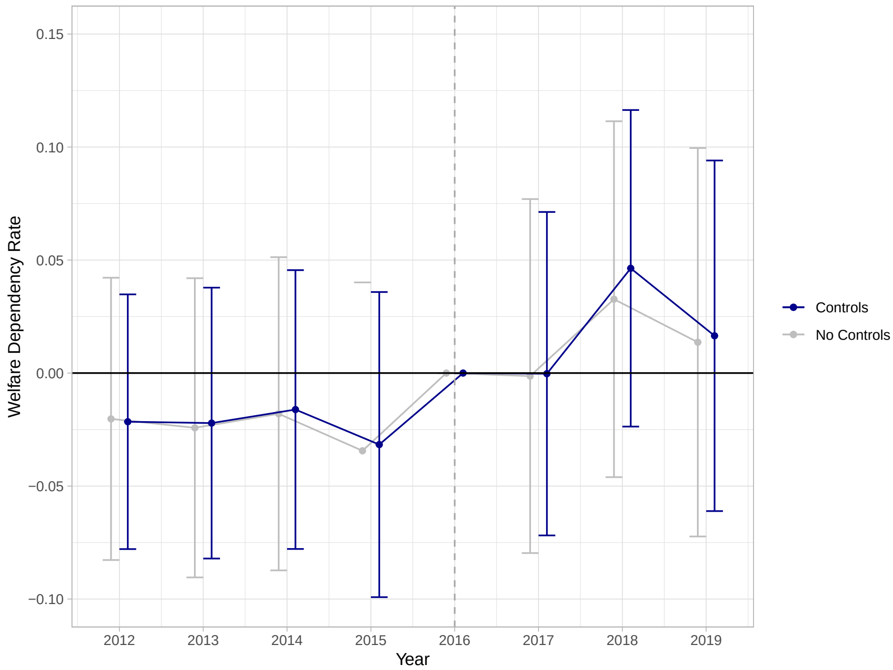
# 7 Results

In this section, the results of the difference-in-difference analysis are shown. Primarily, the results with regard to welfare dependency and unemployment are presented. Then, I test the labor market discrimination channel as a potential mechanism. In Section 7.3, I am evaluating the robustness of my results.

## 7.1 Labor Supply Channel

I am starting my analysis by estimating Equation (1) for the three educational levels. Before investigating the results, I need to assess whether the parallel trends assumption is valid, as it is crucial for the interpretation of causal results. This is often done by pre-testing and a graphical analysis. Nevertheless, the parallel trends assumption cannot be tested directly. Therefore, it remains an assumption about the nature of the data. Further robustness checks regarding the assumption are evaluated in Section 7.3. Results from the pre-testing can be found in Table A.2. There are no statistically significant treatment effects before the crisis in any of the specifications. Hence, I can see this as support for the parallel trends assumption. Although the treatment and control group seem to have parallel trends before the refugee crisis, they have different levels in welfare dependency and unemployment. Low educated immigrants depend more heavily on welfare and have higher rates of unemployment, which could be explained by the weaker labor market attachment of low-skilled people. Moreover, the treatment effects with their 95% confidence intervals from Table A.2 are graphically displayed in Figure 7.1 and Figure 7.2. The graphs also show that unemployment precedes welfare dependency.

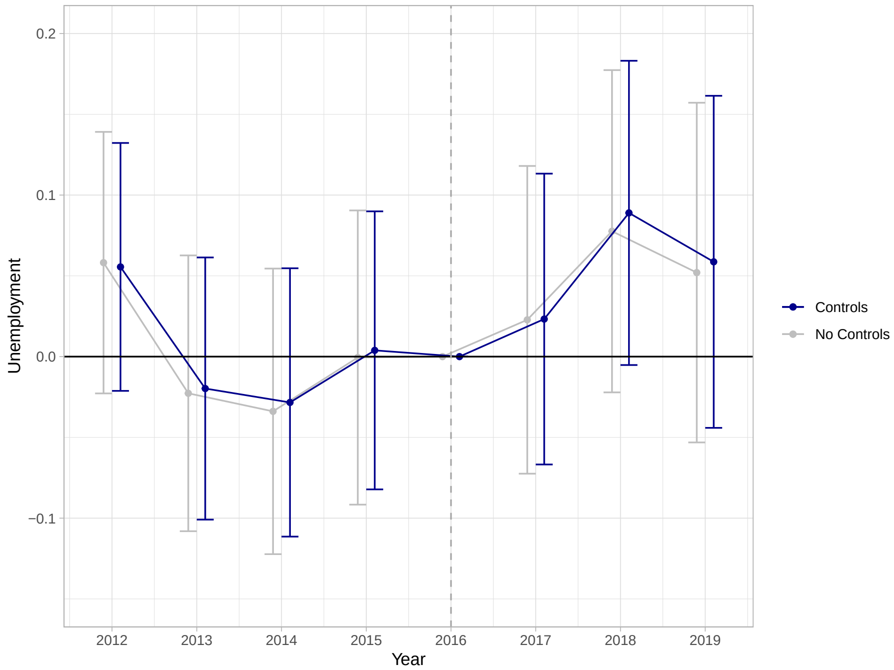
Figure 7.1: Event Study Plot of Welfare Dependency for Low Educated Immigrants




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (1) and (2) in Table A.2 displaying results for low educated immigrants from the following regression: $Dependency_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Results from Equation (1) are reported in Table 7.1. In column (1), I display results for the welfare dependency without any controls. The negative and significant effect for *After* ($\beta_2$) shows that on average welfare dependency decreased after the crisis by 2.1 percentage points. As explained above, *After* is specified as 2017 or later because of the delayed labor market entry eligibility and processing backlog of the asylum applications. The interaction term between low educated immigrants and *After* ($\beta_3$) is not statistically significant in this specification. However, when adding control variables (column (2)), the

Figure 7.2: Event Study Plot of Unemployment for Low Educated Immigrants




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (3) and (4) in Table A.2 displaying results for low educated immigrants from the following regression: $Unemployment_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

treatment effect becomes significant. On average, low educated immigrants experience a 3.9 percentage points higher welfare dependency after the crisis compared to the control group. This is statistically significant at a 5% level. Hence, there is some evidence of an "immigrant shock" on previous low educated immigrants. In column (3) and (4), the results for unemployment are shown. Unemployment decreases statistically significant between 2.3 and 2.4 percentage points after the refugee crisis. However, the treatment effect ($\beta_3$) is positive and statistically significant at the 10% level in the specification without control variables. When adding controls, the treatment effect increases from 4.8 to 5.3 percentage points and is statistically significant at a 5% level. This supports the hypothesis that newly arriving refugees are substitutes for previous low educated immigrants. The interaction term between medium educated immigrants and *After* is in none of the specifications statistically significant. Hence, this shows that there was no differing effect between high and medium educated immigrants after the refugee crisis. The decrease

Table 7.1: Difference-in-Difference: Welfare Dependency and Unemployment on Educational Level

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.056*** | 0.062*** | 0.031*** | 0.043*** |
| | (0.008) | (0.008) | (0.011) | (0.010) |
| Low | 0.153*** | 0.135*** | 0.142*** | 0.139*** |
| | (0.010) | (0.010) | (0.013) | (0.013) |
| After | −0.021** | −0.024** | −0.023 | −0.024* |
| | (0.011) | (0.011) | (0.014) | (0.014) |
| Medium*After | −0.005 | 0.001 | −0.008 | −0.004 |
| | (0.014) | (0.014) | (0.019) | (0.018) |
| Low*After | 0.034 | 0.039** | 0.048* | 0.053** |
| | (0.021) | (0.019) | (0.026) | (0.025) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 22,950 | 22,950 | 22,950 | 22,950 |
| $R^2$ | 0.085 | 0.215 | 0.042 | 0.090 |
| Mean | 0.200 | 0.200 | 0.175 | 0.175 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2016. The sample consists of yearly observations from 2012 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

in unemployment for high and medium educated immigrants could potentially show the complementarity between higher and lower skilled people.

Instead of higher unemployment, more intense competition in the labor market could induce individuals to receive lower wages or work fewer hours. Eventually, this could lead to higher welfare dependency, as the German welfare state supports people up to a certain threshold, if they cannot reach the amount through their own labor market activities. I am investigating this margin in Table A.5 and find no significant effect on low educated immigrants. Due to the data structure, the sample only includes employed immigrants, hence, it is not easily comparable to the observations from the previous analysis. However, it shows that the refugee crisis did not affect low educated immigrants in employment differently. They are not receiving lower wages nor work fewer hours because of the inflow of new refugees. Possibly, this dynamic is driven by labor market rigidity created by the minimum wage, which hinders wage adjustments in the labor market. Nevertheless, this can be seen as further support for the channel described above, in which the refugee crisis led to higher unemployment among low educated immigrants, and eventually caused them to increase their welfare dependency.

## 7.2 Labor Market Discrimination

As previously shown in the summary statistics, the composition of low educated and high educated immigrants with regard to their citizenship differs. Hence, the underlying mechanism through which previous immigrants are affected by newly arriving immigrants is possibly discriminatory in nature. To understand the relationship between citizenship and welfare dependency, I am splitting the sample into three groups of immigrants based on their country of origin and estimate Equation (1). As aforementioned, I am using 2013 as the year of event in this specification, since in the following year asylum applications from Syrian citizens quadrupled (Bundesamt für Migration und Flüchtlinge, 2016) and refugees were increasingly seen as a threat to the German society due to the media attention and right-wing political parties. Hence, the sample in these regressions is larger, as I am including observations from 2010 to 2019. Here again, the parallel trends assumption is important for the identification of treatment effects. I am running Equation (2) and show the results in Table A.3. The treatment effects are generally indistinguishable from zero with one exception. When regressing welfare dependency on the country of origin without controls, there is a statistically significant effect in 2011. However, when adding control variables, the effect size decreases substantially from negative 21 percentage points to negative 12.2 percentage points and the significance of the effect is gone. Hence, there is support for the parallel trends assumption but the results should be analyzed with caution. I illustrate the treatment effects and their 95% confidence intervals in Figure A.1 and Figure A.2. Interestingly, both graphs show a spike in treatment effects in 2017, corresponding to the year of labor market entry of the refugees from the refugee crisis. However, only the treatment effect on unemployment in the specification with control variables is statistically significant at a 10% significance level in that year.

Table 7.2: Difference-in-Difference: Welfare Dependency and Unemployment on Citizenship

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.040*** | 0.030*** | 0.025* | 0.021 |
| | (0.010) | (0.011) | (0.015) | (0.015) |
| Refugee | 0.324*** | 0.225*** | 0.305*** | 0.234*** |
| | (0.042) | (0.036) | (0.056) | (0.052) |
| After | −0.017 | −0.021* | 0.009 | 0.002 |
| | (0.012) | (0.012) | (0.017) | (0.016) |
| NonEU*After | −0.006 | −0.0004 | −0.024 | −0.016 |
| | (0.014) | (0.013) | (0.019) | (0.018) |
| Refugee*After | 0.084 | 0.108** | 0.011 | 0.045 |
| | (0.053) | (0.051) | (0.070) | (0.068) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.066 | 0.191 | 0.026 | 0.069 |
| Mean | 0.222 | 0.222 | 0.188 | 0.188 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2013. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

In Table 7.2, I show the results for welfare dependency and unemployment on different groups of country of origin. The results show that immigrants from one of the top 5 countries of origin during the refugee crisis have generally higher welfare dependency compared to immigrants from the EU, or immigrants from neither the EU nor one of the refugee countries. The difference in levels in welfare dependency to EU immigrants ($\beta_1$) is 32.4 percentage points in the specification without controls and 22.5 percentage points in the specification with controls. Both estimates are statistically significant at the 1% significance level. Furthermore, the negative and significant effect of the refugee crisis is indicative that immigrants experienced on average lower welfare dependency after 2013 ($\beta_2$). The interaction term of being from one of the refugee countries and *After* ($\beta_3$) is only significant in the specification with control variables. After the crisis, refugees had on average 10.8 percentage points higher welfare dependency compared to EU immigrants. This is statistically significant at a 5% significance level. Hence, there is some evidence in support of an "refugee shock" on previous refugee immigrants. When looking at the unemployment in column (3) and (4) of Table 7.2, you can see that there is no statistically significant effect among refugees that differs from the one on EU immigrants. In other words, I do not observe a significantly positive $\beta_3$ for unemployment. Furthermore, there is no effect of the refugee crisis on unemployment of EU immigrants either, as $\beta_2$ is statistically insignificant.

Table 7.3: Difference-in-Difference: Welfare Dependency and Unemployment on Citizenship (Low Educated)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.050* | 0.025 | 0.061* | 0.054* |
| | (0.028) | (0.025) | (0.033) | (0.032) |
| Refugee | 0.174*** | 0.082 | 0.233*** | 0.173** |
| | (0.068) | (0.054) | (0.085) | (0.081) |
| After | 0.008 | −0.015 | 0.024 | 0.005 |
| | (0.034) | (0.028) | (0.039) | (0.036) |
| NonEU*After | −0.011 | 0.011 | −0.026 | −0.014 |
| | (0.039) | (0.032) | (0.045) | (0.041) |
| Refugee*After | 0.207** | 0.312*** | 0.156 | 0.238** |
| | (0.083) | (0.072) | (0.104) | (0.100) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 5,368 | 5,368 | 5,368 | 5,368 |
| $R^2$ | 0.105 | 0.308 | 0.069 | 0.155 |
| Mean | 0.344 | 0.344 | 0.299 | 0.299 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2013. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany that have low education. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

In order to investigate whether labor market discrimination drives the results behind the observation of higher welfare dependency among low educated immigrants after the refugee crisis, I am running another difference-in-difference specification in which I only include low educated immigrants. I am using Equation (1) for the analysis. The sample in this specification includes observations from 2010 to 2019. Before looking at the results, I am pre-testing for treatment effects before the refugee crisis to assess whether the parallel trends assumptions seems plausible. The results can be found in Table A.4. The event study shows similar patterns as before. The treatment effects are overall indistinguishable from zero. However, in 2011, there is a statistically significant effect on welfare dependency for refugees, which questions the appropriateness of the low educated EU immigrants as a control group for low educated refugees. However, the significance level is 10% and it disappears when controls are added to the specification. When plotting the treatment effects in Figure A.3 and Figure A.4 with the standard 95% confidence intervals, the treatment effect in 2011 is insignificant. Moreover, there is no significant treatment effect for unemployment as the outcome variable. Hence, the parallel trends generally evolve in a similar manner. Nonetheless, the results should be interpreted with caution. Once again, there is a spike in treatment effects during the refugee crisis in 2017, which corresponds to the observation from Section 7.1. Both for welfare dependency and unemployment, the treatment effects in 2017 are statistically significant when including control variables. Levels in welfare dependency and unemployment differ substantially for low educated refugees and low educated EU immigrants. This can potentially be explained by cultural differences, language barriers, and differences in the ease of the immigration process that effect the integration into the labor market.

Results for the difference-in-difference analysis can be found in Table 7.3 for welfare dependency and unemployment. The event year in this specification is 2013. Considering the specification in column (1), refugees have on average a 17.4 percentage point higher welfare dependency then their EU immigrant counterparts. This is statistically significant at a 1% level. Nonetheless, the significance disappears when controlling for covariates. Furthermore, the refugee crisis substantially increased their welfare dependency. With a significance level of 1%, refugees have a 31.2 percentage point higher welfare dependency after the crisis. Moreover, they experience a spike in unemployment after the refugee crisis, with an increase of 23.8 percentage points. The treatment effect is statistically significant at a 5% level. The effect sizes are considerably larger and more significant than in the previous regressions, which might indicate that labour market discrimination against people from refugee countries is the mechanism behind the observations that low educated immigrants increased their welfare dependency in the aftermath of the refugee crisis. Given that the year of event in this specification is 2013, there is reason to believe that people were laid off because of their origin instead of increased competition in the labor market. Nevertheless, as the newly arriving refugees are most likely the closest substitutes for previous low educated refugees, I cannot rule out the labor market channel completely.

## 7.3 Robustness Checks

In this section I assess and comment on the robustness of the empirical results. Primarily, I evaluate the choice of standard errors for the parallel trends assumption. Secondly, I am using an alternative definition of experimental groups. Lastly, I am defining the treatment period differently to verify the baseline results.

Instead of using the applied clustered standard errors that I have used to account for within-cluster correlation, there is the possibility to use heteroscedasticity and autocorrelation (HAC) robust standard errors. The results with HAC standard errors for Equation (2) can be found in Table A.6 and Table A.7. The reported standard errors are smaller or equal to the clustered standard errors, resulting in higher significance levels. However, the only interaction with a statistically significance level remains in column (1) of Table A.7. The treatment effect of refugees in 2011 in the specification without controls is significant at a 10% significant level. This finding challenges the validity of the parallel trends assumption. However, the effect becomes indistinguishable from zero when adding controls. As it is preferred to use more conservative standard errors to avoid the identification of false effects, it is reasonable to use clustered standard errors for the analysis. Nonetheless, this robustness check shows the insensitivity of the parallel trends assumption to the selection of standard errors in this analysis and supports the robustness of the specification.

Next, I test the robustness of my main results by considering German natives as another control group. This allows me to assess whether the treatment effect changes subject to the choice of the control group. Neither low educated EU immigrants nor low educated natives should experience an effect of the refugee crisis through the discriminatory channel. Hence, when comparing low educated refugees with low educated natives, similar results as in Table 7.3 should be observed. Before dissecting the results, I am assessing the parallel trends assumption between the control group and the treatment group. Results from the pre-testing can be found in Table A.8. There is a statistically significant treatment effect at the 5% level in 2011. This effect remains when adding control variables. Hence, natives are not an appropriate control group for low educated refugees, as their trends seem to differ before the refugee crisis. If I cannot make the parallel trends assumption, the identification of causal effects is not justified. Nonetheless, when comparing the effect size from Table A.9 with the effect size from Table 7.3, they are remarkably similar. Especially column (2) and column (4) are alike. Similar to the baseline results, refugees show higher welfare dependency and unemployment in general and the refugee crisis increased both rates by over 20 percentage points. Similar to the low educated refugees, I consider low educated EU and non-EU immigrants as treatment groups. However, low educated natives do not seem to be an appropriate control group for non-EU immigrants either, as Table A.8 shows statistically significant pre-testing effects in 2011. Regardless, it seems realistic to assume that low educated natives and low educated EU immigrants have more similar trends than low educated natives and low educated non-EU immigrants. Table A.9 shows the results for the difference-in-difference analysis. Compared to natives, EU and non-EU immigrants seem to increase their welfare dependency and have higher probability of being unemployed after the crisis. However, the effect sizes are much smaller than those for refugees. Welfare dependency increases for them between 2.9 and 4.4 percentage points and unemployment increases between 4.9 and 6.1 percentage points in the specifications with controls. Taken together, these findings support my hypothesis that the discriminatory channel is the mechanism behind higher welfare dependency of low educated immigrants after the refugee crisis, as refugees are affected much more heavily than their EU counterparts for example.

According to the labor supply channel, native Germans should be relatively protected from the increased competition of the newly arriving immigrants. Possibly, there could even be a positive effect on native workers, as they can be complements to the refugees or have better labor market conditions if employers favor them due to the discriminatory channel. Hence, I investigate the effect on natives depending on their educational level. The control group in this analysis includes high educated natives and treatment group is specified as having a low educational level. Medium educated individuals are included separately to further differentiate the effects. Generally, as you can see in Table A.10, there are no differing trends before the crisis between natives with high and low educational levels. Hence, it is reasonable to use this specification for identification. In Table A.11, the results for the difference-in-difference specification are shown. There are statistically significant effect for low educated natives in all four specifications. Welfare dependency decreases after the crisis between 2.6 and 2.8 percentage points. Unemployment decreases between 2.9 and 3.1 percentage points after the crisis compared to high educated natives. This specification shows the importance of choosing the correct treatment group, as the dynamics in the population can differ substantially among individuals with different characteristics.

To assess the suitability of the citizenship for grouping immigrants, I am using the country of birth as a measure to differentiate between control and treatment group for the discriminatory channel. To assess the parallel trends assumption, I am also conducting an event study with the results shown in Figure A.5 and Figure A.6. When examining the graphs, you can see that there are no statistically different before the refugee crisis. The regression output for the difference-in-difference specification can be found in Table A.13. They are displaying a similar picture as the specification using the citizenship of immigrants as a grouping variable. However, the effect size is smaller. Welfare dependency increases only by 7 percentage points in column (2). The treatment effects for unemployment look remarkably similar to the ones in Table 7.2. Similar as before, both are indistinguishable from zero. Overall, the results do not differ substantially from the findings using an immigrant's citizenship as a grouping variable. Hence, the results presented in the table provide supporting evidence to my baseline findings.

Next, I qualify my results with the consideration of alternative treatment definitions. In the baseline Equation (1), I am considering 2016 as the baseline year. The treatment definition is justified by the delayed labor market entry of refugees due to the German refugee policies and the processing backlog of asylum applications in 2016. However, as the refugee crisis begun already in 2015, I am using 2014 as an alternative baseline year to assess whether treatment effects were observable before the crisis. The results in Table A.14 show that there is no treatment effect for low educated immigrants when using 2014 as the baseline year.

Similarly, I am considering different treatment definitions for the discriminatory channel. In Equation (1), the baseline year is 2013. The inflow of refugees from Syria quadrupled in 2014 compared to 2013 (Bundesamt für Migration und Flüchtlinge, 2016) and the media attention on refugees increased. Furthermore, right-wing parties started to instrumentalize refugees for their political motives. However, the Syrian Civil War already broke out in 2011, which led to media reports and focus on refugee flows. I am showing in Table A.15 that the outbreak of the Syrian Civil War did not increase the welfare dependency nor the unemployment level for refugees. Furthermore, when making 2016 the baseline year in the discriminatory channel, there is no statistically significant effect for refugees. Hence, this supports the hypothesis that the discriminatory channel showed effects before the labor supply channel.

# 8 Discussion

Overall, the findings of this study show that the refugee crisis impacted unemployment and welfare dependency among low educated immigrants already residing in Germany. The labor supply channel derived from theory suggests a negative effect on low educated immigrants because of higher competition in the labor market, as the newly arriving refugees were mostly low educated. Moreover, increased competition in the labor market should lead to higher unemployment if wages cannot adjust freely. As predicted by the theory, I observe higher unemployment and welfare dependency among low educated immigrants already residing in Germany. Wages earned and hours worked do not differ in the aftermath of the refugee crisis. Most likely because of the labor market rigidity from minimum wages and labor market policies. While there is supporting evidence for the labor supply channel, another mechanism might be the underlying cause for the observation. With the offspring of the Syrian Civil War and the beginning of heightened refugee arrivals in Germany, media outlets and right-wing political parties started to focus on refugees as a potential threat to the German society and welfare system. In this context, I am observing higher welfare dependency among refugees but do not find statistically significant treatment effects on unemployment. When restricting the sample to low educated immigrants, especially refugees experience higher unemployment and welfare dependency. Both measures increase by over 20 percentage points for low educated refugees. This is in line with the discriminatory channel. Further support for the channel comes from the robustness checks in which I use low educated Germans as a control group. When using low educated refugees as the treatment group, the estimated treatment effects is similar to the baseline results. Therefore, this is further support for the discriminatory channel. However, as previous low educated refugee cohorts are the closest substitutes to the newly arriving refugees, the labor supply channel cannot be discarded completely.

There are a number of limitations of this thesis that need to be acknowledged. Firstly, there are some concerns regarding the validity of the parallel trends assumption. As I have noted before, the treatment and control group show statistically significant differences in the year 2011, which is before the refugee crisis. The parallel trends assumption is the most important assumption when estimating causal effects with a difference-in-difference estimation. When adding control variables, the significance level usually disappears. Furthermore, the robustness checks are showing similar results when using different control groups. Hence, the estimated effect should be a reliable estimate.

Another issue are missing information in the dataset. For some observations, there is no data for different variables. If the response to certain questions is correlated with individual characteristics, the estimated results would be biased. Unfortunately, there is no information for the reason of the missing data. Hence, I am unable to determine whether there is any selection bias resulting from the responses. Due to the data constraint, I am also unable to cluster the standard errors at the municipality level. Possibly, local economic conditions induce correlations among household in the same municipality. As only information on regions were provided, I had to cluster on the household level. To assure correct standard errors, this would have been a nice robustness check.

Lastly, I cannot rule out that the refugee crisis had no effect on the control groups. As low and high skilled labor are usually complements, the control groups might have experienced a positive effect of the refugee crisis on the outcome variables. In this case, the estimated effects would be positively biased.

Generally, the identified effects of the refugee crisis should be of concern to policy makers, as similar events are possible in the future with the ongoing threats and crises worldwide. If there is persistent higher unemployment across low educated refugees, this could carry on to future generations of incoming immigrants. Åslund and Fredriksson (2005) find peer effects in of welfare use among immigrants in Sweden. The rate of welfare usage by individuals increases by almost 7% when the fraction of welfare dependents in the ethnic group increases by 10%. Barrett et al. (2008) also note that welfare use of existing migrants can influence the use of newly arrived co-nationals. The refugee crisis induced higher welfare dependency and unemployment among refugees, hence, it is likely that within this group, the stigma with welfare take-up is reduced and the identified effect persist over time.

# 9 Conclusion

This paper investigates the effect of the 2015/16 refugee crisis on previous cohorts of immigrants in Germany. Using individual microdata from the SOEP and a difference-in-difference approach, I find that the refugee crisis impacted unemployment and welfare dependency negatively among low educated immigrants already residing in Germany. Following, I test a potential mechanism: labor market discrimination. With the offspring of the Syrian Civil War and the beginning of heightened refugee arrivals in Germany, media outlets and right-wing political parties started to focus on refugees as a potential threat to the German society and welfare system. In this context, I am observing higher welfare dependency among refugees. When restricting the sample to low educated immigrants, especially refugees experience higher unemployment and welfare dependency. Both measures increase by over 20 percentage points for low educated refugees.This is further support for the discriminatory channel. However, as previous low educated refugee cohorts are the closest substitutes to the newly arriving refugees, the labor supply channel cannot be discarded completely.

The findings suggests that measures to prevent discriminatory behavior should be implemented in order to avoid negative long-term effects. As initial labor market conditions have an impact on the long-run welfare dependency for immigrants, it is important to foster integration into the labor market to prevent a continuation of heightened welfare dependency.

The insights provided by this paper are valuable to understand the short-term dynamics of labor supply shocks caused by sudden inflows of immigrants. However, there should be further research in this direction to understand the long-term dynamics of immigrant shocks. A more granular analysis using more precise spatial information would be beneficial in order to determine the effect of local labor markets. Furthermore, a comparison with different European countries would be insightful, as the effectiveness of possible policies could be evaluated. Sweden would be an interesting case to investigate, as it has an extensive welfare system in place and received larger numbers of refugees during the crisis.

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# A Appendix

## A.1 Additional Material for Descriptive Statistics

Table A.1: Descriptive Statistics Discriminatory Channel

| Variable | Treated | Control | Difference | P-Value |
|---|---|---|---|---|
| Welfare Dependency | 0.626 | 0.156 | 0.471*** | 0.000 |
| Unemployment | 0.535 | 0.179 | 0.356*** | 0.000 |
| Low Education | 0.606 | 0.219 | 0.387*** | 0.000 |
| Medium Education | 0.245 | 0.466 | -0.222*** | 0.000 |
| High Education | 0.149 | 0.315 | -0.165*** | 0.000 |
| | | | | |
| Female Household Head | 0.262 | 0.469 | -0.207*** | 0.000 |
| Age Household Head | 40.338 | 42.558 | -2.221*** | 0.000 |
| Partnered Household Head | 0.727 | 0.773 | -0.046** | 0.034 |
| Household Members | 4.712 | 3.092 | 1.620*** | 0.000 |
| Household Members below 13 | 1.333 | 0.813 | 0.521*** | 0.000 |
| | | | | |
| Years of Residency | 10.487 | 15.381 | -4.894*** | 0.000 |
| Female | 0.446 | 0.542 | -0.097*** | 0.000 |
| Age | 37.498 | 41.675 | -4.178*** | 0.000 |
| Married | 0.617 | 0.635 | -0.018 | 0.452 |
| Never Married | 0.290 | 0.204 | 0.086*** | 0.000 |
| Separated | 0.050 | 0.039 | 0.011 | 0.291 |
| Divorced | 0.041 | 0.109 | -0.068*** | 0.000 |
| Widowed | 0.002 | 0.013 | -0.011*** | 0.000 |
| Observations | 462 | 5064 | | |

*Note:* This table presents means and mean differences for the set of outcome and control variables in my discriminatory channel. All variables are measured on a pooled sample of immigrants in my dataset for the period 2010-2019. Treated are all refugee immigrants. Control are all EU immigrants. The last column displays p-values for the t-test. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01.

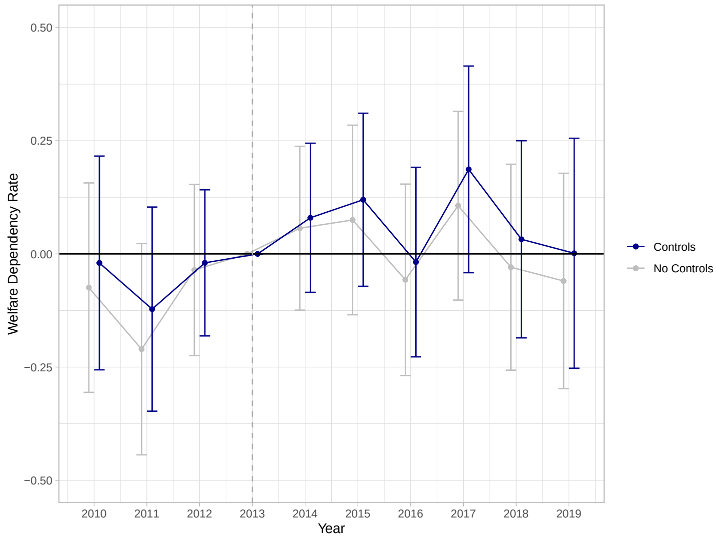
## A.2 Additional Material for Results

Table A.2: Event Study: Welfare Dependency Rate and Unemployment on Educational Level

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.062*** | 0.066*** | 0.043* | 0.053** |
| | (0.018) | (0.017) | (0.023) | (0.023) |
| Low | 0.172*** | 0.153*** | 0.140*** | 0.135*** |
| | (0.026) | (0.023) | (0.033) | (0.031) |
| Medium*2012 | −0.002 | 0.002 | −0.001 | 0.001 |
| | (0.024) | (0.023) | (0.030) | (0.030) |
| Low*2012 | −0.020 | −0.022 | 0.058 | 0.056 |
| | (0.032) | (0.029) | (0.041) | (0.039) |
| Medium*2013 | −0.011 | −0.007 | −0.021 | −0.017 |
| | (0.025) | (0.024) | (0.033) | (0.033) |
| Low*2013 | −0.024 | −0.022 | −0.023 | −0.020 |
| | (0.034) | (0.031) | (0.044) | (0.041) |
| Medium*2014 | −0.002 | −0.001 | −0.011 | −0.007 |
| | (0.027) | (0.026) | (0.035) | (0.034) |
| Low*2014 | −0.018 | −0.016 | −0.034 | −0.028 |
| | (0.035) | (0.031) | (0.045) | (0.042) |
| Medium*2015 | −0.015 | −0.017 | −0.028 | −0.029 |
| | (0.030) | (0.028) | (0.035) | (0.034) |
| Low*2015 | −0.034 | −0.032 | −0.001 | 0.004 |
| | (0.038) | (0.034) | (0.046) | (0.044) |
| Medium*2017 | −0.015 | −0.014 | −0.026 | −0.024 |
| | (0.028) | (0.027) | (0.034) | (0.033) |
| Low*2017 | −0.001 | −0.0003 | 0.023 | 0.023 |
| | (0.040) | (0.037) | (0.049) | (0.046) |
| Medium*2018 | −0.002 | 0.012 | −0.008 | 0.003 |
| | (0.027) | (0.026) | (0.034) | (0.033) |
| Low*2018 | 0.033 | 0.046 | 0.078 | 0.089* |
| | (0.040) | (0.036) | (0.051) | (0.048) |
| Medium*2019 | −0.016 | −0.008 | −0.025 | −0.018 |
| | (0.027) | (0.026) | (0.037) | (0.036) |
| Low*2019 | 0.014 | 0.016 | 0.052 | 0.059 |
| | (0.044) | (0.040) | (0.054) | (0.052) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 22,950 | 22,950 | 22,950 | 22,950 |
| $R^2$ | 0.086 | 0.216 | 0.044 | 0.092 |
| Mean | 0.200 | 0.200 | 0.175 | 0.175 |

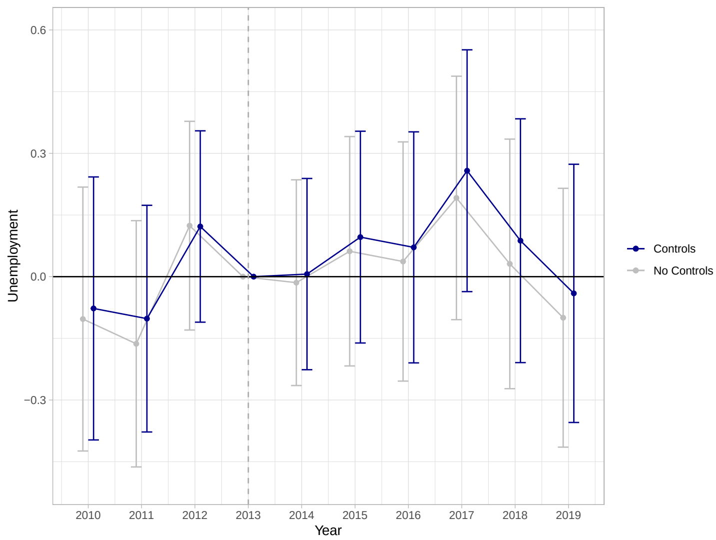
*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2012 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Figure A.1: Event Study Plot of Welfare Dependency for Refugees




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (1) and (2) in Table A.3 displaying results for refugee immigrants from the following regression:
$Dependency_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Figure A.2: Event Study Plot of Unemployment for Refugees



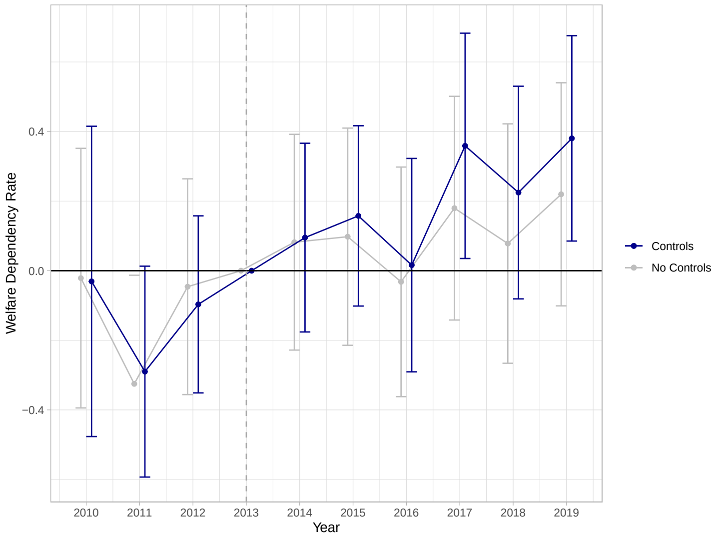

*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (3) and (4) in Table A.3 displaying results for refugee immigrants from the following regression:
$Unemployment_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Table A.3: Event Study: Welfare Dependency Rate and Unemployment on Citizenship

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.049*** | 0.033* | 0.027 | 0.021 |
| | (0.017) | (0.017) | (0.026) | (0.025) |
| Refugee | 0.388*** | 0.262*** | 0.278*** | 0.198** |
| | (0.074) | (0.065) | (0.104) | (0.093) |
| NonEU*2010 | −0.038 | −0.028 | −0.034 | −0.032 |
| | (0.032) | (0.033) | (0.043) | (0.044) |
| Refugee*2010 | −0.074 | −0.020 | −0.103 | −0.077 |
| | (0.118) | (0.120) | (0.164) | (0.163) |
| NonEU*2011 | −0.023 | −0.010 | −0.012 | −0.008 |
| | (0.028) | (0.030) | (0.042) | (0.042) |
| Refugee*2011 | −0.210* | −0.122 | −0.163 | −0.102 |
| | (0.119) | (0.115) | (0.153) | (0.141) |
| NonEU*2012 | 0.020 | 0.022 | 0.027 | 0.026 |
| | (0.023) | (0.023) | (0.033) | (0.032) |
| Refugee*2012 | −0.035 | −0.020 | 0.124 | 0.122 |
| | (0.096) | (0.082) | (0.129) | (0.119) |
| NonEU*2014 | −0.012 | −0.007 | −0.025 | −0.022 |
| | (0.025) | (0.024) | (0.035) | (0.034) |
| Refugee*2014 | 0.057 | 0.080 | −0.015 | 0.006 |
| | (0.092) | (0.084) | (0.128) | (0.119) |
| NonEU*2015 | 0.003 | 0.013 | −0.022 | −0.014 |
| | (0.026) | (0.025) | (0.037) | (0.036) |
| Refugee*2015 | 0.075 | 0.120 | 0.062 | 0.096 |
| | (0.107) | (0.098) | (0.142) | (0.131) |
| NonEU*2016 | −0.044 | −0.028 | −0.048 | −0.036 |
| | (0.029) | (0.027) | (0.040) | (0.038) |
| Refugee*2016 | −0.057 | −0.018 | 0.037 | 0.071 |
| | (0.108) | (0.107) | (0.148) | (0.143) |
| NonEU*2017 | −0.008 | 0.009 | −0.004 | 0.009 |
| | (0.027) | (0.026) | (0.035) | (0.034) |
| Refugee*2017 | 0.106 | 0.187 | 0.191 | 0.258* |
| | (0.106) | (0.116) | (0.151) | (0.150) |
| NonEU*2018 | −0.009 | −0.003 | −0.018 | −0.013 |
| | (0.030) | (0.029) | (0.041) | (0.040) |
| Refugee*2018 | −0.029 | 0.032 | 0.031 | 0.087 |
| | (0.116) | (0.111) | (0.155) | (0.151) |
| NonEU*2019 | −0.010 | 0.003 | −0.038 | −0.028 |
| | (0.030) | (0.029) | (0.044) | (0.044) |
| Refugee*2019 | −0.060 | 0.001 | −0.100 | −0.041 |
| | (0.121) | (0.130) | (0.161) | (0.160) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.068 | 0.193 | 0.028 | 0.072 |
| Mean | 0.222 | 0.222 | 0.188 | 0.188 |

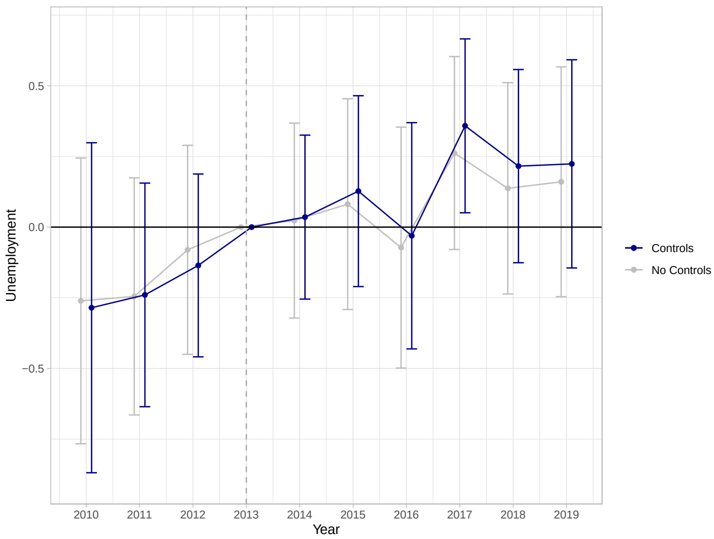
*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Figure A.3: Event Study Plot of Welfare Dependency for Low Educated Refugees




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (1) and (2) in Table A.4 displaying results for low educated refugee immigrants from the following regression: $Dependency_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Figure A.4: Event Study Plot of Unemployment for Low Educated Refugees




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (3) and (4) in Table A.4 displaying results for low educated refugee immigrants from the following regression: $Unemployment_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Table A.4: Event Study: Welfare Dependency Rate and Unemployment on Citizenship (Low Educated)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.043 | 0.010 | 0.067 | 0.055 |
| | (0.051) | (0.039) | (0.057) | (0.050) |
| Refugee | 0.231* | 0.136 | 0.293* | 0.252* |
| | (0.135) | (0.095) | (0.160) | (0.129) |
| NonEU*2010 | 0.048 | 0.057 | 0.027 | 0.034 |
| | (0.084) | (0.072) | (0.099) | (0.093) |
| Refugee*2010 | 0.029 | 0.052 | −0.222 | −0.233 |
| | (0.194) | (0.221) | (0.265) | (0.301) |
| NonEU*2011 | −0.029 | −0.014 | −0.023 | −0.014 |
| | (0.083) | (0.069) | (0.086) | (0.074) |
| Refugee*2011 | −0.273* | −0.208 | −0.209 | −0.196 |
| | (0.165) | (0.145) | (0.225) | (0.208) |
| NonEU*2012 | 0.014 | 0.015 | −0.039 | −0.041 |
| | (0.067) | (0.053) | (0.083) | (0.077) |
| Refugee*2012 | −0.014 | −0.048 | −0.049 | −0.101 |
| | (0.165) | (0.115) | (0.200) | (0.170) |
| NonEU*2014 | −0.031 | −0.004 | −0.034 | −0.012 |
| | (0.075) | (0.058) | (0.078) | (0.068) |
| Refugee*2014 | 0.106 | 0.140 | 0.042 | 0.068 |
| | (0.165) | (0.125) | (0.187) | (0.153) |
| NonEU*2015 | −0.025 | 0.019 | −0.062 | −0.025 |
| | (0.078) | (0.057) | (0.087) | (0.078) |
| Refugee*2015 | 0.178 | 0.253** | 0.112 | 0.166 |
| | (0.165) | (0.121) | (0.204) | (0.183) |
| NonEU*2016 | −0.085 | −0.060 | −0.093 | −0.067 |
| | (0.087) | (0.057) | (0.095) | (0.076) |
| Refugee*2016 | 0.039 | 0.095 | −0.072 | −0.023 |
| | (0.181) | (0.154) | (0.230) | (0.214) |
| NonEU*2017 | −0.008 | 0.026 | −0.023 | −0.007 |
| | (0.080) | (0.065) | (0.094) | (0.086) |
| Refugee*2017 | 0.215 | 0.406** | 0.283 | 0.383** |
| | (0.173) | (0.160) | (0.187) | (0.164) |
| NonEU*2018 | 0.086 | 0.105 | 0.010 | 0.003 |
| | (0.085) | (0.072) | (0.106) | (0.097) |
| Refugee*2018 | 0.149 | 0.301* | 0.146 | 0.225 |
| | (0.192) | (0.156) | (0.210) | (0.191) |
| NonEU*2019 | 0.060 | 0.085 | 0.030 | 0.016 |
| | (0.090) | (0.082) | (0.103) | (0.102) |
| Refugee*2019 | 0.290* | 0.471*** | 0.178 | 0.263 |
| | (0.174) | (0.147) | (0.229) | (0.204) |
| Observations | 5,368 | 5,368 | 5,368 | 5,368 |
| $R^2$ | 0.110 | 0.315 | 0.078 | 0.164 |
| Mean | 0.344 | 0.344 | 0.299 | 0.299 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany that have a low education level. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.5: Difference-in-Difference: Gross Wages and Hours Worked on Educational Level

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Gross Wages | | Hours Worked | |
| | (1) | (2) | (3) | (4) |
| Medium | −5.795*** | −5.960*** | −2.125*** | −2.048*** |
| | (0.486) | (0.514) | (0.527) | (0.481) |
| Low | −8.351*** | −8.407*** | −5.136*** | −4.776*** |
| | (0.495) | (0.555) | (0.621) | (0.578) |
| After | 3.149*** | 2.822*** | 1.473** | 1.707*** |
| | (0.666) | (0.642) | (0.683) | (0.635) |
| Medium*After | −1.130 | −1.147 | −0.469 | −0.502 |
| | (0.781) | (0.765) | (0.829) | (0.766) |
| Low*After | −0.877 | −0.760 | −0.954 | −1.144 |
| | (0.796) | (0.782) | (1.043) | (0.950) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 16,770 | 16,770 | 16,770 | 16,770 |
| $R^2$ | 0.135 | 0.192 | 0.028 | 0.210 |
| Mean | 14.454 | 14.454 | 35.565 | 35.565 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2016. *Wages* is the gross basic hourly wage rate for the main job. Overtime payments, bonuses and gratuities, family allowances and other social security payments made by employers, as well as ex gratia payments in kind supplementary to normal wage rates, are all excluded from the calculation of the basic gross hourly wage. *Hours* are the regular hours worked at all jobs currently held (including family work and overtime, whether paid or unpaid). The sample consists of yearly observations from 2012 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

## A.3 Additional Material for Robustness Checks

Table A.6: Event Study: Welfare Dependency Rate and Unemployment on Education (HAC Errors)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.062*** | 0.066*** | 0.043* | 0.053** |
| | (0.018) | (0.016) | (0.023) | (0.023) |
| Low | 0.172*** | 0.153*** | 0.140*** | 0.135*** |
| | (0.025) | (0.023) | (0.032) | (0.031) |
| Medium*2012 | −0.002 | 0.002 | −0.001 | 0.001 |
| | (0.024) | (0.022) | (0.030) | (0.029) |
| Low*2012 | −0.020 | −0.022 | 0.058 | 0.056 |
| | (0.031) | (0.029) | (0.041) | (0.039) |
| Medium*2013 | −0.011 | −0.007 | −0.021 | −0.017 |
| | (0.024) | (0.022) | (0.033) | (0.032) |
| Low*2013 | −0.024 | −0.022 | −0.023 | −0.020 |
| | (0.033) | (0.030) | (0.043) | (0.041) |
| Medium*2014 | −0.002 | −0.001 | −0.011 | −0.007 |
| | (0.026) | (0.023) | (0.033) | (0.031) |
| Low*2014 | −0.018 | −0.016 | −0.034 | −0.028 |
| | (0.033) | (0.030) | (0.044) | (0.041) |
| Medium*2015 | −0.015 | −0.017 | −0.028 | −0.029 |
| | (0.030) | (0.028) | (0.034) | (0.033) |
| Low*2015 | −0.034 | −0.032 | −0.001 | 0.004 |
| | (0.037) | (0.034) | (0.044) | (0.043) |
| Medium*2017 | −0.015 | −0.014 | −0.026 | −0.024 |
| | (0.027) | (0.026) | (0.033) | (0.032) |
| Low*2017 | −0.001 | −0.0003 | 0.023 | 0.023 |
| | (0.038) | (0.035) | (0.047) | (0.044) |
| Medium*2018 | −0.002 | 0.012 | −0.008 | 0.003 |
| | (0.026) | (0.024) | (0.034) | (0.033) |
| Low*2018 | 0.033 | 0.046 | 0.078 | 0.089* |
| | (0.039) | (0.035) | (0.051) | (0.048) |
| Medium*2019 | −0.016 | −0.008 | −0.025 | −0.018 |
| | (0.025) | (0.024) | (0.037) | (0.036) |
| Low*2019 | 0.014 | 0.016 | 0.052 | 0.059 |
| | (0.043) | (0.039) | (0.055) | (0.054) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 22,950 | 22,950 | 22,950 | 22,950 |
| $R^2$ | 0.086 | 0.216 | 0.044 | 0.092 |
| Mean | 0.200 | 0.200 | 0.175 | 0.175 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2012 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. HAC robust standard errors are applied. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.7: Event Study: Welfare Dependency Rate and Unemployment on Citizenship (HAC Errors)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.049*** | 0.033** | 0.027 | 0.021 |
| | (0.016) | (0.016) | (0.025) | (0.025) |
| Refugee | 0.388*** | 0.262*** | 0.278*** | 0.198** |
| | (0.069) | (0.060) | (0.098) | (0.088) |
| NonEU*2010 | −0.038 | −0.028 | −0.034 | −0.032 |
| | (0.031) | (0.031) | (0.044) | (0.045) |
| Refugee*2010 | −0.074 | −0.020 | −0.103 | −0.077 |
| | (0.114) | (0.118) | (0.161) | (0.161) |
| NonEU*2011 | −0.023 | −0.010 | −0.012 | −0.008 |
| | (0.027) | (0.028) | (0.041) | (0.041) |
| Refugee*2011 | −0.210* | −0.122 | −0.163 | −0.102 |
| | (0.115) | (0.112) | (0.159) | (0.147) |
| NonEU*2012 | 0.020 | 0.022 | 0.027 | 0.026 |
| | (0.022) | (0.021) | (0.032) | (0.032) |
| Refugee*2012 | −0.035 | −0.020 | 0.124 | 0.122 |
| | (0.089) | (0.078) | (0.124) | (0.115) |
| NonEU*2014 | −0.012 | −0.007 | −0.025 | −0.022 |
| | (0.025) | (0.023) | (0.034) | (0.033) |
| Refugee*2014 | 0.057 | 0.080 | −0.015 | 0.006 |
| | (0.086) | (0.079) | (0.123) | (0.115) |
| NonEU*2015 | 0.003 | 0.013 | −0.022 | −0.014 |
| | (0.025) | (0.023) | (0.036) | (0.036) |
| Refugee*2015 | 0.075 | 0.120 | 0.062 | 0.096 |
| | (0.096) | (0.089) | (0.130) | (0.121) |
| NonEU*2016 | −0.044 | −0.028 | −0.048 | −0.036 |
| | (0.028) | (0.026) | (0.039) | (0.038) |
| Refugee*2016 | −0.057 | −0.018 | 0.037 | 0.071 |
| | (0.103) | (0.103) | (0.144) | (0.139) |
| NonEU*2017 | −0.008 | 0.009 | −0.004 | 0.009 |
| | (0.025) | (0.024) | (0.035) | (0.034) |
| Refugee*2017 | 0.106 | 0.187* | 0.191 | 0.258* |
| | (0.097) | (0.106) | (0.144) | (0.144) |
| NonEU*2018 | −0.009 | −0.003 | −0.018 | −0.013 |
| | (0.029) | (0.029) | (0.040) | (0.038) |
| Refugee*2018 | −0.029 | 0.032 | 0.031 | 0.087 |
| | (0.113) | (0.107) | (0.152) | (0.148) |
| NonEU*2019 | −0.010 | 0.003 | −0.038 | −0.028 |
| | (0.030) | (0.029) | (0.043) | (0.044) |
| Refugee*2019 | −0.060 | 0.001 | −0.100 | −0.041 |
| | (0.115) | (0.124) | (0.153) | (0.151) |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.068 | 0.193 | 0.028 | 0.072 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. HAC robust standard errors are applied. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.8: Event Study: Welfare Dependency Rate and Unemployment on Citizenship (Control: Low Educated Natives)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| EU | −0.042 | 0.019 | −0.025 | 0.023 |
| | (0.043) | (0.036) | (0.049) | (0.044) |
| NonEU | 0.050 | 0.066** | 0.068* | 0.086** |
| | (0.032) | (0.029) | (0.036) | (0.034) |
| Refugee | 0.267** | 0.262** | 0.322** | 0.328** |
| | (0.123) | (0.120) | (0.142) | (0.128) |
| EU*2010 | −0.047 | −0.048 | −0.038 | −0.037 |
| | (0.066) | (0.058) | (0.075) | (0.070) |
| NonEU*2010 | −0.045 | −0.036 | −0.047 | −0.042 |
| | (0.055) | (0.048) | (0.063) | (0.058) |
| Refugee*2010 | −0.137 | −0.102 | −0.365* | −0.344 |
| | (0.164) | (0.188) | (0.222) | (0.237) |
| EU*2011 | −0.013 | −0.027 | −0.101 | −0.110* |
| | (0.064) | (0.056) | (0.068) | (0.061) |
| NonEU*2011 | −0.087* | −0.075 | −0.145** | −0.140** |
| | (0.053) | (0.049) | (0.058) | (0.056) |
| Refugee*2011 | −0.358** | −0.360** | −0.351 | −0.352* |
| | (0.147) | (0.166) | (0.218) | (0.209) |
| EU*2012 | −0.034 | −0.028 | 0.023 | 0.028 |
| | (0.058) | (0.049) | (0.070) | (0.066) |
| NonEU*2012 | −0.045 | −0.036 | 0.001 | 0.005 |
| | (0.042) | (0.038) | (0.049) | (0.046) |
| Refugee*2012 | −0.116 | −0.140 | −0.052 | −0.081 |
| | (0.149) | (0.135) | (0.178) | (0.161) |
| EU*2014 | 0.001 | −0.023 | 0.024 | 0.009 |
| | (0.063) | (0.054) | (0.078) | (0.075) |
| NonEU*2014 | −0.023 | −0.016 | −0.073 | −0.069 |
| | (0.047) | (0.041) | (0.053) | (0.050) |
| Refugee*2014 | 0.084 | 0.038 | −0.002 | −0.029 |
| | (0.147) | (0.149) | (0.167) | (0.157) |
| EU*2015 | −0.039 | −0.053 | −0.008 | −0.019 |
| | (0.064) | (0.054) | (0.071) | (0.064) |
| NonEU*2015 | −0.061 | −0.041 | −0.059 | −0.045 |
| | (0.047) | (0.041) | (0.054) | (0.052) |
| Refugee*2015 | 0.054 | 0.079 | 0.078 | 0.099 |
| | (0.145) | (0.140) | (0.180) | (0.176) |
| EU*2016 | 0.053 | 0.028 | 0.044 | 0.026 |
| | (0.069) | (0.053) | (0.077) | (0.066) |
| NonEU*2016 | −0.042 | −0.034 | −0.039 | −0.036 |
| | (0.045) | (0.040) | (0.050) | (0.047) |
| Refugee*2016 | −0.004 | −0.004 | −0.035 | −0.034 |
| | (0.154) | (0.168) | (0.204) | (0.210) |
| EU*2017 | 0.032 | −0.007 | 0.025 | −0.003 |
| | (0.068) | (0.061) | (0.075) | (0.072) |
| NonEU*2017 | −0.021 | −0.002 | 0.006 | 0.017 |
| | (0.047) | (0.041) | (0.054) | (0.050) |
| Refugee*2017 | 0.147 | 0.275* | 0.269* | 0.354** |
| | (0.149) | (0.164) | (0.159) | (0.154) |
| EU*2018 | 0.049 | 0.006 | 0.092 | 0.064 |
| | (0.068) | (0.060) | (0.089) | (0.085) |
| NonEU*2018 | 0.018 | 0.037 | 0.038 | 0.048 |
| | (0.048) | (0.042) | (0.059) | (0.056) |
| Refugee*2018 | 0.047 | 0.150 | 0.187 | 0.263 |
| | (0.168) | (0.162) | (0.174) | (0.172) |
| EU*2019 | 0.038 | 0.0001 | 0.077 | 0.058 |
| | (0.072) | (0.071) | (0.085) | (0.085) |
| NonEU*2019 | 0.016 | 0.039 | 0.064 | 0.076 |
| | (0.052) | (0.046) | (0.060) | (0.057) |
| Refugee*2019 | 0.170 | 0.278* | 0.246 | 0.317* |
| | (0.155) | (0.169) | (0.182) | (0.179) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 14,356 | 14,356 | 14,356 | 14,356 |
| $R^2$ | 0.099 | 0.266 | 0.068 | 0.126 |
| Mean | 0.363 | 0.363 | 0.315 | 0.315 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes low educated immigrants arriving before 2010 in Germany and low educated natives. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.9: Difference-in-Difference: Welfare Dependency Rate and Unemployment on Citizenship (Control: Low Educated Natives)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| EU | −0.077*** | −0.014 | −0.059** | −0.009 |
| | (0.024) | (0.021) | (0.027) | (0.025) |
| NonEU | −0.011 | 0.016 | 0.011 | 0.037* |
| | (0.017) | (0.016) | (0.019) | (0.019) |
| Refugee | 0.099 | 0.073 | 0.175** | 0.163** |
| | (0.062) | (0.050) | (0.081) | (0.073) |
| After | −0.043*** | −0.041*** | −0.037** | −0.037** |
| | (0.014) | (0.012) | (0.016) | (0.015) |
| EU*After | 0.055* | 0.029 | 0.080** | 0.061* |
| | (0.032) | (0.028) | (0.038) | (0.036) |
| NonEU*After | 0.037* | 0.044** | 0.043* | 0.049* |
| | (0.022) | (0.020) | (0.026) | (0.025) |
| Refugee*After | 0.244*** | 0.295*** | 0.224** | 0.266*** |
| | (0.075) | (0.070) | (0.097) | (0.093) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 13,762 | 13,762 | 13,762 | 13,762 |
| $R^2$ | 0.094 | 0.261 | 0.061 | 0.121 |
| Mean | 0.336 | 0.336 | 0.286 | 0.286 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2013. The sample consists of yearly observations from 2010 to 2019. The panel includes low educated immigrants arriving before 2010 in Germany and low educated natives. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table A.10: Event Study: Welfare Dependency Rate and Unemployment on Educational Level (Natives)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.045*** | 0.046*** | 0.035*** | 0.034*** |
| | (0.005) | (0.005) | (0.007) | (0.007) |
| Low | 0.205*** | 0.194*** | 0.177*** | 0.163*** |
| | (0.016) | (0.015) | (0.019) | (0.019) |
| Medium*2012 | 0.012* | 0.009 | 0.029*** | 0.026*** |
| | (0.007) | (0.006) | (0.010) | (0.010) |
| Low*2012 | 0.021 | 0.017 | 0.037 | 0.034 |
| | (0.023) | (0.021) | (0.027) | (0.026) |
| Medium*2013 | 0.012* | 0.009 | 0.017 | 0.014 |
| | (0.007) | (0.007) | (0.010) | (0.010) |
| Low*2013 | 0.002 | −0.0001 | 0.006 | 0.004 |
| | (0.023) | (0.021) | (0.027) | (0.027) |
| Medium*2014 | 0.010 | 0.008 | 0.018* | 0.016 |
| | (0.007) | (0.007) | (0.010) | (0.010) |
| Low*2014 | 0.011 | 0.010 | 0.031 | 0.028 |
| | (0.024) | (0.022) | (0.029) | (0.028) |
| Medium*2015 | 0.009 | 0.007 | 0.016 | 0.014 |
| | (0.007) | (0.007) | (0.010) | (0.010) |
| Low*2015 | 0.008 | 0.007 | 0.033 | 0.032 |
| | (0.024) | (0.022) | (0.029) | (0.029) |
| Medium*2017 | 0.002 | 0.002 | 0.008 | 0.008 |
| | (0.007) | (0.006) | (0.010) | (0.010) |
| Low*2017 | 0.007 | 0.004 | 0.006 | 0.005 |
| | (0.023) | (0.022) | (0.027) | (0.026) |
| Medium*2018 | −0.008 | −0.006 | −0.006 | −0.005 |
| | (0.007) | (0.007) | (0.010) | (0.010) |
| Low*2018 | −0.021 | −0.020 | −0.003 | −0.003 |
| | (0.023) | (0.021) | (0.028) | (0.028) |
| Medium*2019 | −0.015** | −0.013** | −0.006 | −0.004 |
| | (0.006) | (0.006) | (0.010) | (0.010) |
| Low*2019 | −0.044** | −0.042** | −0.034 | −0.032 |
| | (0.021) | (0.020) | (0.026) | (0.026) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 99,404 | 99,404 | 99,404 | 99,404 |
| $R^2$ | 0.093 | 0.179 | 0.040 | 0.059 |
| Mean | 0.105 | 0.105 | 0.085 | 0.085 |

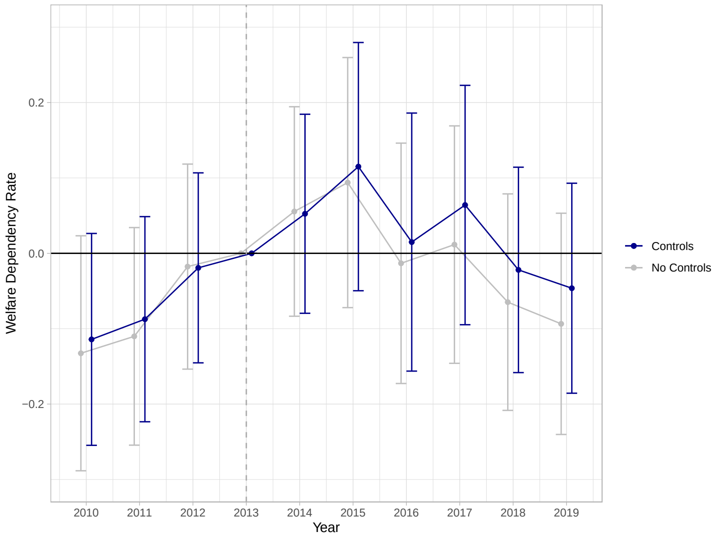
*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes natives in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.11: Difference-in-Difference: Welfare Dependency Rate and Unemployment on Educational Level (Natives)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.054*** | 0.053*** | 0.051*** | 0.048*** |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| Low | 0.213*** | 0.200*** | 0.198*** | 0.182*** |
| | (0.008) | (0.007) | (0.009) | (0.009) |
| After | −0.004** | −0.008*** | 0.0001 | −0.002 |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| Medium*After | −0.015*** | −0.012*** | −0.017*** | −0.015*** |
| | (0.003) | (0.003) | (0.005) | (0.005) |
| Low*After | −0.028** | −0.026** | −0.031** | −0.029** |
| | (0.012) | (0.011) | (0.014) | (0.014) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 99,404 | 99,404 | 99,404 | 99,404 |
| $R^2$ | 0.093 | 0.178 | 0.040 | 0.059 |
| Mean | 0.105 | 0.105 | 0.085 | 0.085 |

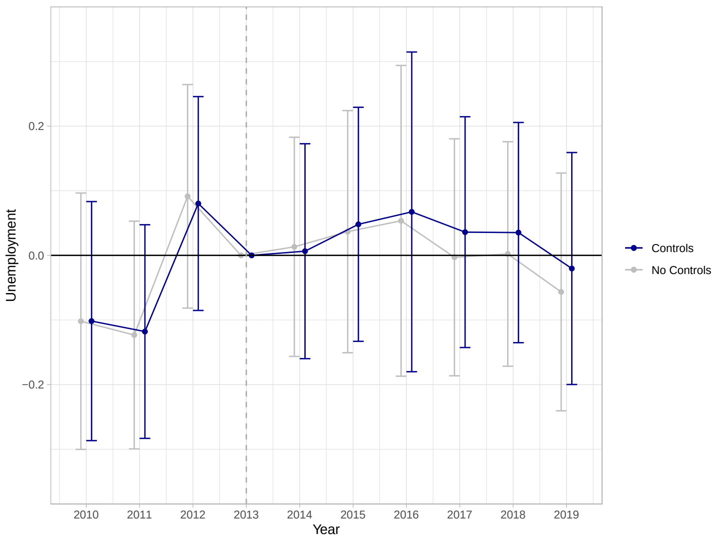
*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2016. The sample consists of yearly observations from 2012 to 2019. The panel includes natives in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Figure A.5: Event Study Plot of Welfare Dependency for Refugees (Country of Birth)




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (1) and (2) in Table A.12 displaying results for low educated refugee immigrants from the following regression: $Dependency_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Figure A.6: Event Study Plot of Unemployment for Refugees (Country of Birth)




*Note:* Event study plot and 1.96*Confidence Intervals of $\delta_{tj}$ from column (3) and (4) in Table A.12 displaying results for low educated refugee immigrants from the following regression: $Unemployment_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$

Table A.12: Event Study: Welfare Dependency Rate and Unemployment on Country of Birth

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.073*** | 0.047*** | 0.065*** | 0.049** |
| | (0.016) | (0.016) | (0.022) | (0.021) |
| Refugee | 0.257*** | 0.186*** | 0.134** | 0.093 |
| | (0.052) | (0.050) | (0.068) | (0.066) |
| NonEU*2010 | −0.005 | 0.007 | −0.027 | −0.020 |
| | (0.028) | (0.027) | (0.035) | (0.035) |
| Refugee*2010 | −0.133* | −0.114 | −0.102 | −0.102 |
| | (0.080) | (0.072) | (0.101) | (0.094) |
| NonEU*2011 | 0.003 | 0.017 | −0.039 | −0.033 |
| | (0.025) | (0.025) | (0.035) | (0.034) |
| Refugee*2011 | −0.110 | −0.087 | −0.123 | −0.118 |
| | (0.074) | (0.069) | (0.090) | (0.084) |
| NonEU*2012 | 0.010 | 0.012 | 0.016 | 0.014 |
| | (0.022) | (0.021) | (0.029) | (0.028) |
| Refugee*2012 | −0.018 | −0.019 | 0.091 | 0.080 |
| | (0.069) | (0.064) | (0.088) | (0.084) |
| NonEU*2014 | −0.022 | −0.014 | −0.042 | −0.036 |
| | (0.025) | (0.023) | (0.033) | (0.032) |
| Refugee*2014 | 0.055 | 0.052 | 0.013 | 0.006 |
| | (0.071) | (0.067) | (0.087) | (0.085) |
| NonEU*2015 | −0.019 | −0.006 | −0.028 | −0.017 |
| | (0.026) | (0.024) | (0.033) | (0.032) |
| Refugee*2015 | 0.094 | 0.115 | 0.037 | 0.048 |
| | (0.085) | (0.084) | (0.096) | (0.092) |
| NonEU*2016 | −0.034 | −0.022 | −0.053 | −0.044 |
| | (0.026) | (0.024) | (0.033) | (0.032) |
| Refugee*2016 | −0.013 | 0.015 | 0.053 | 0.067 |
| | (0.081) | (0.087) | (0.123) | (0.126) |
| NonEU*2017 | −0.013 | −0.002 | −0.027 | −0.016 |
| | (0.025) | (0.023) | (0.033) | (0.032) |
| Refugee*2017 | 0.012 | 0.064 | −0.003 | 0.036 |
| | (0.080) | (0.081) | (0.094) | (0.091) |
| NonEU*2018 | 0.008 | 0.016 | −0.011 | −0.005 |
| | (0.027) | (0.025) | (0.035) | (0.033) |
| Refugee*2018 | −0.065 | −0.022 | 0.002 | 0.035 |
| | (0.073) | (0.070) | (0.089) | (0.087) |
| NonEU*2019 | 0.008 | 0.007 | −0.018 | −0.016 |
| | (0.026) | (0.025) | (0.036) | (0.036) |
| Refugee*2019 | −0.094 | −0.046 | −0.057 | −0.020 |
| | (0.075) | (0.071) | (0.094) | (0.092) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.074 | 0.197 | 0.024 | 0.068 |
| Mean | 0.222 | 0.222 | 0.188 | 0.188 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_1 + \beta_2 Treat_j + \sum \gamma_t Year_t + \sum \delta_{tj} Treat_j * Year_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. The sample consists of yearly observations from 2010 to 2019. The panel includes low educated immigrants arriving before 2010 in Germany and low educated natives. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.13: Difference-in-Difference: Welfare Dependency Rate and Unemployment on Country of Birth

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.075*** | 0.056*** | 0.056*** | 0.043*** |
| | (0.009) | (0.009) | (0.012) | (0.012) |
| Refugee | 0.208*** | 0.144*** | 0.130*** | 0.086** |
| | (0.028) | (0.026) | (0.036) | (0.033) |
| After | −0.015 | −0.017* | 0.003 | −0.001 |
| | (0.009) | (0.009) | (0.013) | (0.012) |
| NonEU*After | −0.015 | −0.013 | −0.022 | −0.016 |
| | (0.013) | (0.012) | (0.016) | (0.016) |
| Refugee*After | 0.045 | 0.070* | 0.012 | 0.037 |
| | (0.037) | (0.036) | (0.047) | (0.046) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.071 | 0.194 | 0.021 | 0.066 |
| Mean | 0.222 | 0.222 | 0.188 | 0.188 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2013. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table A.14: Difference in Difference: Welfare Dependency Rate and Unemployment on Educational Level (Baseline 2013)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| Medium | 0.056*** | 0.064*** | 0.032** | 0.046*** |
| | (0.012) | (0.011) | (0.015) | (0.015) |
| Low | 0.150*** | 0.131*** | 0.160*** | 0.156*** |
| | (0.014) | (0.013) | (0.019) | (0.019) |
| After | −0.020* | −0.019* | −0.019 | −0.017 |
| | (0.011) | (0.011) | (0.014) | (0.014) |
| Medium*After | −0.002 | −0.002 | −0.006 | −0.005 |
| | (0.014) | (0.014) | (0.019) | (0.018) |
| Low*After | 0.020 | 0.023 | −0.003 | 0.002 |
| | (0.018) | (0.017) | (0.024) | (0.023) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 22,950 | 22,950 | 22,950 | 22,950 |
| $R^2$ | 0.084 | 0.215 | 0.042 | 0.089 |
| Mean | 0.222 | 0.222 | 0.188 | 0.188 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2013. The sample consists of yearly observations from 2012 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table A.15: Difference in Difference: Welfare Dependency Rate and Unemployment on Citizenship (Baseline 2010)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.011 | 0.004 | −0.007 | −0.011 |
| | (0.027) | (0.028) | (0.035) | (0.036) |
| Refugee | 0.313*** | 0.240** | 0.175 | 0.118 |
| | (0.092) | (0.101) | (0.126) | (0.134) |
| After | −0.042* | −0.043* | −0.009 | −0.015 |
| | (0.025) | (0.026) | (0.033) | (0.035) |
| NonEU*After | 0.028 | 0.028 | 0.020 | 0.024 |
| | (0.028) | (0.028) | (0.037) | (0.037) |
| Refugee*After | 0.075 | 0.064 | 0.144 | 0.153 |
| | (0.096) | (0.105) | (0.131) | (0.139) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.065 | 0.190 | 0.025 | 0.069 |
| Mean | 0.266 | 0.266 | 0.211 | 0.211 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2010. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01

Table A.16: Difference in Difference: Welfare Dependency Rate and Unemployment on Citizenship (Baseline 2016)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Welfare Dependency Rate | | Unemployment | |
| | (1) | (2) | (3) | (4) |
| NonEU | 0.036*** | 0.028*** | 0.012 | 0.011 |
| | (0.008) | (0.008) | (0.011) | (0.011) |
| Refugee | 0.379*** | 0.284*** | 0.308*** | 0.248*** |
| | (0.029) | (0.029) | (0.038) | (0.038) |
| After | −0.023* | −0.027** | −0.010 | −0.015 |
| | (0.013) | (0.013) | (0.018) | (0.018) |
| NonEU*After | 0.004 | 0.008 | −0.003 | 0.003 |
| | (0.015) | (0.015) | (0.021) | (0.020) |
| Refugee*After | 0.021 | 0.058 | 0.023 | 0.063 |
| | (0.060) | (0.066) | (0.078) | (0.082) |
| Region Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| Controls | | ✓ | | ✓ |
| Observations | 26,276 | 26,276 | 26,276 | 26,276 |
| $R^2$ | 0.066 | 0.191 | 0.025 | 0.069 |
| Mean | 0.200 | 0.200 | 0.175 | 0.175 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

*Note:* This table represents the results from: $Y_{ijst} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + X_{ijt} + \lambda_s + \epsilon_{ijst}$ *Welfare Dependency Rate* is the share of public social benefits (excl. pensions) of the total household income. *Unemployment* is the individual labor market situation of a survey participant. *After* is a dummy variable equal to 1 for each year $t$ after 2016. The sample consists of yearly observations from 2010 to 2019. The panel includes immigrants arriving before 2010 in Germany. Only observations with no missing information on any of the variables used in the analysis are included. Observations are weighted by SOEP survey weights. Statistical significance is determined by the following p-values: *p<0.1; **p<0.05; ***p<0.01