Refugees and their impact on the labor market: quasi-experimental evidence from the Netherlands

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Abstract

This paper examines the impact of an exogenous refugee influx on the labor market outcomes of individuals with different skill levels. Immigration and its economic implications are crucial for policymakers and researchers, and this topic remains a prominent subject of political and social debate. While existing literature has explored the labor market outcomes of refugee immigration, the effect of refugee localization when it is random and unrelated to economic conditions and personal preferences is still uncertain. To address this, I analyze the Syrian refugee influx into the Netherlands from 2011 to 2020, where refugees were subjected to a spatial dispersal policy. Data from the Dutch Labor Force Survey (EBB) is utilized to construct a proxy for the labor market, the delta unemployment rate. Employing a fixed effects estimation with municipalities as the unit of analysis, I find that an increased concentration of refugees significantly raises the delta unemployment rate for low-educated and medium-educated individuals. However, high-educated individuals, with more complex skills, remain unaffected by the increased refugee concentration. These results are further validated through multiple robustness analyses, enhancing the reliability of the findings. This study sheds light on labor market dynamics and how different population groups are impacted by refugee influxes. It suggests the need for further research targeting specific population groups and using different labor market proxies to improve policymaking and foster sustainable economic outcomes.

Keywords: refugees, immigration, unemployment rate, municipalities, spatial dispersal policy.

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Contents

1 Introduction

Immigration has become a main issue for Western countries. With over 1.2 million asylum requests in 2015 in the European Union (EU), it is not odd that migration policy is high on the political agenda in the West. Whereas the influx of refugees was quite static and evenly at the beginning of the 2000s, the Syrian civil war has caused a massive wave of new refugees. Since then, more than 1 million Syrian refugees have found shelter in the EU. As the Syrian civil war is still raging and a new war has started in Ukraine, the number of refugees that will locate themselves inside European countries will only increase the coming years.

Accommodating and integrating these incoming refugees has its impact on public finances and local economies. A key point of discussion regarding immigration concerns the costs and benefits for host countries' labor markets. The standard labor model suggests that migration increases labor supply which leads to a decline in wages and increased competition in the local labor market. Natives often perceive these consequences to be true, which causes hostility towards immigrants (Dennison & Geddes, 2018).

Analyzing the costs and benefits that migration causes on host countries' labor markets has been broadly examined in existing scientific research. Although there are many different studies, the outcomes vary significantly. This disparity in outcomes is frequently attributed to differences between economic migrants and refugee migrants in various studies. Economic migrants move to host countries due to better economic opportunities. Refugee migrants move to host countries due to unexpected environmental or political shocks. Because the migration motive varies significantly between these two groups, so does the corresponding impact on the labor market. As refugee migrant movement is often exogenous of economic conditions, refugee migrants are used in this paper to improve the likelihood of measuring a causal relationship between immigration and labor market outcomes.

Predicting the impact that refugees have on the labor market relies on the context and country of observation. In immigration literature, two types of studies are commonly identified to validate these predictions: structural studies and non-structural studies. Structural studies rely on theoretical modelling to simulate the impact of immigration on employment (Aydemir & Borjas, 2007; Edo & Toubal, 2015). These studies rely on basic assumptions regarding labor, capital, and the substitutability between immigrants and natives. However, they are often subject to structural changes in economic models.

In contrast, non-structural studies adopt empirical methods to assess the impact of immigrants and often find evidence that does not support the basic economic models used in

structural studies (Edo, 2017; Friedberg, 2001; Peri & Yasenov, 2018). Despite the standard labor model expecting increased competition and less employment opportunities for natives, non-structural studies often reveal only minor or negligible effects.

More recent non-structural have revisited earlier work, questioning whether certain subgroups should have been created. These studies indicate that refugees are often perceived as low-skilled and low-educated individuals compared to the host-country population (Bagir, 2018; Cengiz & Tekguc, 2021; Ceritoğlu et al., 2017; del Carpio and Wagner, 2015), and they tend to have fewer touchpoints with high-skilled individuals or those who have acquired complex skills in the labor market. Thus, it becomes crucial to categorize the host country population based on their skill-level or educational attainment to effectively assess the impact of refugee influx on different segments of society. This nuanced understanding of how refugees affect specific groups within the labor market can lead to improved policy interventions for successful integration.

In the field of non-structural studies, three primary methods are commonly employed to empirically assess the impact of immigration on labor markets: the spatial correlation method, natural experiments, and the skill cell approach. The spatial correlation method involves comparing areas with a low refugee concentration to areas with a high refugee concentration (Altonji & Card, 1991; Breunig et al., 2017; Dustmann et al., 2017). The idea behind this method is to use the least-affected areas to approximate the missing counterfactual, incorporating sufficient control variables to increase comparability. These studies analyze all types of migrants and are often subject to migration movement influenced by economic conditions.

The second method to examine the impact of immigration on the labor market involves natural experiments studies (Card, 1990; Friedberg, 2001; Glitz, 2012; Tumen, 2016). These studies utilize an exogenous refugee shock to ensure that immigrants are not moving to destination countries primarily for economic reasons. The literature on this method is divided into studies that focus on low- and middle-income[1] host countries (LMICs) and those that focus on high-income countries (HICs). However, both areas have obtained mixed or minimal effects (Akgündüz, Berg & Hassink, 2015; Borjas & Monras, 2017).

One potential reason for these outcomes is that LMICs often face limited capacities to integrate refugees into their economic systems. Moreover, inadequate regulations can result in

[1] The World Bank identifies countries as low- and middle-income when the Gross National Income per capita is less than $13,205.

the clustering of refugees in specific areas. Even in HICs, which are generally known for better integration capabilities and regulations, the clustering of refugees persists, leading to endogeneity problems that may offset any observed effects attributed to immigrants.

The third and lest method used to approximate the impact of immigration on labor markets is to the skill cell approach (Borjas, 2014; Carrasco et al., 2008; Edo, 2015). This approach analyzes the impact of immigration on labor market outcomes at the national level by considering different skill cells based on educational attainment and work experience (Bodvarsson & van den Berg, 2013). Consequently, the estimation process relies on the variation observed among these different skill cells. However, executing this method requires detailed and individual-specific data, which is not available in the context of this paper. Therefore, this paper will primarily focus on spatial correlation and natural experiment studies.

The main challenge with the spatial correlation method and natural experiment method stems from immigrants' potentially endogenous localization choice. Immigrants tend to cluster and choose residence in areas which have the best labor market opportunities, making it particularly challenging for spatial correlation studies to establish valid counterfactual regions. While some studies attempt to address this difficulty by implementing an instrumental variable approach, finding a valid instrument that is exogenous to labor market conditions is proven to be a difficult task. Consequently, it remains uncertain how immigrants impact the labor market in host countries when their settlement is truly random and not influenced by clustering.

Spatial dispersal policies aim to allocate immigrants or refugees across the host country without considering their economic capabilities and social preferences. The rationale for implementing such a policy includes the equitable distribution of the financial and social costs, improved efficiency in finding accommodations, and enhanced integration processes. However, the direct impact of spatial dispersal policies on host country labor markets lacks substantial evidence in the existing literature. While some studies indicate positive employment effects among native workers, particularly with low-educated workers (Foged & Peri, 2016; Gehrsitz & Ungerer, 2018), they tend to overlook variations in skills, education, and integration capabilities among different refugee groups. Additionally, the non-random nature of these spatial dispersal policies, influenced by factors like housing availability and ethnic clusters in non-rural areas, contribute to uncertainties surrounding the outcomes of these studies.

In this paper, I employ a combination of the spatial correlation and natural experiment method, incorporating subgroups similar to the skill cell approach. The exogenous refugee shock caused by the Syrian civil war is utilized as a quasi-natural experiment to evaluate the impact on the Dutch labor market. The focus lies on examining local variations in Syrian

refugee concentrations across municipalities before and after the peak influx, following a quasi-experimental approach similar to the spatial correlation method. To assess the effects on the labor market, I analyze the annual changes in unemployment rates at the municipality level. While different skill cells are not created, I investigate the effects of refugee migration on three different populations categorized by educational attainment, aligning with the skill cell approach. To ensure the absence of clustering among refugees, I take advantage of the unique spatial dispersal policy in the Netherlands, which exogenously and evenly distributes refugees across municipalities.

The primary objective of this paper is to investigate the impact of an increased refugee concentration, resulting from a spatial dispersal policy, on the labor market outcomes of individuals categorized by their educational attainment. I use existing literature and data from the Netherlands to predict with which population group Syrian refugees compete on the labor market. In this paper, educational attainment is considered the main determinant of skill, leading to the categorization of the Dutch population into three levels based on the classification of the Central Agency for Statistics (CBS)[2]: low-educated, medium-educated, and high-educated. These populations consist of natives or other individuals who permanently reside in the Netherlands and fluently speak the Dutch language. Migrants with a temporary residence permit and individuals without proper knowledge of the Dutch language are excluded from these populations.

The labor market analysis suggests that Syrian refugees are expected to compete and act as substitutes with the low-educated population due to their educational attainment in Syria, profession level in the Netherlands, and Dutch language proficiency. As indicated in Table 3 and further elaborated in Paragraph 2, this expectation forms the basis for the first hypothesis (H1), which posits that an increase in the proportion of work-entitled (WE) Syrian refugees relative to the low-educated work-entitled population, increases the unemployment rate among low-educated individuals compared to the previous year.

Conversely, for individuals outside the skill group of refugees, I expect that they do not acts as substitutes, nor as complements, and that the effect is close the null. Leading to the second hypothesis (H2), which suggests that an increase in the proportion of work-entitled Syrian refugees relative to the medium or high-educated population does not have a significant

[2] Low educated (LE): attained education at the level of primary education, vmbo, the first three years of havo/vwo or assistant training (MBO-1).
Medium educated (ME): attained education at the upper years of havo/vwo, MBO-2, MBO-3, or MBO-4.
High educated (HE): attained educated at the HBO or WO (University)

impact on the unemployment rates among medium-educated and high-educated individuals compared to the previous year.

I utilize rich data from the *Enquête beroepsbevolking* (EBB) and the *Stelsel van Sociaal-statistische Bestanden* (SBB), covering each Dutch municipality from 2011 to 2020. I follow a similar approach of Dustmann et al. (2017) in which a measure of employment among individuals in a given municipality is regressed on the relative number of refugees in that same municipality. I conduct a fixed-effects estimation, incorporating municipality and year fixed effects, while clustering robust standard errors at municipality level. All coefficients are interpreted *ceteris paribus,* meaning that all other variables are being held constant during the analysis.

The findings reveal significant and positive coefficients for the delta unemployment rate of low-educated and medium-educated individuals. This implies that when the work-entitled Syrian refugee concentration increases, the unemployment rate significantly increases relative to the previous year for individuals with low-and medium educational attainment. However, no significant results are observed for individuals with high educational attainment. Overall, these results support the validity of hypothesis 1 and partially support the validity of hypothesis 2.

To enhance the robustness of the estimation, three additional tests are conducted. Firstly, standard errors are clustered at COROP-level instead of municipality level. The results from this test remained consistent with the main estimation, indicating the reliability of the findings.

Secondly, to explore the potential impact that refugees have on individuals working in another municipality than the one that they reside in, the unit of analysis is changed to COROP-areas. Surprisingly, the results indicate that when COROP-areas are used as the unit of analysis, an increase in the proportion of work-entitled Syrian refugees relative to the high-educated work-entitled population increases the delta unemployment rate among high-educated individuals. This finding is contrary to the second hypothesis and differs from the outcomes in the main estimation. I suspect that these differences may be attributed to missing data on small municipalities, data aggregation patterns, and spatial mismatches, as explained further in Paragraph 7.2 of this paper.

As third and final robustness test, the number of work-entitled Syrian refugees prior to the first observational year is predicted instead of being treated as a missing value. The corresponding results do not indicate any changes in the significance or sign of the coefficients. Overall, the main results indicate that work-entitled Syrian refugees tend to act as substitutes on the labor market for individuals with low-and medium educational attainment. The effect on low-educated individuals aligns with the expectations, but the observed effect on medium-

educated individuals contradicts the hypothesis. This suggests that while Syrian refugees were initially classified within the low-educated Dutch population, in reality, they might also compete with medium-educated individuals on the labor market. Moreover, increased competition on the low-educated labor market due to the presence of refugees may have led to a shift of natives, or other individuals who were previously working or actively seeking work in this sector, to the labor market of medium-educated individuals.

In conclusion, most results align with the formulated hypotheses. The contrary results that are obtained on the medium-educated population are not entirely opposite to the expectations, and there are some reasonable arguments in favor of these outcomes. The overall findings shed light on the complex dynamics of refugee integration and the corresponding impact on the labor market.

I aim to contribute to existing literature on refugees and their impact on local labor markets, specifically within the context of a spatial dispersal policy. By taking advantage of unique evidence from the Netherlands, I provide empirical evidence on how spatial dispersal policies shapes the employment rates of natives within different education levels. This sheds light on the effectiveness of random refugee distribution in simplifying the economic integration and highlights the need for a comprehensive understanding of how refugees' skills and educational backgrounds influence their integration within the labor market.

Additionally, my aim is to contribute to existing methodological approaches used in immigration literature by implementing a spatial regression analysis. This approach allows me to capture local labor market effects, utilizing a provisional analysis between different municipalities with different levels of refugee concentration. By considering spatial heterogeneity that exists within the Netherlands, I can provide a more nuanced understanding of spatial dynamics and local labor market outcomes, addressing a research gap in existing literature.

The remainder of this paper is structured as follows. In Paragraph 2, background information is provided on Syrian refugees in the Netherlands and how they correlate to the Dutch labor market. Paragraph 3 discusses relevant literature on immigration that is essential to predict how refugees impact the labor market and how this effect can be empirically verified. In Paragraph 4, the data collection process is outlined, while Paragraph 5 describes the methodology and empirical strategy. The results are presented and interpreted in Paragraph 6, followed by Paragraph 7, which presents multiple robustness tests conducted. In Paragraph 8, the results are summarized, and lastly, Paragraph 9 discusses the implications of the findings.

2 Background information

Individuals requesting asylum in the Netherlands has been an important topic for many years[3] (Table A.1 in the Appendix presents an overview of the main nationalities and corresponding years when asylum requests were prominent). However, it was in 2011 that the Syrian Civil War triggered a new worldwide refugee crisis.

When peaceful protests were crushed violently by the Regime of Bashar Al-Assad, violence in Syria increased rapidly, compelling people to flee to neighboring countries like Turkey, Lebanon, Jordan, Iraq, and Egypt. These countries, known for their open-door policies (Cengiz & Tekguc, 2021), became the primary destination for the majority of Syrian refugees. However, from 2014 onwards, European countries started receiving massive waves of Syrian refugees. As of 2022, the Netherlands has over 126,260 Syrian inhabitants[4].

When analyzing Syrian immigrants in the Netherlands, it becomes coherent that they are almost identical in terms of immigration motives. Nearly all Syrian migrants, around 93%, entered the country as asylum seekers (Table 1). The remainder of Syrian immigrants mostly compromised family members of those who were granted asylum. In terms of gender, Syrian men are overrepresented in roughly each age group. Table 2 displays that for both genders, most people fall within the age bracket of 15 to 30 years. This can be attributed to the fact that the people within this age group are typically mature and healthy enough to undertake the refugee journey. As of January 1, 2022, approximately 56.83% of all Syrian refugees living in the Netherlands are male (Table 2).

Table 1. Migration motivate for incoming Syrian migrants and their year of arrival.

	Year of migration									
Migration motive	2013	2014	2015	2016	2017	2018	2019	2020	2021	**Total**
Labor	10	10	15	15	15	15	20	15	40	155
Family	40	80	340	675	2060	760	480	510	1005	5950
Asylum	660	6855	17035	24415	13245	4480	5160	5255	10790	87895
Study	10	15	20	15	25	25	25	10	45	190
Other	40	20	20	5	5	5	5	0	5	105

[3] Because the application and integration procedure of refugees in the Netherlands is an extensive process, this process is not included in the main text of this paper. Table A.2 (Appendix) summarizes the full procedure.
[4] According to statistics of the Central Agency for Statistics (CBS).

Table 2. Age distribution and gender of Syrian migrants

Age	<15	15-30	30-40	40-50	50-65	65-75	75+	Total
Men	12081	20232	12125	8654	7083	1125	247	56.83%
Women	10833	14201	9367	6771	4553	741	287	43.17%

Source: CBS.

In order to understand and predict which individuals on the Dutch labor market are impacted by Syrian refugees, I utilize data from the *Survey Nieuwe Statushouders in Nederland (*NSN). In this survey, demographic, educational and occupational characteristics are collected from 3209 Syrian refugees who entered the Netherlands between 1 January 2014, and 1 July 2016. By using this data, I am able to develop a predictive model which helps to assess how these attributes correlate with individuals on the Dutch labor market.

Table 3 presents the highest received certificate among Syrian refugees in Syria, while Table 4 showcases the highest received certificate among Dutch natives in the Netherlands. On average, relatively more Dutch natives have either finished secondary education or higher education, indicating that, Dutch natives possess higher educational qualifications compared to Syrian refugees.

Although the Tables provide valuable insights on how well educated these refugees are and how they relate to Dutch natives, it is difficult to understand and predict how they will impact individuals on the Dutch labor market. Various barriers, including the lack of Dutch language proficiency, the lack of legal documents, and differences in cultural values, hinder the construction of a predictive model solely based on education.

Table 3. Highest received certificate in Syria.

		Gender		**Age**			
Level of education	Total	Male	Female	15-24	25-34	35-44	45+
Low education level	43%	43%	40%	59%	29%	45%	36%
Secondary education level	36%	35%	37%	38%	42%	28%	32%
High education level	21%	22%	23%	3%	29%	27%	32%

Note: this Table only includes Syrian refugees who have followed any education (92%).
Source: Survey Nieuwe Statushouders in Nederland.

Table 4. Highest received certificate in the Netherlands for Dutch natives in 2016.

	Gender			Age			
Level of education	Total	Male	Female	15-24	25-34	35-44	45+
Low education level	32%	29%	36%	47%	12%	15%	40%
Secondary education level	39%	41%	37%	43%	40%	40%	36%
High education level	29%	30%	27%	10%	48%	45%	24%

I further utilize occupational data from the NSN to develop the predictive model. In the Netherlands, as indicated in Table 5, Syrian refugees mostly occupy professions classified under the International Standard Classification of Occupations[5] (ISCO) levels 1 or 2. ISCO-level 1 professions typically require minimum skills, whereas ISCO-level 4 professions mostly require the most complex skills. Lower skills tend to correspond to low educational attainment, while more complex skills align with higher educational attainment (ILO, 2012). Consequently, low-skilled individuals and low-skilled jobs are characterized by lower educational qualifications. Further utilizing data from the NSN, only 12% of all Syrian refugees completed the Dutch language in 2017, which was roughly 54% in 2019. As a result, the prospects of Syrian refugees acquiring complex jobs that necessitate higher education and good Dutch language proficiency are unlikely. This also implies that Syrian refugees, in the Netherlands, are likely characterized on the Dutch labor market as low-skilled individuals with a lower educational qualification. In support of this, 47% of employed Syrian refugees perceive their current profession to be something which requires a lower educational level than their own. In conclusion, I predict that Syrian refugees in the Netherlands compete with low-educated individuals on the labor market.

Table 5. ISCO-levels and percentage of Syrian working force occupying them.

ISCO-level	2017	2019
Level 1	32%	29%
Level 2	53%	54%
Level 3	8%	8%
Level 4	6%	9%

[5] The ISCO is an international classification of professions based on similarity in level of the skills and specialization required to practice the profession. Table A.6 in the Appendix provides a description per ISCO-level and some example professions.

3 Theoretical framework

This section of the paper provides a comprehensive review of relevant studies related to immigration and its impact on labor markets. First, I present the economic models that are commonly used to predict the effects of immigration on the labor market, which consequently leads to two main hypotheses. Then, I discuss the three main empirical methods that are utilized in existing scientific research. Finally, I provide justification for selecting the most suited method to effectively test my hypotheses.

3.1 Immigration and the impact on labor markets

Many economists have been struggling with evaluating how immigrants impact local labor markets. The process typically begins with the utilization of a theoretical model in which the labor market outcomes, induced by immigration, are predicted. Typically, this involves a model in which labor supply is increased due to the influx of immigrants. The resulting estimates rely on the assumptions made within this framework regarding labor and capital. These assumptions also depend on the 'type' of immigrant that is analyzed. Often, there is confusion regarding the generalizability of immigrants and their capabilities. The terms 'refugees' and 'migrants' are frequently interchangeably used in public debate and literature, despite their different empirical and theoretical considerations. In this paper, I follow the approach taken by Dustmann et al. (2017) and categorize migrants into two groups, that is, refugee migrants and economic migrants, and review the corresponding literature separately.

Refugee migrants are generally forced to leave their home country due to an environmental or political exogenous shock. They usually have little time to think about their optimal strategy and mostly move to the closest country possible. Their chosen destination country is often exogenous to economic conditions, employment priorities or behavioral characteristics. Economic migrants on the other hand often freely choose to resettle in another country. Their timing and destination country is an outcome of a thoughtful optimization process (Chklalova et al., 2008). Generalizing all types of immigrants in their skill composition is a difficult task, certainly for economic migrants. Additionally, economic migrants are expected to select countries with favorable economic conditions. Therefore, estimating a causal relationship between voluntary refugee movement and labor market outcomes is difficult if positive outcomes can be attributed to pre-existing characteristics, something which is often the case for economic migrants. In contrast, refugee migrants mostly have low choice involvement and exhibit greater similarity in their skill composition. Their movements are often large-scale and

unexpected, which increases the likelihood of estimating a causal relationship. Therefore, in this paper, I will focus on refugee migrants and their impact on labor markets.

To predict how refugees impact the labor market, I introduce a simplified model which involves an industry producing an output, denoted as X, that requires a combination of labor and capital. In this model it is assumed that labor is homogenous, capital is fixed, and refugees are perfectly substitutable for other workers. Consequently, it is assumed that immigration creates an abundance of labor supply, leading to increased competition in the labor market and downward pressure on wages (Borjas, 2013). Even though total employment may increase, employment among natives and non-refugees is expected to decrease as some exit the labor force due to decreased wages, while others may face job losses due to intensified competition.

However, it is important to notify that the assumption of fixed capital is not realistic (Peri, 2016). In a dynamic economy, firms invest in new assets and relocate capital across different locations and industries. With homogenous labor and elastic capital, refugee influx increases the return on capital. Consequently, firms can accumulate their capital and enhance production, thereby increasing labor demand and mitigating the initial wage effects caused by the excess labor supply. In this more realistic scenario where capital is elastic, the economy grows, the capital-labor ratio remains unchanged, and wages maintain their pre-refugee migration levels.

In both models presented above, it is assumed that refugees are perfect substitutes of other workers, and that labor is homogenous. These models treat labor as a constant factor of production, without considering variations across individuals (Edo, 2018). Suppose that labor is a combination of two different skill levels, that is, low-skilled and high-skilled. To predict how refugee migration will impact the local labor market, it is required to know how refugees can be perceived in their skill level. As concluded in Paragraph 2, Syrian refugees are generally regarded as low-skilled individuals, and this understanding serves as a critical factor in the prediction of refugee migration on labor market outcomes.

Considering different skill-levels, the revised model now assumes that capital is elastic, labor is heterogenous, and refugees are perfect substitutes of low-skilled workers. This implies that the impact of immigration on the wage structure varies among different skill groups. If the skill distribution of refugees is similar to the skill distribution in the destination country, the relative supply of skills remains the same, resulting in unchanged wages. However, if refugees are predominantly low-skilled workers and the destination country also has a mix of other skill levels, the influx of refugees can create an excess supply of low-skilled labor. Consequently, wages and employment among low-skilled workers who directly compete with refugees are

likely to decrease. Conversely, the wages and employment of high-skilled workers may remain unaffected because high-skilled individuals generally possess specialized knowledge and qualifications that differentiate them from low-skilled and immigrant workers (Dustmann et al., 2016). Therefore, they may be less affected by an increase in the low-skilled labor supply.

Although this model expects decreased wages, it is important to acknowledge the existence of inflexibility in the labor market. Factors such as strong unions, employer agreements, and minimum wage legislation, contribute to wage rigidities, particularly for HICs (Glitz, 2012; Labanca, 2020). Following empirical evidence from Baddeley, Martin & Tyler (2002), I believe that also holds true for the Netherlands, and that increased influx of Syrian refugees does only impact employment and not the wage structure, even among individuals within the same skill group.

Overall, I expect that when the number of work-entitled Syrian refugees relative to work-entitled low-educated population increases, increased competition leads to increased unemployment rates of low-educated individuals relative to the year before, which constitutes the first hypothesis (H1).

Furthermore, I hypothesize that the delta unemployment rates of medium-educated and high-educated individuals will not be significantly impacted by the presence of work-entitled Syrian refugees, as they do not belong to the same skill group, leading to the second hypothesis (H2).

3.2 Methodological approaches in immigration literature

There are two main approaches, that is, structural and nonstructural, in which the impact of immigration on the labor market is assessed. Structural studies derive their estimates on theoretical frameworks, which are sensitive to changes in basic economic models. Nonstructural studies on the other hand utilize empirical methods to examine the impact of immigration on local labor markets. While simple and well-known economic models predict that refugees act as perfect substitutes for individuals within the same skill group and that immigration leads to a decrease in relative wages, nonstructural studies often present evidence that does not align with these economic models. In the following section, I will discuss the three most commonly employed empirical methods in scientific research for analyzing refugee migration and its subsequent impact on local labor markets.

3.2.1 The spatial correlation method

The spatial correlation method is widely used to analyze the impact of immigration on labor markets. Researchers using this method exploit the fact that immigrants tend to cluster in specific areas. They compare employment levels in regions with low refugee concentration and high refugee concentration, while controlling for factors that enhance comparability, utilizing low refugee concentration areas as counterfactuals (Edo, 2018).

Within the spatial correlation method, a commonly used approach is the difference-in-difference method. This statistical approach compares the difference in outcomes before and after immigrant influx for regions with a high immigrant concentration to regions with a small immigrant concentration. (Altonji & Card, 1991; Breunig et al., 2017; Dustmann et al., 2013). The main limitation in this approach is that immigrants tend to cluster in areas with better employment opportunities and good economic conditions, which implies that estimates tend to be biased towards zero because of endogeneity. If there is a spurious positive correlation between immigration settlement and favorable labor market conditions, the measured effects of immigration on employment may be misleading. It is important to note that positive estimates obtained from this method may not necessarily imply better employment outcomes among other workers, but rather reflect that areas with low immigrant concentrations do not serve as valid counterfactuals.

To address this limitation, some studies have attempted to employ instrumental variable approaches, something which has proven to be difficult. Finding a valid instrument that is exogenous to labor market conditions is challenging. An alternative approach involves leveraging a sudden immigration shock which is not driven by economic conditions, so-called *quasi-natural experiments.*

3.2.2 Quasi-natural experiments

Quasi-natural experiments utilize unexpected, extraordinary supply shocks *(*UESS) (Bodvarsson & van den Berg, 2013) to assess the impact of immigration on labor market outcomes. This approach involves comparing 'normal' years of migration to years with a sudden exogenous influx of immigrants using time-series data. Regression analysis is then conducted in which the regions and years with low immigrant concentrations are compared to regions and years with high immigrant concentrations. Examples of such UESS studies include the Mariel Boatlift analyzed by Card (1990), the movement of former Soviet Union refugees to Israel (Borjas & Monras, 2017; Clemens & Hunt, 2019; Friedberg, 2001), the repatriates' movement from Algeria to France (Clemens & Hunt, 2019; Hunt, 1992) or more recent studies

on the movement of Syrian refugees to Turkey (Bagir, 2018; Tumen, 2016). Before the start of the Syrian civil war, studies that exploited quasi-natural experiments were relatively scarce. However, the short-term movement of over 6 million Syrian refugee migrants has led to an increase in studies employing this method to assess the impact on labor markets (Schuettler & Verne, 2021). The main advantage of this method is that it reduces the possibility of immigration settlement being concentrated in areas with favorable economic conditions.

Studies conducting quasi-natural experiments need to be divided into two areas: those focusing on the impact of refugee migrants on the labor markets in LMICs and those focusing on their impact in HICs. In LMICs, one prominent challenge is the clustering of refugees in areas closest to their home countries. This often includes countries bordering the refugee-sending nations, resulting in higher refugee concentrations in these areas compared to inland regions. The proximity of destination countries to refugee-sending countries can influence local labor markets due to factors unrelated to refugee settlement, such as trade disruption and capital flow (Peri, 2016). Additionally, clustering can lead to increased demand for goods and services, potentially creating job opportunities that offset any negative labor market effects. As a result, it becomes challenging to attribute changes in the labor market solely to the presence of refugees, especially when they are concentrated in specific areas within LMICs.

Moreover, LMICs may face difficulties in successfully integrating refugees into their social and economic systems. Limited infrastructure and resources can make the absorption of refugees more burdensome. Additionally, challenges in providing support services like language courses can hinder the long-term integration of refugees into the economy (Sarzin, 2021). These factors may impact the prospects of refugees' economic and social integration in LMICs.

On the other hand, research on HICs has received significant attention due to the availability of high-quality data in these countries. HICs often have well-functioning labor markets, which can effectively incorporate refugees into their economic systems through effective policies and integration programs. By improving employment opportunities for refugees and enhancing their economic integration, HICs can create a positive environment for refugee inclusion in society. These countries also tend to have low rates of unemployment, high labor productivity, strong labor regulations, and active labor market policies (Sarzin, 2021).

However, most studies focusing on HICs analyze the influx of immigrants into a selected number of labor markets, limiting the generalizability of the findings. The results might only apply to specific areas, restricting external validity. Additionally, labor markets vary in their economic characteristics and industry frameworks, and analyzing a limited number of labor

markets might not capture all the variations in these environmental factors. It also hinders a comprehensive understanding of the implications of the study, as it fails to capture the context and characteristics of other regions within the country.

One common limitation for both LMICs and HICs is that labor markets are not closed systems, and refugees can still cluster in areas with favorable economic conditions. This poses challenges when trying to isolate the labor market effects of immigration, as other workers and firms have the freedom to respond to the influx of low-skilled labor. Native workers might migrate away if they believe that immigrants negatively impact their wages and employment opportunities, undermining the possibility of obtaining clear labor market effects as a result of immigration. This phenomenon has been empirically observed by Borjas (2006), who found that immigration into a particular area decreases internal migration of natives into that area and increases internal migration of natives out of that area, potentially reducing the effect immigration has on native employment in these areas. Furthermore, clustering in economically favorable areas also leads to unreliable estimates.

As a result, many studies within the field of quasi-natural experiments obtain null or adverse effects on unemployment (Akgündüz, Berg & Hassink, 2015; Borjas & Monras, 2017; Card, 1990; Friedberg, 2001). It is evident that for studies that use a sudden and large immigrant shock, it is essential to assure that clustering of immigrants is minimized or impossible in order to obtain reliable and accurate estimates of the impact on local labor markets.

3.2.3 The skill cell approach

The third and last method to assess labor market outcomes is the so-called *skill cell approach*. This approach focuses on measuring the labor market effects of immigration at the national level across different skill groups. The aim of this method is to divide the labor market into skill cells that differ in terms of educational attainment and working years' experience (Bodvarsson & van den Berg, 2013). Estimation relies on the variation between different skill groups instead of geographical areas (as was for the first two methods). The positive implication of this approach is that the estimates are unbiased from any labor market adjustments. Internal migration of natives and other workers do not pose a problem and educational attainment and working years' experience cannot suddenly change due to relocation.

However, also the skill cell approach has its limitations. Firstly, it only captures a small portion of the labor market effects as it only estimates within-cell effects. This implies that it may not fully account for broader labor market dynamics and interactions between different skill groups. Secondly, natives and other workers may still respond to any changes in labor

demand which can lead to spurious correlation between labor market outcomes and immigrant penetration between skill groups. Lastly, classifying an individual into a specific skill cell based on their educational attainment may lead to biased estimates, as immigrants and other individuals can employ professions that require a completely different level of education. In this paper, the limitability of data hinders the possibility to use the skill cell approach as empirical method to assess any caused labor market effects by immigrants.

Instead, I utilize the sudden and significant exogenous supply shock caused by Syrian refugees to analyze their impact on the Dutch labor market. This approach is based on the framework introduced by Altonji & Card (1991), which uses the variation in the fraction of immigrants across areas to measure the effects of immigration on labor market outcomes. I will compare years before the influx, characterized by a low concentration of Syrian refugees, with years during and after the influx, characterized by a high concentration of Syrian refugees. To address endogeneity and clustering issues, I utilize the unique spatial dispersal policy that is implemented in the Netherlands, which distributes incoming refugees across the country without regard to economic conditions and other favorable characteristics.

3.3 Spatial dispersal policies

Spatial dispersal policies aim to distribute refugees across different geographical areas to avoid clustering, evenly distribute integration and accommodation costs, facilitate economic integration, and ease housing demand. However, there are limited countries that have implemented such policies, and research on spatial dispersal is underrepresented in the literature.

Denmark stands out as one of the early adopters of a spatial dispersal policy, which was implemented between 1986 and 1998. Initially, refugees were distributed equally across 14 counties, considering the number of inhabitants in each county. Later, the policy extended to distribute refugees across municipalities within these counties, with a preference for placing most refugees in cities and towns, and to a lesser extent in rural areas. Additionally, the council aimed at creating local ethnic clusters of around 100 refugees in specific areas. Despite the quasi-random design of this spatial dispersal policy, positive effects were found on the employment of natives. Researchers Foged and Peri (2016) argue that the influx of refugees pushed less-educated individuals towards more cognitive professions, leading to complementarity between refugees and less-educated natives and resulting in increased employment in the local labor market. Similar positive employment effects were observed in

Germany, where a semi-similar spatial dispersal policy was implemented during an influx of over a million refugees. Gehrsitz and Ungerer (2018) found evidence of positive employment outcomes for natives in this context.

However, it is crucial to note that these studies often generalized different refugee groups, overlooking significant variations in behavioral characteristics, prior work experience, and educational backgrounds among different refugee nationalities[6].

In conclusion, the limited research on spatial dispersal policies has shown some positive employment effects among natives. However, it is essential to consider the specific characteristics of refugee populations and the quasi-random nature of allocation when interpreting these results. Further research is needed to explore the effectiveness of spatial dispersal policies and their impact on the labor market for different refugee populations.

3.3.1 The Dutch spatial dispersal policy

The spatial dispersal policy in the Netherlands ensures a random allocation of refugees across the country, providing an opportunity to assess the impact of refugees on the local labor market when the distribution is strictly exogenous to their preferences. The exogenous shift in the labor supply caused by the Syrian civil war offers a quasi-experiment to utilize the regional variation in refugee concentration before and after the peak influx. Since the migration motives for Syrian refugees entering the Netherlands are identical, their impact on the labor market is expected to be the same (Chklalova et al., 2008). Therefore, Syrian refugees subject to the spatial dispersal policy in the Netherlands are suitable to assess the impact of refugees on the labor market.

The Dutch spatial dispersal policy process begins when asylum seekers request a residence permit. They are then randomly assigned to a refugee center based on availability, without considering any specific criteria related to their preferences or characteristics. Once their residence permit request is approved, the asylum seekers become permit holders and are connected to a municipality within the same province as the last refugee center they resided in.

The connection to the municipality, which is in the same province of the last refugee center, is based on three criteria. The first and most important criterion is the target of each municipality and how many permit holders they still must provide shelter. Each municipality must provide shelter to a relatively equal amount of permit holders. Municipalities with a larger

[6] As an example, the number Afghan refugee women that currently work in the Netherlands is three times higher than Syrian refugee women, according to the 2022 *'Integratie en samenleven'* report of the CBS.

population are assigned a higher number of incoming refugees to accommodate relative to municipalities with a smaller population (Table 6). The second criterion involves the soft criteria of permit holders: education and work experience in the country of origin, ambitions, and social network. If permit holders for example have experience of working in a harbor, the Central Organ Asylum (COA) tries to place them in a municipality where there is harbor work. The third and last criterion relates to the hard criteria of permit holders: first-degree family, medical details, work, and education in the Netherlands. If a permit holder has family members residing in a specific municipality, efforts are made to place them in or near that municipality to support family reunification. By combining these three criteria, the goal of the COA is to provide the best living environment for refugees to facilitate an effective integration process.

An interview I have conducted with the COA has provided evidence that refugees have a neglectable influence on their locational settlement. The interview's summary, available in Paragraph 11.3, indicates that many refugees enter the Netherlands without any legal documents that force them into certain areas, although most refugees wish to be placed in a big city. Without critical and legal evidence for why a certain refugee should be placed in a particular municipality, their involvement in localization is minimal. This observation is also supported by the research of Liempt & Staring (2020). As a result, it can be concluded that the distribution of Syrian refugees throughout the Netherlands is primarily determined by factors unrelated to the labor market outcomes being investigated.

Table 6. Number of inhabitants and number of refugees that shelter must be provided to for 5 municipalities in the Netherlands.

Municipality	Total number of inhabitants	Number of refugees that must be provided shelter to in the first 6 months of 2023	Number of refugees relative to total inhabitants
Rotterdam	664,071	784	0,12%
Amsterdam	921,468	1081	0,12%
Hengelo	82,343	98	0,12%
Utrecht	367,951	433	0,12%
Leeuwarden	127,088	164	0,13%

Note: data is maintained from 'Overzicht huisvesting vergunninghouders 1 januari 2023'

3.3.2 Comparing municipalities

To facilitate a comparison of labor market outcomes and to be able to assess the causal impacts of the spatial dispersal policy, it is essential to have variations in refugee concentrations across municipalities. Figure 1 illustrates the distribution of work-entitled Syrian refugees across municipalities in the Netherlands in 2021 in absolute numbers. A dark green area indicates a relatively high number of Syrian refugees while a light green area indicates a relatively low number of Syrian refugees. It is evident that there are significant variations between municipalities, primarily driven by factors as population size and the presence of Syrian churches and communities. On the right side of Figure 1, the municipality Enschede displays a dark green area, caused by the presence of a Syrian Orthodox Church. Since the clustering of Syrian refugees into these areas are not caused by favorable economic conditions, it provides no problems for the analysis in this paper. Although Figure 1 provides some basic information on the absolute refugee distribution, it does not provide any information on the relative distribution.

Figure 1. The absolute number of Syrian refugees belonging to the labor force distributed across municipalities in the Netherlands, 2021 distribution.

Figure 2 provides valuable insights into the relative distribution of Syrian refugees across the Netherlands. Dark green areas represent municipalities with a high number work-entitled Syrian refugees relative to the total work-entitled population in that municipality. Light green areas represent municipalities with a low number of work-entitled Syrian refugees relative to the work-entitled population in that municipality. The variation observed between municipalities

indicates that there are distinct comparison groups, allowing for a justified assessment of the impact of different refugee concentrations on labor market outcomes.

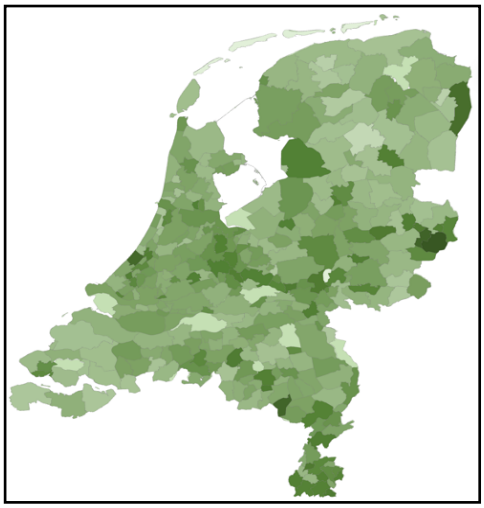

Figure 2. The percentage of Syrian refugees belonging to the labor force relative to the total number of inhabitants belonging to the labor force across municipalities in The Netherlands, 2021 distribution.

3.4 Endogenous localization

Data reveals that some Syrian refugees resettle after their initial placement. In certain municipalities in certain years, there is a net outmigration of Syrian refugees, indicating that more refugees have left this municipality than have arrived. Since refugees face no restrictions on resettlement, it is possible that they move into economic preferable areas. This raises doubts about the randomness of the Dutch spatial dispersal policy, suggesting that the resettlement decision of Syrian refugees is influenced by endogenous factors. As a consequence, if these refugees resettle in economic preferable locations, it is difficult to attribute changes in the unemployment rate exclusively to the presence of refugees (Del Carpio & Wagner, 2015).

The CPB[7] however provides evidence that resettlement of Syrian refugees does not improve their employment opportunities. Figure 3 illustrates the relative use of financial aid by Syrian relocators. The permit holders from the 1995 – 1999 cohort have diverse origins, including Iran, Iraq, Afghanistan, Somalia, and former Yugoslavia. On the other hand, the permit holders from the 2014 – 2019 cohort are mostly Syrian. In the years before the relocation,

[7] Https://www.cpb.nl/sites/default/files/omnidownload/CPB-Policy-Brief-Investeren-in-de-arbeidsmarktintegratie-van-statushouders.pdf

the relative use of financial aid is quite static among both cohorts. However, at the moment of relocation (represented as zero on the x-axis), there is a negative peak, which is attributable to administrative changes associated with the relocation process. After relocation, the use of financial aid increases again, with the 1995 – 1999 cohort even reaching a higher level of relative used financial aid before relocation. It is not within the interest of this paper to analyze the reasons behind this increased utilization of financial aid for the 1995-1999 cohort after relocation, as there are various factors to consider such as housing, implementation of the integration process, and social perspectives.

The focus of this paper lies within the 2014 – 2019 cohort, where evidence suggests that relocation does not present significant issues. The CPB argues that relocators do not move to municipalities with better labor market perspectives. Although the motive behind relocation might be to have better employment opportunities, relocators fail to actually increase their job prospects. Moreover, the CPB suggests that better job opportunities do not serve as a pulling factor for relocation, but rather the inability to find a job as a pushing factor. These findings indicate that even when Syrian refugees relocate, it does not enhance their integration into the labor market or improve their employment prospects.

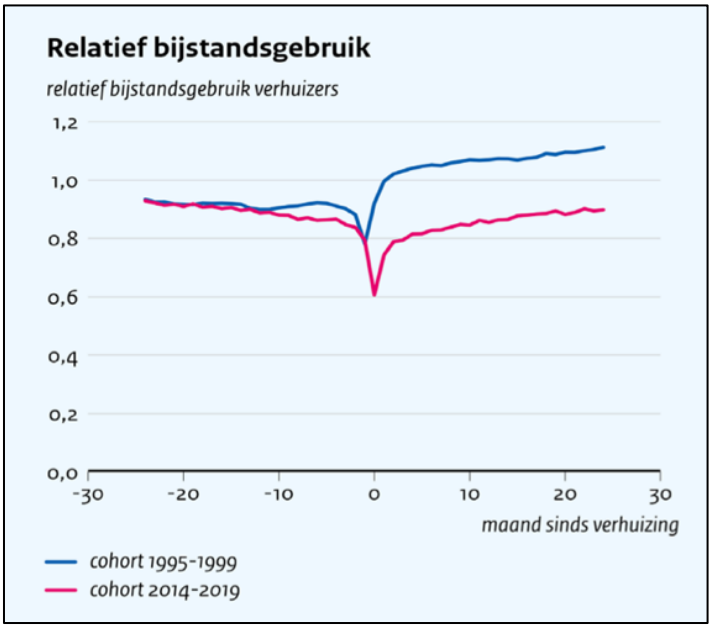

Figure 3. Use of financial aid of Syrian relocators

4 Data

This section of the paper presents a comprehensive overview of the relevant datasets utilized for estimating the regression models. The geographic unit of analysis used to approximate local labor markets in all estimations are the Dutch municipalities. The data covers the period from 2011 to 2020, assuring a representative timeframe for analysis.

4.1 Variables

I collected data on the Dutch labor market from the *Enquete Beroepsbevolking* (EBB), a repeated cross-sectional survey distributed annually to around 150,000 individuals aged between 15 and 90 in the Netherlands. The survey captures individuals' characteristics and their positions in the labor market. Since individual-level data is not publicly accessible due to privacy regulations, I use aggregated data, published published by the *Centraal Bureau voor de Statistiek* (CBS), at the municipality level for the years 2011 to 2020 to test my hypotheses.

I further utilize the EBB to construct the dependent variable, which represents the delta unemployment rate. It is important to note that the EBB only contains data on individuals that that permanently reside in the Netherlands and fluently speak the Dutch language. Refugees, permit holders and individuals with a temporary residence permit are not included in the data. This particular characteristic of the data has important implications for my estimations and interpretation of the results. Glitz (2012) provides evidence that when employment conditions of refugees are included in a dependent variable that measures employment outcomes, the estimates are likely to be biased due to composition effects. As most Syrian refugees are unemployed in their first years of arrival, their inclusion in the calculation of the unemployment rate would lead to biased outcomes for the rest of the population. Since the employment conditions of Syrian refugees are not captured in the data, there is no evidence of potential composition effects resulting from their inclusion in the analysis.

The data I obtained from the EBB follows the municipal division of each year from 2011 to 2020. However, it's important to consider that the total number of municipalities has decreased over the years due to splits or aggregations. For instance, I take the example of municipality Molenwaard, established on 1 January 2013, which consisted of the municipalities Graafstroom, Liesveld, and Nieuw-Lekkerland in 2011 and 2012. The data limitation only allows the municipal division from 2014 onwards, which means that the dataset includes data for Molenwaard in 2011 and 2012, even though it officially did not exist during that period. Instead, the 2011 and 2012 data for Molenwaard is aggregated data from the municipalities

Graafstroom, Liesveld, and Nieuw-Lekkerland. Although this doesn't pose a problem for this analysis, it's important to consider when merging datasets from different sources. For this paper, it implies aggregated data for 20 municipalities, and a complete overview of the aggregated municipalities is provided in Tables A.3 - A.5 (Appendix).

Additionally, I obtain data from the *Stelsel van Social-statistische Bestanden* (SSB) on the population, income, the economy, and education. The SSB data represents the entire Dutch population because registrations are integral, making it a complete dataset rather than a sample. With this data, I construct the independent variables and a number of control variables.

4.2 Sample and inclusion in the SSB

When Syrian refugees are awaiting their residence permit in refugee centers, they are not included in the SSB dataset because they are not officially recognized as part of the Dutch population. This raises the possibility that Syrian refugees already enter the labor market while they are still awaiting their residence permit. That implies that these refugees impact the labor market while they are not included in the dataset, potentially leading to biased outcomes in the analysis.

To counter this concern, Figure A.1 (Appendix) displays that Syrian refugees typically leave the refugee center within 100 days. As there is an employment ban which prohibits working for refugees waiting for a shorter time period than 6 months in refugee centers, Syrian refugees are not expected to enter the labor market while still in a refugee center. Moreover, empirical evidence indicates that the majority of Syrian refugees are unable to find paid work within their first months of entering the Netherlands (Besselsen et al., 2017). Consequently, it is unlikely that Syrian refugees enter or significantly impact the labor market while they are waiting on their residence permit.

5 Methodology

This section of the paper provides an outline of the methodology used in this paper, including the validation of the estimation technique and an overview of the relevant variables included in the estimations.

5.1 Panel data

Most papers in existing scientific research on immigration employ a standard Ordinary Least Squares (OLS) estimation method or one of its variants to obtain the estimates (Schuettler & Verne, 2021). In the case of this paper, the dataset follows a panel data structure, and the standard notation is as follows:

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \alpha_i + \varepsilon_{i,t}$$

Here, β_0 is the constant, which represents the value of $Y_{i,t}$ when all variables are equal to zero. B_1 represents the coefficient of the main independent variable, $X_{i,t}$. Furthermore, α_i represents the error term for unobserved time-invariant components such as demographics or other factors that do not change over time. The error term $\varepsilon_{i,t}$ represents the unobserved time-variant components such as skill development or other factors that do change over time. In order to obtain unbiased estimates in a Pooled OLS estimation, both error terms should be uncorrelated with $X_{i,t}$, which is known as the zero conditional mean assumption (ZCM). Additionally, it is important to consider that the error terms may not be serially correlated across time to ensure efficient estimates.

In panel data, the standard errors are likely to be serially correlated across time as α_i is an unobserved effect common to all observations of a unit. This serial correlation can lead to inefficient estimates. Therefore, if there is evidence of serial correlation, a Pooled OLS estimation is not suitable for testing the hypotheses in this paper.

To investigate whether there is evidence of serial correlation in the dataset, I perform a Wooldridge test on the main estimation[8] for each *e* educated population. The null hypothesis of this test is that there is no evidence for first-order autocorrelation. The results, presented in the Tables A.7 – A.9 in the Appendix, provide evidence that the null hypothesis can be rejected, and it can be assumed that there is autocorrelation in the dataset. Consequently, it is assumed

[8] See page 30, Paragraph 5.2.

that the error term of municipality *i* is correlated over time, implying the presence of serial correlation. This finding highlights the essence to employ an estimation technique that accounts for serial correlation in panel data analysis to ensure accurate estimation outcomes.

Both fixed effects and random effects models can address serial correlation in panel data analysis. The decision on which model to use relies on whether it can be assumed that the ZCM holds, something which is unlikely for panel data as the unobserved time-invariant components are likely to be correlated with $X_{i,t}$ over time.

A random effects model is only unbiased if the ZCM holds. For a fixed effects model to be unbiased, only $\varepsilon_{i,t}$ needs to be uncorrelation over time with $X_{i,t}$. By time demeaning the data and eliminating α_i, a fixed effects model can address unobserved time-invariant components that may be correlated with the independent variable. To assess the presence of endogeneity in the model and determine which model is preferred, a Hausman test is conducted for the main equation for each *e* educated population. This test indicates whether the unobserved heterogeneity α_i matters. The null hypothesis is that the random effects model is consistent, efficient, and preferred above a fixed effects model. The results of the Hausman test, displayed in the Tables A.10 – A.12 in the Appendix, show that the null hypothesis is rejected and that there are systematic differences between the fixed effects model and the random effects model.

Based on these results, a fixed effects model is preferred over the random effects model because a random effects model would yield biased estimates. This decision assures that the model accounts for the unobserved heterogeneity and that the most reliable coefficients are produced.

5.2 Main analysis

To investigate hypotheses 1 and 2, the following main equation is estimated:

$$\Delta\ Unemployment\ rate_{i,t,e} = \beta_0 + \beta_1 \ln(Syrian\ refugee\ concentration_{i,t,e}) + \beta_{x,i,t} N_{x,i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

In this equation, the dependent variable, represented as the $\Delta\ Unemployment\ rate_{i,t,e}$, is a continuous variable that captures the change in the average unemployment rate[9] in region *i* in year *t* of the *e* educated population, relative to the previous year's average unemployment rate

[9] The unemployment rate is measured as the percentage of the unemployed labor force relative to the total labor force.

for the same population. This approach of using the change in the unemployment rate as the dependent variable, rather than its absolute value, has been supported by empirical evidence in previous research of Borjas & Monras (2017).

The rationale for transforming the dependent variable into delta form (Δ) is to address stationarity issues. Non-stationarity occurs when the mean of a variable is not constant over time. With many economic variables, such as the consumer price index (CPI), there is a natural growth trend over time. When analyzing two non-stationary variables, rain levels in Nigeria and the CPI for example, there is a chance of finding a significant correlation. This is known as spurious regression, where the observed relationship is merely a result of shared trends rather than a meaningful cause-and-effect relationship.

To ensure a true causal relationship between the dependent and the independent variable, it is essential to have a stationary dependent variable. Initially, when using the absolute unemployment rate as the dependent variable, the adjusted R^2 was found to be extremely high (0.91 and 0.94). A R^2 of 1.00 means that all of the variation in the dependent variable is completely explained by the independent variable, and the model perfectly fits the data. As the R^2 obtained in the initial model went to this value, it raised concerns about potential spurious regression.

To empirically investigate whether a trend exists in the mean unemployment rate, three graphs are created, showing the mean unemployment rate for each *e* educated population across time (Figures A.2 – A.4, Appendix). These graphs reveal a trend over time, highlighting the importance of accounting for it in the analysis. To create a stationary variable, the first difference of the unemployment rate is taken. This transformation represents the change between Y_t and Y_{t-1}, capturing the dynamics of the unemployment rate rather than its absolute value. This ensures that the analysis focuses on the change in the unemployment rate compared to the previous year, making the variable stationary. Figures A.5 – A.7 in the Appendix show the mean values of the delta unemployment rate, which fluctuates across time but remains constant around the mean.

Using the delta unemployment rate in the analysis deviates from most studies that employ employment measures to approximate local labor market outcomes. The reason for this difference is the specific use of the economic indicator, the unemployment rate, which necessitates addressing non-stationarity issues since individual-level data is not available in this analysis. By utilizing the delta unemployment rate, I can capture the dynamics of the unemployment rate and obtain more robust estimates for evaluating labor market outcomes.

The main independent variable in the analysis is ln(*Syrian refugee concentration*$_{i,t,e}$). It is a continuous variable that measures the total number of work-entitled[10] Syrian refugees in region *i* on January 1 in year *t*, per 10000 *e* educated work-entitled individuals in the same region on the same date. This formulation aligns with the studies of Altonji & Card (1991) and Altindag, Bakis & Rozo (2020). The variable distribution is visualized in the Figures A.5 – A.7 (Appendix) and shows a right-skewed distribution. Consequently, to reduce the impact of outliers and to linearize the relationship between the independent and the dependent variable, the variable is logarithmic transformed.

In the main equation, $N_{x,i,t}$ concerns all observed time-varying municipality-level control variables (as described in Paragraph 5.3). To control for unobserved municipality-specific time-invariant characteristics such as constant wage disparities, infrastructure, and industrial design, municipality fixed effects μ_i are included. To control for time-specific shocks and trends that impact all municipalities in the same manner, time fixed effects, δ_t, are included. Lastly, $\varepsilon_{i,t}$ provides the error term. To address issues of autocorrelation and heteroskedasticity, a similar strategy employed by Akgündüz, Berg & Hassink (2015) is used, and the standard errors are clustered at municipality level to account for potential correlation within municipality. This specification aims to provide more reliable estimates while controlling for relevant characteristics.

5.3 Control variables

The control variables included in this analysis aim to account for alternative causes that could potentially explain any observed changes in the delta unemployment rate, ensuring a more valid estimation of the relationship between the Syrian refugee concentration and the unemployment rate.

The first control variable is *economic growth.* It is included because previous empirical studies (Kapsos, 2005; Khan, 2007) have highlighted the significant association between economic growth and employment opportunities. Positive economic growth is indicative of good labor market conditions, which may lead to biased estimates if not accounted for. The variable *economic growth* measures the average gross domestic product of the COROP-area[11] corresponding to region *i* in year *t* relative to the average regional gross domestic product in the

[10] Those between the age of 15 and 75.
[11] The Netherlands has 40 different COROP-areas which are created on social-economic and geographical characteristics. They were created for statistical and research purposes. See Appendix for the map (Figure A.8)

same region in year *t-1*, corrected for inflation. By including this control variable, the influence of regional economic conditions on the unemployment rate is captured.

Two other control variables are added which are empirically verified by Borjas (2006). *Absolute native migration* controls for internal migration of natives which might be impacted after the influx of refugees. The variable measures the net migration of natives in region *i* between January 1 in year *t* and January 1 in year *t-1*. A positive value indicates a higher native influx than a native outflux, increasing competition on the labor market and potentially raising unemployment rates. Conversely, a negative value suggests that natives who experienced negative consequences on the labor market have left the municipality, potentially offsetting any changes in the local unemployment rate. Not including this variable could lead to an underestimation of the effect that Syrian refugees have on local unemployment rates.

Work-entitled population is added as third control variable, also empirically verified by Borjas (2006). It measures the total number of *e* educated work-entitled individuals in region *i* on January 1 in year *t.* An increase in this variable can induce more competition in the labor market, potentially reducing employment opportunities. More importantly, including this control variable ensures that any observed causal effect of refugee concentration on the local unemployment rate is attributed to changes in the number of Syrian refugees rather than changes in the work-entitled population.

Another factor that might influence the unemployment rate is the net labor force participation rate, as empirically verified by Emerson (2011). The *net labor participation rate* is a measure of the working labor force relative to the work-entitled population. A higher rate indicates a relatively larger number of work-entitled individuals actively employed. When the net labor participation rate increases (decreases), it suggests an improvement (deterioration) of labor market conditions. To account for potential changes in labor market conditions on the unemployment rate, the *Δ net labor participation rate* is included in the model. This variable captures the difference between the average net labor participation rate in region *i* for the *e* educated population in year *t* and the net labor participation rate in the same region for the same population in the previous year, *t-1*.

The Common Basic Principles (CPB) for Immigrant Integration Policy, formulated by the Organization for Economic Co-operation and Development (OECD), emphasizes the importance of ‘frequent interaction between immigrants and natives’ as a fundamental

mechanism for integration[12]. To account for municipalities with a higher likelihood of achieving such interaction, two control variables are added. The first is *Dutch natives,* which measures the percentage of the population in a municipality that are Dutch natives. A higher percentage indicates a relatively larger presence of Dutch natives, potentially enhancing integration through increased interaction between immigrants and natives. The second control variable is *population density,* which represents the number of individuals per km^2. A higher population density may foster increased interaction and potentially offer better integration opportunities. Both control variables are added because they can influence the employment of refugees and the corresponding effect on local unemployment rates.

Additionally, a trend control variable is added that measures the absolute influx of Syrian refugees *n* years prior the observational year. Bodvarsson & van den Berg (2013) argue that the labor market effects, caused by immigration, may not immediately manifest upon arrival because it takes time for refugees to integrate and have an impact. Supporting this notion, Dagevos et al. (2020) find that from 2017 to 2019, employment among Syrian refugees represented in the NSN increased with 23% and the Dutch language course completion rate went from 12% to 54%. Representing such effects in a control variable ensures that the coefficient of the main independent variable is not under- or overestimated. For example, if the influx of refugees in 2014 is remarkably high and most of these refugees start competing on the labor market in 2017, this variable is able to capture this effect, ensuring that the main independent variable is not biased. The control variable is added separately four times and measures the absolute influx 1 to 4 years prior the observational year.

By incorporating these control variables, the analysis accounts for additional characteristics that can affect the unemployment rate, assuring a more complete examination on the relationship between Syrian refugee concentration and local labor market outcomes. This improves the accuracy while considering the dynamics of labor market conditions, integration mechanisms, and population characteristics. A complete overview of all relevant dependent, independent and control variables is provided in Table A.13 (Appendix).

5.4 Multicollinearity

To ensure the reliability and stability of coefficient estimates, it is essential to address the possibility of multicollinearity, which can be present when there is a high correlation between

[12] https://www.europarl.europa.eu/RegData/etudes/STUD/2016/578956/IPOL_STU(2016)578956_EN.pdf

the independent variables. Control variables with a high correlation do not particularly cause a problem to the interpretation of the main independent variables as the control variables are not interpreted. However, multicollinearity among the independent variables can lead to unreliable and unstable coefficient estimates, making interpretation challenging. Tables A.14 – A.16 (Appendix) provide the pairwise correlation matrices with the inclusion of the independent variable. As a rule of thumb, a correlation above 0.8 is considered to potentially indicate multicollinearity issues (Berry & Feldman, 1985).

After the models are estimated, the corresponding correlation matrices of the coefficients produce no correlations above 0.7. Additionally, Tables A.17 – A.19 (Appendix) provide the Variance Inflation Factor (VIF) values for all variables in the main equation. A VIF value above 5 can induce correlation problems, but this is not generated. Therefore, there is no suspicion of multicollinearity in the estimated models. Because the issue of multicollinearity is effectively addressed, the reliability and validity of the coefficient estimates obtained in the analysis is ensured.

6 Results

This section of the paper provides a comprehensive analysis and discussion of the obtained results from estimating the model. It starts with an overview of the descriptive statistics and a summary of the key variables. Subsequently, the regression outcomes are presented and interpreted, shedding light on the relationships between the investigated variables. Overall, this section aims to provide an insightful analysis of the obtained results, offering an understanding into the relationship between refugees and their impact on labor market outcomes in the context of spatial dispersal policies.

6.1 Descriptive statistics

In this paper, the unit of analysis are municipalities. Small municipalities without data on the local labor market are excluded from the dataset. The final dataset consists of 3,825 observations spanning from 2011 to 2020. As municipalities can undergo aggregation and separation processes each year, the total number of municipalities changes over time. In the final dataset, there are 417 different municipalities, with data available for 331 of them in each year. The data is unbalanced, as can be observed in Figure A.12 (Appendix) meaning that not all municipalities have data for every year. However, this unbalanced nature of the dataset does not introduce any issues of attrition bias, as the missing observations are due to renaming or aggregation of municipalities, rather than systematic dropout of specific units.

Table 7 presents descriptive statistics for all the main variables included in the analysis. On average, each municipality had at least 81 work-entitled Syrian refugees during the period of 2011 to 2020. The unemployment rate exhibits the highest average for the low-educated population and the lowest for the high-educated population. This pattern is also clear in the net labor participation rate, which is the lowest for the low-educated population and the highest for the high-educated population. The average unemployment rate growth, the dependent variable, shows a decrease across all *e* educated populations, as indicated by the negative mean values. Additionally, the work-entitled population is largest for the medium-educated population. This is reflected in the mean value of the independent variable, which is the lowest for the medium-educated population as the work-entitled population is reflected in the denominator.

It is important to note that some municipalities with a low number of inhabitants have missing values for the unemployment rate for the high-educated population. This is reflected in table 5, where the unemployment rate and the delta unemployment rate has less observations than the low-educated and medium-educated population.

Table 7. Descriptive statistics

Variables	Obs	Mean	SD	Min	Max
Number of work-entitled Syrian refugees	3825	81.015	193.876	0	2977
Unemployment rate LE population in %	3825	7.781	2.62	3	24.7
Unemployment rate ME population in %	3825	4.569	1.726	1.7	13.7
Unemployment rate HE population in%	1997	3.024	1.018	1.2	7.8
Unemployment rate LE population growth in %	3408	-.064	1.625	-6.1	6.4
Unemployment rate ME population growth in %	3408	-.078	1.006	-3.7	3.9
Unemployment rate HE population growth in %	1686	-.054	.72	-3.4	3
Syrian refugees per 10000 work entitled LE	3544	81.439	85.543	.8	1328.3
Syrian refugees per 10000 work entitled ME	3825	53.741	58.836	0	797
Syrian refugees per 10000 work entitled HE	3825	82.763	94.032	0	1635
Net labor participation growth LE in %	3408	-.181	3.49	-14.4	11.2
Net labor participation growth ME in %	3408	.002	2.64	-10.4	8.4
Net labor participation growth HE in %	3408	.177	4.34	-15.6	17.6
Net labor participation rate LE in %	3825	49.645	4.617	33.8	64.1
Net labor participation rate ME in %	3825	71.885	3.932	56.5	84.5
Net labor participation rate HE in %	3825	79.979	4.635	52.2	96.4
Economic growth in %	3825	.833	2.612	-9.3	23.9
Net migration of natives in thousands	3825	0	.43	-11.108	4.833
The LE work-entitled population in thousands	3825	9.915	14.089	1	178
The ME work-entitled population in thousands	3825	13.078	17.51	1	212
The HE work-entitled population in thousands	3825	9.853	21.008	1	352
Dutch natives in %	3825	85.453	8.26	44.4	97.1
Total individuals per km^2 (population density)	3825	6.198	1.015	4.007	8.798

6.2 Main results

Hypothesis 1 posits that an increase in the proportion of work-entitled Syrian refugees relative to the low-educated work-entitled population will lead to an increase in the delta unemployment rate of low-educated individuals. Hypothesis 2, on the other hand, explores the impact on individuals who are expected to be unaffected by the influx of Syrian refugees. Specifically, H2 posits that an increase in the proportion of work-entitled Syrian refugees relative to the

medium-educated or high-educated work-entitled population does not have a significant impact on the unemployment rate for medium-educated or high-educated individuals. The main independent variable, the proportion of work-entitled Syrian refugees relative to the work-entitled *e* educated population, is logarithmically transformed. This transformation enables to interpret the estimated coefficients as the percentage effect on the unemployment rate resulting from a 1% increase in the number of Syrian refugees relative to the work-entitled population.

Table 8 presents the estimates for the main equation for the low educated population. For the first hypothesis to be true, the coefficient of the independent variable has to be significant and positive. The first column displays the estimation in which the absolute influx *n* years prior the observational year is not added. Columns 2 – 5 display the absolute influx 1 – 4 years prior the observational year respectively.

In column 1, the results show that a 1% increase in the proportion of work-entitled Syrian refugees per 10000 individuals within the low-educated work-entitled population, on average, leads to a 0.108 percentage points increase in the unemployment rate among low-educated individuals relative to the previous year, holding all other variables constant. This effect statistically significant at the 1% significance level, supporting hypothesis 1, which expects that Syrian refugees increase the delta unemployment rate for low-educated individuals.

Comparing the coefficient of the Syrian refugee concentration (0.108) to the mean of the delta unemployment rate of the low-educated population (-0.064), the change is relatively high. It implies that a 1% increase in the number of work-entitled Syrian refugees per 10000 individuals within the low-educated work-entitled population leads to a relative increase of 168.75% in the delta unemployment rate of low-educated individuals.

Columns 2 to 5 present the results with the inclusion of the 'absolute influx *n* years ago' control variable. In columns 2 and 3, the sign and significance of the main independent variable remains consistent with column 1. In column 4, the coefficient is still positive but significant at the 10% significance level instead of the 1% significance level. However, in column 5, the coefficient becomes negative and insignificant, contradicting hypothesis 1. Observable is that the number of observations decreases from column 2 to 5, caused by missing observations that are dropped from the dataset as it is unknown how many refugees entered before the first observational year 2011. It is likely that the coefficient becomes less significant and eventually insignificant in column 5 because for the variable *Δ Refugee migration t-4,* the first observational year is 2015 and no valid comparison years are available before refugee influx. To address this, a robustness check will be performed in Paragraph 7, where predictions of the influx before 2011 will be added to ensure accurate measurements.

Table 8. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the low-educated population with independent delta variables.

	(1) ΔU rate LE	(2) ΔU rate LE	(3) ΔU rate LE	(4) ΔU rate LE	(5) ΔU rate LE
Log: Syrian refugees per 10000 work-entitled individuals	0.108***	0.120***	0.0946***	0.0832**	-0.00963
	(0.0209)	(0.0211)	(0.0251)	(0.035)	(0.0459)
Δ Net labor productivity	-0.210***	-0.211***	-0.211***	-0.209***	-0.200***
	(0.00550)	(0.00551)	(0.00576)	(0.00619)	(0.00629)
Economic growth	0.0119	0.0124	0.00709	0.0122	0.0111
	(0.00823)	(0.00821)	(0.00913)	(0.00995)	(0.0102)
Net migration of natives in thousands	0.101	0.100	0.0995	0.0367	-0.0732
	(0.0766)	(0.0761)	(0.0836)	(0.143)	(0.120)
Log: the work-entitled population in thousands	-1.656***	-1.653***	-1.748***	-1.531***	-1.587***
	(0.158)	(0.158)	(0.171)	(0.180)	(0.201)
Dutch natives	-0.0224	-0.0321	-0.0384	-0.0128	-0.0954***
	(0.0217)	(0.0214)	(0.0241)	(0.0297)	(0.0336)
Log: population density	0.543	0.522	0.443	0.238	0.432
	(0.381)	(0.377)	(0.528)	(0.431)	(0.395)
Δ Refugee migration t-1		-0.000875***			
		(0.000214)			
Δ Refugee migration t-2			-9.49e-06		
			(0.000293)		
Δ Refugee migration t-3				-0.000126	
				(0.000290)	
Δ Refugee migration t-4					0.000324
					(0.000565)
Constant	1.207	2.132	3.207	1.604	7.704**
	(3.468)	(3.429)	(4.289)	(4.283)	(3.784)
Observations	3398	3398	2988	2571	2172
Adjusted R^2	0.746	0.746	0.736	0.653	0.627
Within R^2	0.475	0.476	0.483	0.476	0.479
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes

Table 9 presents the estimates for the first part of hypothesis 2, which aims to examine the impact of the influx of Syrian refugees on the labor market, specifically focusing on individuals belonging to different skill groups. The hypothesis posits that medium-educated individuals would not be affected by an increased concentration of Syrian refugees, suggesting that the main independent variable should be insignificant.

However, the findings in columns 1 to 5 of Table 9 reveal contrasting results, showing positive and significant coefficients for the main independent variable. This contradicts the initial expectations of hypothesis 2. The results in column 1 display that a 1% increase in the number of work-entitled Syrian refugees per 10000 individuals within the medium-educated work-entitled population, on average, leads to a 0.0799 percentage points increase in the unemployment rate among medium-educated individuals relative to the previous year, holding all other variables constant. This effect is statistically significant at the 1% significance level.

The results in columns 2 to 5 do not substantially alter the magnitude and significance of the main independent variable's coefficient. Only column 5 displays a significance level of 5% instead of 1%, which might be explained by similar arguments as was with the low-educated population.

The relative magnitude of the coefficient in relation to the average unemployment rate growth among medium-educated individuals is quite substantial. A 1% increase in the proportion of work-entitled Syrian refugees relative per 10000 individuals within the medium-educated work-entitled population leads to a relative increase of 102.44% in the delta unemployment rate of medium-educated individuals.

Although the coefficients are not according to expectations, they do align with the coefficients obtained for the low-educated population. This might suggest that expectations of Syrian refugees were too low, and that they do have an impact on the labor market of medium-educated individuals.

Table 10 presents the results for the second part of H2, the high-educated population. Hypothesis 2 posits that individuals which do not belong to the same skill group of Syrian refugees, will not be affected by an increase in the refugee concentration. In other words, high-educated individuals should not be affected on the labor market when the refugee concentration increases. The results align with this expectation, as none of the coefficients is significant.

Table 9. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the medium-educated population with independent delta variables.

	(1) ΔU rate ME	(2) ΔU rate ME	(3) ΔU rate ME	(4) ΔU rate ME	(5) ΔU rate ME
Log: Syrian refugees per 10000 work-entitled individuals	0.0799***	0.0815***	0.0786***	0.0542***	0.0650**
	(0.0142)	(0.0147)	(0.0160)	(0.0208)	(0.0288)
Δ Net labor productivity	-0.109***	-0.109***	-0.109***	-0.104***	-0.0990***
	(0.00349)	(0.00348)	(0.00362)	(0.00385)	(0.00393)
Economic growth	-0.00632	-0.00626	-0.00712	-0.00368	-0.00669
	(0.00484)	(0.00484)	(0.00538)	(0.00566)	(0.00700)
Net migration of natives in thousands	0.0565	0.0564	0.0289	-0.0472	-0.0991***
	(0.0364)	(0.0363)	(0.0365)	(0.0305)	(0.0330)
Log: the work-entitled population in thousands	-1.146***	-1.145***	-1.212***	-1.212***	-1.051***
	(0.136)	(0.136)	(0.133)	(0.127)	(0.138)
Dutch natives	0.00911	0.00799	0.00269	-0.0104	-0.0215
	(0.0134)	(0.0138)	(0.0138)	(0.0163)	(0.0177)
Log: population density	0.248	0.246	0.0304	0.224	0.135
	(0.268)	(0.267)	(0.247)	(0.263)	(0.619)
Δ Refugee migration t-1		-0.000147			
		(0.000268)			
Δ Refugee migration t-2			-0.000670**		
			(0.000281)		
Δ Refugee migration t-3				-3.49e-05	
				(0.000183)	
Δ Refugee migration t-4					0.000467**
					(0.000195)
Constant	-0.123	-0.0173	1.821	1.566	2.529
	(2.426)	(2.446)	(2.330)	(2.520)	(4.863)
Observations	3398	3398	2988	2571	2172
Adjusted R2	0.799	0.799	0.796	0.642	0.628
Within R2	0.320	0.320	0.317	0.310	0.310
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effect	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at municipality level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the high-educated population with independent delta variables.

	(1) ΔU rate HE	(2) ΔU rate HE	(3) ΔU rate HE	(4) ΔU rate HE	(5) ΔU rate HE
Log: Syrian refugees per 10000 work-entitled individuals	0.0169	0.0176	0.0170	0.0282	0.0368
	(0.0295)	(0.0299)	(0.0348)	(0.0406)	(0.0675)
Δ Net labor productivity	-0.0819***	-0.0819***	-0.0804***	-0.0784***	-0.0749***
	(0.00505)	(0.00506)	(0.00507)	(0.00561)	(0.00539)
Economic growth	-0.00250	-0.00248	-0.00841	-0.0131	-0.00676
	(0.00790)	(0.00790)	(0.00792)	(0.00820)	(0.00983)
Net migration of natives in thousands	0.00460	0.00463	0.00948	0.0257	0.0359
	(0.00989)	(0.00991)	(0.0122)	(0.0210)	(0.0273)
Log: the work-entitled population in thousands	-1.293***	-1.293***	-1.242***	-1.326***	-1.316***
	(0.166)	(0.166)	(0.187)	(0.191)	(0.217)
Dutch natives	-0.0622***	-0.0626***	-0.0785***	-0.112***	-0.116***
	(0.0162)	(0.0171)	(0.0182)	(0.0211)	(0.0330)
Log: population density	-0.247*	-0.248*	-0.131	-0.425**	-0.444
	(0.147)	(0.146)	(0.211)	(0.194)	(0.419)
Δ Refugee migration t-1		-3.97^{e}-05			
		(0.000258)			
Δ Refugee migration t-2			-6.44^{e}-05		
			(0.000626)		
Δ Refugee migration t-3				3.73^{e}-05	
				(0.000371)	
Δ Refugee migration t-4					-3.20^{e}-05
					(0.000266)
Constant	9.744***	9.785***	10.14***	14.87***	15.24***
	(1.968)	(2.022)	(2.337)	(2.461)	(4.543)
Observations	1667	1667	1493	1316	1133
Adjusted R2	0.399	0.398	0.404	0.272	0.281
Within R2	0.267	0.267	0.265	0.267	0.257
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at municipality level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7 Robustness checks

This section of the paper conducts multiple robustness checks to examine the robustness, reliability and stability of the results presented in Tables 8 – 10. These tests are performed to evaluate whether the obtained outcomes remain consistent across various conditions or specifications.

7.1 Clustering standard errors at COROP-level

In all estimations, standard errors are clustered at municipality level to address the potential correlation and heteroskedasticity of standard errors within municipalities. However, it is important to acknowledge that certain interaction effects within labor markets might extend beyond the municipality level, particularly when municipalities are geographically close or share similar characteristics within a larger regional context known as the COROP area. To account for possible interaction effects between labor markets in the same COROP area, standard errors are clustered at COROP level.

Tables A.20 – A.22 (Appendix) present the results where instead of standard errors being clustered at municipality level, they are clustered at COROP level. The statistical significance of the coefficients estimated in the main analysis do not change when clustering the standard errors at COROP level, enhancing the reliability of the results.

7.2 COROP-areas as unit of analysis

In this paper I have chosen municipalities as unit of analysis the assess the impact of refugee influx on local labor markets. Selecting municipalities as unit of analysis, rather than COROP areas or provinces, enlarges the number of units in the data, reducing the risk of bias due to a low number of units and improving the generalizability of the results. Additionally, it allows for many comparison groups, enhancing the statistical power for the estimations. It also provides greater robustness as outliers are less likely to exert a significant influence on the overall results.

Although there are valid arguments as why to choose municipalities as unit of analysis, concerns may arise that it does not capture the correct labor market effects. In 2017, the CBS published data on the living and working distances of individuals in the Netherlands[13], indicating that only 4 out of 10 individuals live and work in the same municipality. That implies

[13] https://www.cbs.nl/nl-nl/nieuws/2017/32/bijna-4-op-de-10-werkt-en-woont-in-dezelfde-gemeente

that it is feasible that there are problems similar to the Stable Unit Treatment Value assumption (SUTVA). This assumption, used in difference-in-difference estimations, assumes that any observed effect is due to the treatment and not due to any interaction between the treatment and control units. Additionally, it assumes no response from the treated or control group because of the existence of the other group. In this paper, I examine whether an increased refugee concentration in municipality A, impacts the delta unemployment rate in the same municipality. That implies that I expect that more refugees in municipality A only impacts the delta unemployment rate in that same municipality. However, the data from the CBS provides evidence that people living in municipality A may work in municipality B or C. That would imply that those people would not, or on a less scale, be impacted by more competition in municipality A, which has touchpoints with the same violation of the SUTVA, potentially causing biased outcomes.

Several studies that employ a spatial correlation method or a natural experiment use larger regions as unit of analysis (Dustmann et al., 2005; Glitz, 2012; Tumen, 2016) rather than cities or municipalities (Card, 1990; Dustmann et al., 2017). The Netherlands has two categories for larger regions: provinces and COROP-areas. The COROP-areas in the Netherlands were created on the basis of the inclusion of a big city, a surrounding catchment area and existing living and working relationships. Therefore, using COROP-areas as the unit of analysis may provide more reliable observations and outcomes.

Table A.23 – A.25 (Appendix) present the estimates when COROP-areas are used as unit of analysis rather than municipalities. The coefficients indicate similar outcomes for the low-educated and medium-educated population compared to the main estimation. The coefficients indicate that the delta unemployment rate among the individuals belonging to these populations increases if the relative number of work-entitled Syrian refugees increases to the work-entitled population. Contrary to hypothesis 2 and the coefficients in the main estimation, the delta unemployment rate among high-educated individuals also appears to increase when the relative number of Syrian refugees increases. Although the observed effect in column 1 is smaller than for the low-educated and medium-educated population, the effect is statistically significant at a 1% significance level. Columns 2 – 5 display a fluctuation in the significance and coefficient. However, because the number of observations becomes significantly low towards column 5, these results cannot be interpreted with certainty.

I suspect three potential reasons that cause the differences in the coefficients for the high-educated population. Firstly, the main estimation contains some missing data on the unemployment rate for high-educated individuals for smaller municipalities. The CBS did not

publish these, as the underlying EBB data was not complete enough. This data limitation might have caused other results than for COROP-areas, in which there is no missing data concerning the unemployment rates.

Secondly, due to data aggregation, it is possible that certain effects are being averaged out from municipalities to COROP-areas. The effect can be evident for larger regions because the obtained results are more coherent, something which might not be the case when municipalities are used as unit of analysis.

Thirdly, there can be spatial mismatches. High-educated individuals possibly have a wider range of job opportunities, increasing the likelihood of working in another municipality than the one they reside in. Additionally, their higher income potential from more complex jobs makes them more mobile and open to considering job opportunities in other areas. This spatial mismatch could result in less significant effects at the municipality level when examining the impact of refugee influx on labor market outcomes. However, when larger regional units of analysis are used, such as the COROP-areas, the picture might change. High-educated individuals are more likely to live and work within the same COROP-area due to limited mobility options, unlike when municipalities are considered as the unit of analysis. This might have altered the significance of the coefficients.

Overall, this robustness test reveals slightly different outcomes compared to the coefficients obtained in the main estimation. It is crucial to consider these differences when drawing overall conclusions about the impact of refugee influx on labor market outcomes.

7.3 Predicting the number of refugees before 2011

The net influx of Syrian refugees is added as control variable in the equation for the years *t*-1*, t*-2*, t*-3*,* and *t*-4*.* These variables measure how many Syrian refugees entered *n* years ago. For the years 2015 – 2020, there are no issues with the calculation of the variables. However, for the years 2011-2014, there are missing values due to data unavailability. For example, when analyzing a municipality in the year 2013, it is unknown how many Syrian refugees entered in the year *t-3* and *t*-4 since the data only reaches back to 2011. Therefore, when analyzing the influx in year *t-3* and *t-4,* it is not possible to observe any years before the peak Syrian refugee influx.

Even though there is no data available on the number of Syrian refugees in each municipality before 2011, it is possible to make a prediction. Table 11 displays the total number of Syrian refugees in the Netherlands for the years 2006 to 2011. The table shows that the net

influx of Syrian refugees in the years before 2011 was rather low. Therefore, I expect that the total number of Syrian refugees in each municipality in 2011 is close to the number of Syrian refugees in each municipality in the years 2006 – 2010.

Table 12 provides a calculation example of municipality X. The first column provides the imaginary number of refugees for the years 2011, 2012 and 2013. Because there is no data on the number of Syrian refugees in 2010, which is also the case in the real dataset, I use Table 11 to estimate how many refugees were approximately in the municipality before 2011. Consequently, the estimated number of refugees in municipality A in 2010 is 97% of those in 2011. This same calculation is applied to each municipality in the dataset in order to prohibit the creation of missing values.

Table 11. Number of WE Syrian refugees in the Netherlands, 2006-2011.

Year	Number of WE Syrian refugees	Net influx	% relative to the next year
2006	5830	-	99%
2007	5870	40	98%
2008	6005	135	96%
2009	6232	227	98%
2010	6387	155	97%
2011	6608	221	-

Table 12. Municipality X and the predicted number of refugees before the data available

Year	Total refugees	Refugees entered at *t*-1	Refugees entered at *t*-2
2013	20	8	2
2012	12	2	(10 - 10*0.97) = 0.3
2011	10	(10 - 10*0.97) = 0.3	(9.7 – 9.7*0.98) = 0.2

Comparing these results to the main estimation, the significance and sign of the coefficients remain largely unchanged, implying that the conclusions drawn from the main results remain valid even after predicting the number of Syrian refugees in the years before 2011.

Moreover, the coefficient stays rather constant across columns 1 to 5 for both the low-educated and medium-educated population. This signals that the dropped observations in the main estimation may indeed have altered the sign and significance of the main independent variable.

Replacing missing values with predicted values does not appear to alter the conclusions and outcomes of the hypotheses. This suggests that the conclusion remains consistent with the main estimation.

In conclusion, the robustness tests conducted on the relationship between the delta unemployment rate and Syrian refugee concentration have reinforced the credibility and reliability of the main estimation. The consistent outcomes obtained through clustering standard errors at the COROP-area level and predicting the number of refugees before 2011, demonstrate the stability of the main results. Despite different coefficients for the high-educated population when COROP-areas are used as unit of analysis, it is likely related to data aggregation and spatial mismatches, and the results of the main estimation seem to be valid.

8 Discussion

The growing political and social discussion regarding immigrants and the economic consequences reflect the importance of the topic studied in this paper. Although many studies have tried to empirically verify how immigrants alter the labor market outcomes of host country labor markets, a clear-cut conclusion remains obscure as it depends on the context of analysis.

In this paper, I have examined how the exogenous influx of Syrian refugees that were subject to the unique spatial dispersal policy in the Netherlands, have impacted the delta unemployment rate of different educated populations. I hypothesized that Syrian refugees would increase the delta unemployment rate for low-educated individuals and that there would be no impact on the delta unemployment rate for medium- and high-educated individuals. The results indicate that for low-educated and medium-educated individuals, there is a significant increase in the unemployment rate compared to the previous year when the refugee concentration in the municipality increases. For the high-educated population, there is no significant impact on the unemployment rate after an increased refugee concentration.

The results obtained for the low-educated and high-educated population align with multiple studies that have provided empirical evidence that refugees will foremost have their impact on the individuals within their skill group, that is, low-skilled individuals, and that they increase their unemployment (Bagir, 2018; Cengiz & Tekguc, 2021; Ceritoğlu et al., 2017; del Carpio and Wagner, 2015).

However, the results obtained for the medium-educated population do not align with expectations. The main argument for this discrepancy is that the effects for the medium-educated population are undervalued. Because there is limited literature on medium-skilled individuals, it was difficult to hypothesize how refugees were going to affect this skill group. Based on the NSN and other data from the CBS, I expected that refugees would not impact medium-educated individuals on the labor market. In reality, the results indicate that they are likely to have similarities with these individuals, substantially competing with them on the labor market. The contradicting outcomes regarding the medium-educated population highlight the importance of further research into this topic and the implications of refugee integration on different population groups. This in-depth exploration will facilitate the development of targeted and evidence-based policies to foster sustainable labor market integration and economic prosperity for both refugees and the host country population.

In general, limited research has been conducted on the implications of a spatial dispersal and certain limitations have to be acknowledged in the context of this paper.

The first limitation of this paper relates to the availability and the structure of the data used to obtain the coefficients. In order to successfully examine labor market outcomes, it is essential to obtain comprehensive data on individual characteristics and the connection to the position on the labor market. As mentioned in Paragraph 4, the EBB contains individual-specific data that is not publicly accessible. Therefore, I am unable to incorporate this dataset into my estimations. Instead, I use aggregated data from the EBB, published by the CBS. Consequently, I can only filter based on one highly specific personal characteristic, thereby impeding the ability to attribute outcomes to more specific groups. Future research should create more distinct evaluation groups, allowing for a better understanding of refugee integration.

The second limitation relates to the missing values that are in the dataset regarding the unemployment rates for high-educated individuals, questioning the use of municipalities as unit of analysis. Namely, the use of COROP-areas as the unit of analysis, without missing values, showed significant disparities in the coefficients for the high-educated population in relation to the main estimation, making it difficult to conclude whether municipalities pose as the most valid unit of analysis. Future research should look into individual data, where it is known in which municipality individuals reside and work. With this data, the optimal unit of analysis can be constructed, enhancing the validity of the analysis.

Lastly, the use of the unemployment rate might not be the best indicator for local labor market outcomes. Because it is an economic indicator, it may be less accurate in determining what the impact of increased refugee concentration is on the whole population. Most studies on immigration and labor market outcomes use individual level data on whether someone is employed or unemployed over time, which provides more accurate results. Also, labor market conditions may change over time due to various factors that I cannot observe, and a static analysis of the unemployment rate might not capture the dynamic nature of the labor market.

It is crucial to recognize that the findings presented in this study are contingent upon the specific context and data available, warranting caution when applying them to other settings. Given the limitation of non-accessible individual-level data in the EBB, future research should delve deeper into the underlying data to enhance the accuracy of measuring unemployment. Consequently, the measurement is more accurate, additional subgroups can be formed, and it possible identify the optimal unit of analysis.

Additionally, future research should explore the long-term effects of spatial dispersal policies on labor market outcomes and examine the factors through which these outcomes occur. This analysis should cover other aspects of the labor market such as wages, allowing for a more nuanced analysis and identification of patters within the labor market.

9 Conclusion

The central objective of this paper was to shed light on how the implementation of a spatial dispersal policy, in response to a significant influx of refugees, affects employment among various educated populations. Leveraging rich data from the EBB, I conducted a fixed-effects estimation to analyze the arrival of Syrian refugees in the Netherlands. The results revealed that refugees tend to act as substitutes in the labor market for low-educated and medium-educated individuals. Specifically, an increase in the proportion of work-entitled Syrian refugees relative to the work-entitled low-educated and medium-educated populations led to a rise in the delta unemployment rate among these groups. However, the impact on the high-educated population remained insignificant when municipalities were considered as the unit of analysis. These findings offered validation for hypothesis 1 and partial validation for hypothesis 2.

To ensure the reliability of the outcomes, additional robustness tests were conducted. Clustering standard errors at the COROP-area level and predicting the number of refugees before 2011 did not alter the estimates of the main results. However, positive delta unemployment rate coefficients were observed among the high-educated population when COROP-areas were used as the unit of analysis. This discrepancy is likely attributed to data aggregation, missing values, and spatial mismatches.

Overall, the robustness tests corroborated the main results and suggested that the coefficients and significance obtained in the primary analysis are likely to be valid. The implications of the findings indicate that refugees have a significant impact on the labor market for low- and medium-educated individuals when they are distributed randomly and evenly across the country. Increased refugee concentration at the municipality level leads to a rise in the delta unemployment rate for these groups. This outcome warrants further exploration in future research, involving additional analysis using individual-level data to gain deeper insights into refugee integration.

By providing valuable insights into the impact of spatial dispersal policies on the employment of different educated populations amid a significant refugee influx, this paper informs policymakers and researchers about the dynamics between refugee integration and labor market outcomes. The insights garnered from this study have the potential to enhance the effectiveness of integration policies, fostering more sustainable economic outcomes for both refugees and the host communities.

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11 Appendix

11.1 Supplementary tables

Table A.1. Application and integration process in the Netherlands.

Upon arrival in the Netherlands, asylum seekers undergo a process conducted by the Immigration and Naturalization Service (IND) to determine whether the asylum seeker will be recognized as refugee and whether their asylum procedure can continue (a reason for rejection could be if they have an active asylum procedure in another country). If the asylum procedure can continue, the refugees are allocated to one of the 179 refugee centers across the Netherlands. The allocation to the refugee center is random and is solely based on which location still has room left.

During the first six months of their stay in the refugee center, asylum seekers are not allowed to work as they await the decision on their asylum request. After this period, they are allowed to enter the labor market and start working 24 weeks over a period of 52 weeks. Once the asylum is granted, all restrictions on entering the labor market are lifted, the refugees become permit holders and they are connected to a municipality. The COA connects permit holders to municipalities within the region of their last refugee center and this connection is carried out by a regional director of the COA. The connection is based on which municipality, within the region of the last refugee center, provides the highest chance of successful integration into Dutch society. Only extraordinary circumstances such as family reunition for a young child or acquiring a complex job in another area can lead to refugees being placed in another province.

In many cases however there is a time gap between receiving the residence permit and the actual placement into a municipality. Due to the current housing shortage in the Netherlands, it can take several months until permit holders are provided with housing (Dagevos et al., 2018). During this waiting period, permit holders can start a pre-integration course in the refugee center. This course can enhance the completion speed of the actual integration course, which is obligated for all refugees from Syria who are between the age of 18 and 67. Municipalities are responsible for guiding and supporting the permit holders to complete the integration course, which aims to teach them the Dutch language, familiarize them with Dutch society, and help them enter the labor market. Where the last goal might be the most important one.

Overall, the process from asylum seeker to permit holder involves various institutions and agencies to ensure successful integration into Dutch society.

Table A.2. Number of first-time asylum requests and family members of some known refugee producing countries, yearly data. (CBS, 2023).

Period	**1993**	**1994**	**1995**	**1997**	**1998**	**1999**	**2000**	**2001**	**2014**	**2015**	**2016**
Total	35400	52575	29260	34445	45215	39305	43560	32580	29890	58880	32840
Former Soviet-Union	1595	4525	1885	1960	3230	**5520**	4180	3245	1205	1500	1380
Former Yugoslavia	**10185**	**13440**	**6150**	3790	**8330**	**5080**	**5650**	2200	515	1380	2180
Afghanistan	1505	2525	1910	5920	**7120**	4400	**5030**	3625	975	2945	1445
Bosnian	4940	**8635**	4225	1970	3770	1170	1635	1025	130	125	295
Eritrean	.	30	55	50	135	270	260	215	**4100**	**8435**	3235
Iraqi	3230	2860	2430	**9640**	**8300**	3705	2745	1330	1570	3450	1240
Iranian	2610	**6075**	2700	1255	1680	1525	2530	1520	745	2075	1035
Somali	4330	**5395**	3975	1280	2775	2730	2095	1100	1525	865	500
Sri Lankan	**1900**	1810	1315	1495	1050	855	970	680	150	110	75
Syrian	265	390	255	460	830	850	1075	520	**11595**	**27710**	**11310**

Table A.3. Newly formed municipalities per 1 January 2012

2012	
Dissolved municipalities	**New municipality**
Anna Paulowna	Hollands kroon
Niedorp	
Wieringen	
Wieringermeer	

Table A.4. Newly formed municipalities per 1 January 2013

2013	
Dissolved municipalities	**New municipality**
Harenkarspel	Schagen
Schagen	
Zijpe	
Dirksland	Goeree-Overflakkee
Goedereede	
Middelharnis	
Oostflakkee	
Graafstroom	Molenwaard
Liesveld	
Nieuw-Lekkerland	

Table A.5. Newly formed municipalities per 1 January 2014

2014	
Dissolved municipalities	**New municipality**
Alphen aan den Rijn	Alphen aan den Rijn
Boskoop	
Rijnwoude	
Dissolved municipalities	**New municipality**
Gaasterlan-Sleat	De Friese Meren
Lemsterland	
Skasterlan	
Boarnsterhim	

Table A.6. ISCO-level professions and the description.

ISCO Level	Description	Examples of profession
1	Simple and routine physical and manual work.	Office cleaner, garbage collector, kitchen helpers.
2	Be able to read information, perform simple calculations, require advanced language, numeracy, and communication skills.	Bus driver, secretary, salesman, car mechanic, hairdresser.
3	Performing complex technical and complex tasks that require extensive factual and technical knowledge.	Legal secretary, technical staff in IT support, sales representative, medical laboratory staff.
4	Solving complex problems and making decisions based on extensive theoretical and practical knowledge. Requires extensive numeracy and language skills at a very high level.	Sales manager, marketing manager, civil engineer, specialist nurse, system analyst.

Table A.7. Wooldridge test for autocorrelation estimation 1 (low-educated)

Wooldridge test

H0: no first-order autocorrelation	Wooldridge test for autocorrelation in panel data
F(1, 403) = 43.489	
Prob > F = 0.0000	

Table A.8. Wooldridge test for autocorrelation estimation 1 (medium-educated)

Wooldridge test

H0: no first-order autocorrelation	Wooldridge test for autocorrelation in panel data
F(1, 403) = 85.451	
Prob > F = 0.0000	

Table A.9. Wooldridge test for autocorrelation estimation 1 (high-educated)

Wooldridge test

H0: no first-order autocorrelation	Wooldridge test for autocorrelation in panel data
F(1, 202) = 18.640	
Prob > F = 0.0000	

Table A.10. Hausman test for autocorrelation estimation 1 (low-educated)

Hausman (1978) specification test

	Coef.
Chi-square test value	321.94
P-value	0.0000

Table A.11. Hausman test for autocorrelation estimation 1 (medium-educated)

Hausman (1978) specification test

	Coef.
Chi-square test value	427.35
P-value	0.0000

Table A.12. Hausman test for autocorrelation estimation 1 (high-educated)

Hausman (1978) specification test

	Coef.
Chi-square test value	61.16
P-value	0.0000

Table A.13. All variables in the dataset and the corresponding description.

Variable	Description
Year	The year of observation
Region	The municipality
Wp_loweg	The % change of the unemployment rate of the low educated population relative to the year before
Wp_mideg	The % change of the unemployment rate of the medium educated population relative to the year before
Wp_higheg	The % change of the unemployment rate of the high educated population relative to the year before
Ln_concthlowe	Log: the number of work-entitled Syrian refugees per 10000 work-entitled low-educated individuals
Ln_concthmide	Log: the number of work-entitled Syrian refugees per 10000 work-entitled medium-educated individuals
Ln_concthhighe	Log: the number of work-entitled Syrian refugees per 10000 work-entitled high-educated individuals
Nbp_loweg	The % change of the net labor participation rate relative to the year before (low-educated population)
Nbp_mideg	The % change of the net labor participation rate relative to the year before (medium-educated population)
Nbp_higheg	The % change of the net labor participation rate relative to the year before (high-educated population)
E_growth	The % change of the gross domestic product relative to the year before, corrected for inflation
Change_natives1000	Net migration of Dutch natives into the municipality over the year
Ln_jobs	Log: the total number of jobs in thousands
Ln_welowe	Log: the number of low educated work-entitled individuals in thousands
Ln_wemide	Log: the number of medium educated work-entitled individuals in thousands
Ln_wehighe	Log: the number of high educated work-entitled individuals in thousands
year_1glowe	Net migration of Syrian refugees at t-1 relative to the work-entitled low-educated population
year_1gmide	Net migration of Syrian refugees at t-1 relative to the work-entitled medium-educated population
year_1ghighe	Net migration of Syrian refugees at t-1 relative to the work-entitled high-educated population
year_2glowe	Net migration of Syrian refugees at t-2 relative to the work-entitled low-educated population
year_2gmide	Net migration of Syrian refugees at t-2 relative to the work-entitled medium-educated population
year_2ghighe	Net migration of Syrian refugees at t-2 relative to the work-entitled high-educated population

year_3glowe	Net migration of Syrian refugees at t-3 relative to the work-entitled low-educated population
year_3gmide	Net migration of Syrian refugees at t-3 relative to the work-entitled medium-educated population
year_3ghighe	Net migration of Syrian refugees at t-3 relative to the work-entitled high-educated population
year_4glowe	Net migration of Syrian refugees at t-4 relative to the work-entitled low-educated population
year_4gmide	Net migration of Syrian refugees at t-4 relative to the work-entitled medium-educated population
year_4ghighe	Net migration of Syrian refugees at t-4 relative to the work-entitled high-educated population
NL_pop	Percentage of Dutch natives relative to all individuals
Ln_popdensity	Log: the number of individuals per km^2

Table A.14 Pairwise correlation of the LE population

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) wp_loweg	1.000							
(2) ln_concthlowe	-0.425	1.000						
(3) nbp_loweg	-0.608	0.132	1.000					
(4) e_growth	-0.402	0.048	0.161	1.000				
(5) ch_natives1000	0.025	0.010	0.007	0.006	1.000			
(6) we_lowe	-0.017	0.079	0.002	0.015	-0.345	1.000		
(7) nl_pop	0.042	-0.235	0.002	-0.004	0.198	-0.598	1.000	
(8) ln_popdensity	-0.005	0.161	-0.011	-0.008	-0.080	0.410	-0.686	1.000
(9) year_1glowe	-0.237	0.312	0.033	0.173	-0.017	0.018	-0.073	0.055
(10) year_2glowe	-0.233	0.354	0.105	0.111	-0.007	0.015	-0.071	0.045
(11) year_3glowe	-0.049	0.371	0.052	-0.048	-0.011	0.012	-0.077	0.046
(12) year_4glowe	0.265	0.361	-0.075	-0.289	-0.014	0.009	-0.075	0.034
	(9)	(10)	(11)	(12)				
(9) year_1glowe	1.000							
(10) year_2glowe	-0.100	1.000						
(11) year_3glowe	-0.183	-0.001	1.000					
(12) year_4glowe	-0.116	-0.136	-0.106	1.000				

Table A.15. Pairwise correlation of the ME population

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) wp_mideg	1.000							
(2) ln_concthmide	-0.496	1.000						
(3) nbp_mideg	-0.510	0.126	1.000					
(4) e_growth	-0.431	0.050	0.138	1.000				
(5) ch_natives1000	0.016	0.003	0.010	0.006	1.000			
(6) we_mide	-0.019	0.124	-0.015	0.012	-0.336	1.000		
(7) nl_pop	0.042	-0.239	0.014	-0.004	0.198	-0.612	1.000	
(8) ln_popdensity	0.006	0.156	-0.030	-0.008	-0.080	0.431	-0.686	1.000
(9) year_1gmide	-0.293	0.320	0.087	0.180	-0.021	0.035	-0.079	0.053
(10) year_2gmide	-0.274	0.360	0.062	0.117	-0.013	0.030	-0.075	0.043
(11) year_3gmide	-0.050	0.351	0.037	-0.037	-0.016	0.026	-0.078	0.042
(12) year_4gmide	0.267	0.331	-0.031	-0.258	-0.019	0.022	-0.071	0.030
	(9)	(10)	(11)	(12)				
(9) year_1gmide	1.000							
(10) year_2gmide	-0.062	1.000						
(11) year_3gmide	-0.216	0.004	1.000					
(12) year_4gmide	-0.115	-0.184	-0.183	1.000				

Table A.16. Pairwise correlation of the HE population

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) wp_higheg	1.000							
(2) ln_concthhighe	-0.239	1.000						
(3) nbp_higheg	-0.437	0.017	1.000					
(4) e_growth	-0.305	0.062	0.034	1.000				
(5) ch_natives1000	0.011	0.006	0.009	0.006	1.000			
(6) we_highe	-0.016	0.056	-0.006	0.006	-0.439	1.000		
(7) nl_pop	0.013	-0.169	0.016	-0.004	0.198	-0.566	1.000	
(8) ln_popdensity	0.007	0.088	-0.018	-0.008	-0.080	0.399	-0.686	1.000
(9) year_1ghighe	-0.171	0.308	0.028	0.164	-0.002	-0.020	-0.015	-0.018
(10) year_2ghighe	-0.159	0.345	0.030	0.111	0.010	-0.020	-0.016	-0.023
(11) year_3ghighe	-0.009	0.352	-0.004	-0.021	0.014	-0.018	-0.013	-0.027
(12) year_4ghighe	0.151	0.339	-0.013	-0.255	0.014	-0.016	-0.019	-0.031
	(9)	(10)	(11)	(12)				
(9) year_1ghighe	1.000							
(10) year_2ghighe	0.003	1.000						
(11) year_3ghighe	-0.174	-0.047	1.000					
(12) year_4ghighe	-0.154	-0.107	-0.063	1.000				

Table A.17. Variance inflation factor values for the low-educated population

	VIF	1/VIF
Syrian refugee concentration	2.574	.389
Dutch natives	2.34	.427
Population density	1.991	.502
Δ Refugee migration t-3	1.81	.552
Δ Refugee migration t-4	1.797	.556
Δ Refugee migration t-2	1.658	.603
Δ Refugee migration t-1	1.646	.608
Work-entitled population	1.594	.627
Net migration natives	1.211	.826
Economic growth	1.169	.856
Net labor productivity growth	1.04	.961
Mean VIF	1.712	.

Table A.18. Variance inflation factor values for the medium-educated population

	VIF	1/VIF
Syrian refugee concentration	2.678	.373
Dutch natives	2.334	.428
Δ Refugee migration t-3	2.029	.493
Δ Refugee migration t-4	2.005	.499
Population density	1.995	.501
Δ Refugee migration t-2	1.733	.577
Δ Refugee migration t-1	1.732	.578
Work-entitled population	1.607	.622
Net migration natives	1.207	.828
Economic growth	1.142	.876
Net labor productivity growth	1.027	.974
Mean VIF	1.772	.

Table A.19. Variance inflation factor values for the high-educated population

	VIF	1/VIF
Dutch natives	3.129	.32
Syrian refugee concentration	2.656	.376
Population density	2.238	.447
Work-entitled population	2.051	.488
Δ Refugee migration t-3	1.968	.508
Δ Refugee migration t-4	1.911	.523
Δ Refugee migration t-2	1.802	.555
Δ Refugee migration t-1	1.647	.607
Net migration natives	1.403	.713
Economic growth	1.157	.865
Net labor productivity growth	1.011	.99
Mean VIF	1.907	.

Table A.20. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the LE educated population with independent delta variables.

	(1) ΔU rate LE	(2) ΔU rate LE	(3) ΔU rate LE	(4) ΔU rate LE	(5) ΔU rate LE
Log: Syrian refugees per 10000 work-entitled individuals	0.108***	0.120***	0.0946***	0.0832**	-0.00963
	(0.0237)	(0.0235)	(0.0431)	(0.0334)	(0.0549)
Δ Net labor productivity	-0.210***	-0.211***	-0.211***	-0.209***	-0.200***
	(0.00543)	(0.00545)	(0.00549)	(0.00579)	(0.00596)
Economic growth	0.0119	0.0124	0.00709	0.0122	0.0111
	(0.0102)	(0.0102)	(0.0109)	(0.0133)	(0.0125)
Net migration of natives in thousands	0.101	0.100	0.0995	0.0367	-0.0732
	(0.0786)	(0.0782)	(0.0875)	(0.145)	(0.129)
Log: the work-entitled population in thousands	-1.656***	-1.653***	-1.748***	-1.531***	-1.587***
	(0.165)	(0.165)	(0.189)	(0.175)	(0.173)
Dutch natives	-0.0224	-0.0321	-0.0384	-0.0128	-0.0954***
	(0.0280)	(0.0275)	(0.0234)	(0.0256)	(0.0288)
Log: population density	0.543	0.522	0.443	0.238	0.432
	(0.401)	(0.397)	(0.547)	(0.419)	(0.406)
Δ Refugee migration t-1		-0.00126**			
		(0.000515)			
Δ Refugee migration t-2			-9.49e-06		
			(0.000327)		
Δ Refugee migration t-3				-0.000126	
				(0.000256)	
Δ Refugee migration t-4					0.000324
					(0.000654)
Constant	1.207	2.132	3.207	1.604	7.704**
	(4.124)	(4.036)	(4.570)	(3.828)	(3.743)
Observations	3398	3398	2988	2571	2172
Adjusted R^2	0.746	0.746	0.736	0.653	0.626
Within R^2	0.475	0.476	0.483	0.476	0.479
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.21. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the ME educated population with independent delta variables.

	(1) ΔU rate ME	(2) ΔU rate ME	(3) ΔU rate ME	(4) ΔU rate ME	(5) ΔU rate ME
Log: Syrian refugees per 10000 work-entitled individuals	0.0799***	0.0815***	0.0786***	0.0542***	0.0650**
	(0.0170)	(0.0174)	(0.0184)	(0.0195)	(0.0246)
Δ Net labor productivity	-0.109***	-0.109***	-0.109***	-0.104***	-0.0990***
	(0.00411)	(0.00411)	(0.00433)	(0.00434)	(0.00418)
Economic growth	-0.00632	-0.00626	-0.00712	-0.00368	-0.00669
	(0.00541)	(0.00541)	(0.00563)	(0.00738)	(0.00906)
Net migration of natives in thousands	0.0565	0.0564	0.0289	-0.0472	-0.0991***
	(0.0370)	(0.0369)	(0.0371)	(0.0328)	(0.0284)
Log: the work-entitled population in thousands	-1.146***	-1.145***	-1.212***	-1.212***	-1.051***
	(0.111)	(0.112)	(0.112)	(0.105)	(0.122)
Dutch natives	0.00911	0.00799	0.00269	-0.0104	-0.0215
	(0.0193)	(0.0195)	(0.0189)	(0.0188)	(0.0191)
Log: population density	0.248	0.246	0.0304	0.224	0.135
	(0.286)	(0.285)	(0.259)	(0.283)	(0.648)
Δ Refugee migration t-1		-0.000147			
		(0.000203)			
Δ Refugee migration t-2			-0.000670**		
			(0.000273)		
Δ Refugee migration t-3				-3.49e-05	
				(0.000171)	
Δ Refugee migration t-4					0.000467**
					(0.000187)
Constant	-0.123	-0.0173	1.821	1.566	2.529
	(2.995)	(3.004)	(2.960)	(3.136)	(5.222)
Observations	3398	3398	2988	2571	2172
Adjusted R2	0.799	0.799	0.796	0.642	0.628
Within R2	0.320	0.320	0.317	0.309	0.310
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.22. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the HE educated population with independent delta variables.

	(1) ΔU rate HE	(2) ΔU rate HE	(3) ΔU rate HE	(4) ΔU rate HE	(5) ΔU rate HE
Log: Syrian refugees per 10000 work-entitled individuals	0.0169	0.0176	0.0170	0.0282	0.0368
	(0.0301)	(0.0316)	(0.0420)	(0.0535)	(0.0867)
Δ Net labor productivity	-0.0819***	-0.0819***	-0.0804***	-0.0784***	-0.0749***
	(0.00526)	(0.00529)	(0.00534)	(0.00558)	(0.00584)
Economic growth	-0.00250	-0.00248	-0.00841	-0.0131	-0.00676
	(0.00961)	(0.00961)	(0.00894)	(0.00788)	(0.0110)
Net migration of natives in thousands	0.00460	0.00463	0.00948	0.0257	0.0359
	(0.0121)	(0.0121)	(0.0138)	(0.0259)	(0.0284)
Log: the work-entitled population in thousands	-1.293***	-1.293***	-1.242***	-1.326***	-1.316***
	(0.152)	(0.152)	(0.177)	(0.183)	(0.191)
Dutch natives	-0.0622***	-0.0626***	-0.0785***	-0.112***	-0.116***
	(0.0158)	(0.0170)	(0.0201)	(0.0209)	(0.0366)
Log: population density	-0.247	-0.248	-0.131	-0.425**	-0.444
	(0.152)	(0.151)	(0.210)	(0.196)	(0.417)
Δ Refugee migration t-1		-3.97e-05			
		(0.000308)			
Δ Refugee migration t-2			-6.44e-05		
			(0.000594)		
Δ Refugee migration t-3				3.73e-05	
				(0.000329)	
Δ Refugee migration t-4					-3.20e-05
					(0.000275)
Constant	9.744***	9.785***	10.14***	14.87***	15.24***
	(1.966)	(2.026)	(2.457)	(2.478)	(4.691)
Observations	1667	1667	1493	1316	1133
Adjusted R2	0.399	0.398	0.404	0.272	0.281
Within R2	0.267	0.267	0.264	0.267	0.257
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.23. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the LE educated population with independent delta variables with COROP areas as unit of analysis.

	(1) ΔU rate LE	(2) ΔU rate LE	(3) ΔU rate LE	(4) ΔU rate LE	(5) ΔU rate LE
Log: Syrian refugees per 10000 work-entitled individuals	0.254**	0.276**	0.204*	0.0870	0.0649
	(0.0976)	(0.107)	(0.101)	(0.174)	(0.238)
Δ Net labor productivity	-0.237***	-0.236***	-0.235***	-0.240***	-0.237***
	(0.0260)	(0.0260)	(0.0270)	(0.0253)	(0.0268)
Economic growth	0.00288	0.00322	-0.00613	0.00335	0.00703
	(0.0127)	(0.0125)	(0.0133)	(0.0137)	(0.0194)
Net migration of natives in thousands	-4.57e-06	-5.21e-06	1.94e-05	-2.49e-05	-3.15e-05
	(2.47e-05)	(2.47e-05)	(2.56e-05)	(4.08e-05)	(3.83e-05)
Log: the work-entitled population in thousands	-1.467	-1.398	-1.452	-0.114	-0.333
	(1.140)	(1.160)	(1.343)	(1.427)	(1.327)
Dutch natives	0.0301	0.0237	-0.0762	0.0565	-0.102
	(0.0724)	(0.0727)	(0.0736)	(0.126)	(0.131)
Log: population density	-0.660	-0.592	-1.292	0.691	-0.336
	(1.206)	(1.207)	(1.341)	(1.367)	(1.084)
Δ Refugee migration t-1		-0.00141*			
		(0.000804)			
Δ Refugee migration t-2			0.000768		
			(0.00110)		
Δ Refugee migration t-3				-0.00148	
				(0.00134)	
Δ Refugee migration t-4					0.00326***
					(0.00112)
Constant	6.806	6.552	19.24	-9.347	10.61
	(14.59)	(14.47)	(16.02)	(18.38)	(17.55)
Observations	360	360	320	280	240
Adjusted R^2	0.834	0.834	0.823	0.765	0.713
Within R^2	0.334	0.335	0.339	0.349	0.377
Time fixed effects	Yes	Yes	Yes	Yes	Yes
COROP area fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.24. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the ME educated population with independent delta variables with COROP areas as unit of analysis.

	(1) ΔU rate ME	(2) ΔU rate ME	(3) ΔU rate ME	(4) ΔU rate ME	(5) ΔU rate ME
Log: Syrian refugees per 10000 work-entitled individuals	0.217***	0.181**	0.244***	0.123	0.185
	(0.0639)	(0.0696)	(0.0707)	(0.0792)	(0.138)
Δ Net labor productivity	-0.152***	-0.156***	-0.155***	-0.140***	-0.127***
	(0.0173)	(0.0159)	(0.0156)	(0.0173)	(0.0184)
Economic growth	-0.0131	-0.0141*	-0.0170*	-0.0112	-0.0171
	(0.00874)	(0.00834)	(0.00990)	(0.00956)	(0.0159)
Net migration of natives in thousands	6.04e-06	7.30e-06	-4.34e-06	-3.00e-05**	-2.44e-05
	(1.08e-05)	(1.08e-05)	(1.01e-05)	(1.35e-05)	(1.94e-05)
Log: the work-entitled population in thousands	-1.438**	-1.390**	-1.077	-1.201	-1.067
	(0.572)	(0.599)	(0.775)	(0.760)	(0.989)
Dutch natives	0.0309	0.0398	0.0339	0.0131	-0.0137
	(0.0446)	(0.0454)	(0.0438)	(0.0500)	(0.0702)
Log: population density	0.0417	0.00591	0.0214	0.555	0.370
	(0.846)	(0.836)	(0.903)	(1.157)	(1.392)
Δ Refugee migration t-1		0.00285*			
		(0.00169)			
Δ Refugee migration t-2			-0.00430***		
			(0.00103)		
Δ Refugee migration t-3				0.00149	
				(0.00119)	
Δ Refugee migration t-4					0.00207**
					(0.000830)
Constant	2.965	2.336	0.987	0.0627	2.351
	(8.561)	(8.676)	(10.23)	(11.39)	(14.56)
Observations	360	360	320	280	240
Adjusted R^2	0.885	0.886	0.879	0.749	0.721
Within R^2	0.273	0.280	0.289	0.238	0.208
Time fixed effects	Yes	Yes	Yes	Yes	Yes
COROP area fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.25. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the HE educated population with independent delta variables with COROP areas as unit of analysis.

	(1) ΔU rate HE	(2) ΔU rate HE	(3) ΔU rate HE	(4) ΔU rate HE	(5) ΔU rate HE
Log: Syrian refugees per 10000 work-entitled individuals	0.145***	0.129**	0.227***	0.258**	0.130
	(0.0476)	(0.0510)	(0.0610)	(0.112)	(0.156)
Δ Net labor productivity	-0.0953***	-0.0953***	-0.0936***	-0.0851***	-0.0777***
	(0.0144)	(0.0143)	(0.0162)	(0.0179)	(0.0169)
Economic growth	-0.00149	-0.00183	-0.000818	-0.000886	0.00215
	(0.00741)	(0.00749)	(0.00712)	(0.00731)	(0.0141)
Net migration of natives in thousands	-3.76e-06	-3.68e-06	-1.02e-06	2.15e-05	3.54e-05
	(9.00e-06)	(8.91e-06)	(1.53e-05)	(2.16e-05)	(2.72e-05)
Log: the work-entitled population in thousands	-1.883***	-1.853***	-1.625***	-1.624***	-1.990***
	(0.507)	(0.513)	(0.475)	(0.535)	(0.602)
Dutch natives	-0.0362	-0.0331	-0.0766	-0.148*	-0.117
	(0.0501)	(0.0498)	(0.0726)	(0.0814)	(0.133)
Log: population density	-1.013	-1.024	-1.207	-2.030***	-1.682*
	(0.774)	(0.759)	(0.870)	(0.446)	(0.958)
Δ Refugee migration t-1		0.000611			
		(0.000746)			
Δ Refugee migration t-2			-0.000368		
			(0.00118)		
Δ Refugee migration t-3				0.000356	
				(0.000932)	
Δ Refugee migration t-4					-0.000238
					(0.000721)
Constant	16.47*	16.22*	19.51*	30.11***	27.52
	(8.973)	(8.818)	(10.93)	(9.031)	(16.43)
Observations	360	360	320	280	240
Adjusted R^2	0.503	0.502	0.508	0.263	0.313
Within R^2	0.191	0.192	0.182	0.179	0.174
Time fixed effects	Yes	Yes	Yes	Yes	Yes
COROP area fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.26. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the LE educated population including the prediction of Syrian refugees

	(1) ΔU rate LE	(2) ΔU rate LE	(3) ΔU rate LE	(4) ΔU rate LE
Log: Syrian refugees per 10000 work-entitled individuals	0.120***	0.109***	0.109***	0.108***
	(0.0211)	(0.0211)	(0.0209)	(0.0209)
Δ Net labor productivity	-0.211***	-0.210***	-0.210***	-0.210***
	(0.00551)	(0.00550)	(0.00550)	(0.00550)
Economic growth	0.0124	0.0119	0.0118	0.0119
	(0.00821)	(0.00823)	(0.00823)	(0.00823)
Net migration of natives in thousands	0.100	0.101	0.101	0.101
	(0.0761)	(0.0766)	(0.0765)	(0.0765)
Log: the work-entitled population in thousands	-1.653***	-1.656***	-1.660***	-1.656***
	(0.158)	(0.158)	(0.158)	(0.158)
Dutch natives	-0.0321	-0.0227	-0.0228	-0.0223
	(0.0214)	(0.0218)	(0.0217)	(0.0216)
Log: population density	0.522	0.543	0.543	0.544
	(0.377)	(0.381)	(0.381)	(0.381)
Δ Refugee migration t-1	-0.000875***			
	(0.000214)			
Δ Refugee migration t-2		-3.23e-05		
		(0.000284)		
Δ Refugee migration t-3			-0.000263	
			(0.000299)	
Δ Refugee migration t-4				-0.000109
				(0.000554)
Constant	2.132	1.235	1.379	1.199
	(3.429)	(3.471)	(3.508)	(3.466)
Observations	3398	3398	3398	3398
Adjusted R2	0.746	0.746	0.746	0.746
Within R2	0.476	0.475	0.475	0.475
Time fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes

Robust standard errors (clustered at municipality level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.27. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the ME educated population including the prediction of Syrian refugees

	(1) ΔU rate ME	(2) ΔU rate ME	(3) ΔU rate ME	(4) ΔU rate ME
Log: Syrian refugees per 10000 work-entitled individuals	0.0815***	0.0830***	0.0800***	0.0803***
	(0.0147)	(0.0144)	(0.0142)	(0.0143)
Δ Net labor productivity	-0.109***	-0.110***	-0.109***	-0.110***
	(0.00348)	(0.00349)	(0.00349)	(0.00350)
Economic growth	-0.00626	-0.00644	-0.00634	-0.00636
	(0.00484)	(0.00483)	(0.00485)	(0.00484)
Net migration of natives in thousands	0.0564	0.0567	0.0565	0.0568
	(0.0363)	(0.0364)	(0.0363)	(0.0365)
Log: the work-entitled population in thousands	-1.145***	-1.147***	-1.147***	-1.140***
	(0.136)	(0.136)	(0.136)	(0.136)
Dutch natives	0.00799	0.00507	0.00900	0.00887
	(0.0138)	(0.0134)	(0.0134)	(0.0133)
Log: population density	0.246	0.241	0.248	0.247
	(0.267)	(0.266)	(0.268)	(0.267)
Δ Refugee migration t-1	-0.000147			
	(0.000268)			
Δ Refugee migration t-2		-0.000675**		
		(0.000284)		
Δ Refugee migration t-3			-0.000108	
			(0.000175)	
Δ Refugee migration t-4				0.000298*
				(0.000166)
Constant	-0.0173	0.265	-0.110	-0.113
	(2.446)	(2.418)	(2.428)	(2.422)
Observations	3398	3398	3398	3398
Adjusted R2	0.799	0.799	0.799	0.799
Within R2	0.320	0.321	0.320	0.321
Time fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.28. Fixed effects estimates of the influx of Syrian refugees on Δ unemployment rates of the HE educated population including the prediction of Syrian refugees

	(1) ΔU rate HE	(2) ΔU rate HE	(3) ΔU rate HE	(4) ΔU rate HE
Log: Syrian refugees per 10000 work-entitled individuals	0.0176	0.0177	0.0169	0.0162
	(0.0299)	(0.0298)	(0.0295)	(0.0296)
Δ Net labor productivity	-0.0819***	-0.0818***	-0.0819***	-0.0819***
	(0.00506)	(0.00506)	(0.00505)	(0.00506)
Economic growth	-0.00248	-0.00256	-0.00253	-0.00246
	(0.00790)	(0.00792)	(0.00791)	(0.00790)
Net migration of natives in thousands	0.00463	0.00482	0.00468	0.00475
	(0.00991)	(0.00982)	(0.00993)	(0.00988)
Log: the work-entitled population in thousands	-1.293***	-1.294***	-1.294***	-1.296***
	(0.166)	(0.166)	(0.167)	(0.167)
Dutch natives	-0.0626***	-0.0629***	-0.0621***	-0.0614***
	(0.0171)	(0.0155)	(0.0161)	(0.0162)
Log: population density	-0.248*	-0.249*	-0.247*	-0.245*
	(0.146)	(0.147)	(0.147)	(0.147)
Δ Refugee migration t-1	-3.97e-05			
	(0.000258)			
Δ Refugee migration t-2		-8.02e-05		
		(0.000660)		
Δ Refugee migration t-3			-5.83e-05	
			(0.000308)	
Δ Refugee migration t-4				-0.000168
				(0.000247)
Constant	9.785***	9.811***	9.741***	9.678***
	(2.022)	(1.923)	(1.963)	(1.966)
Observations	1667	1667	1667	1667
Adjusted R2	0.398	0.398	0.398	0.398
Within R2	0.267	0.267	0.267	0.267
Time fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes

Robust standard errors (clustered at COROP-area level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

11.2 Supplementary figures

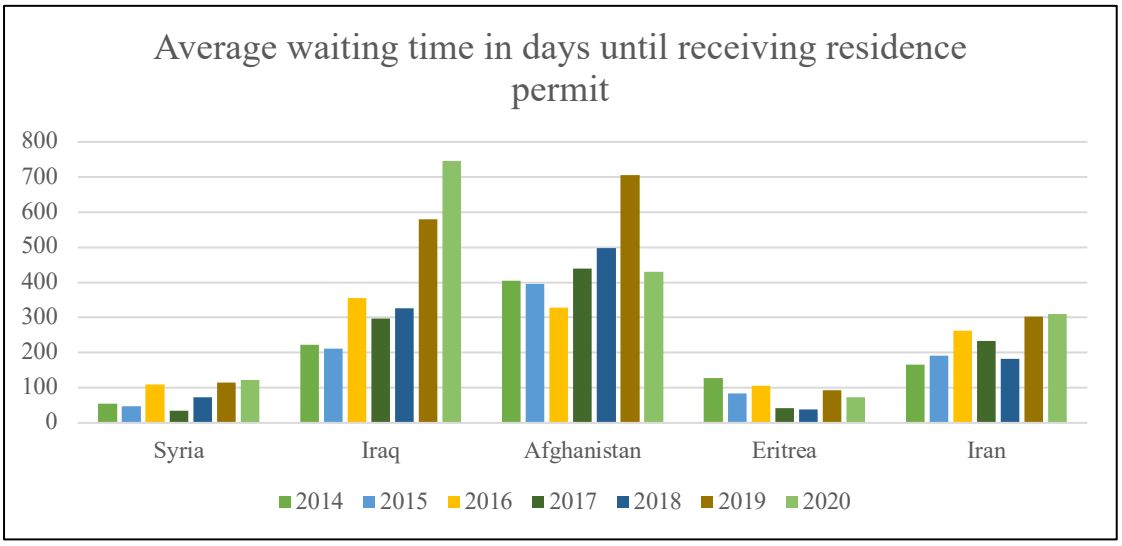

Figure A.1. Average waiting time in days until receiving residence permit. (CBS, 2021).

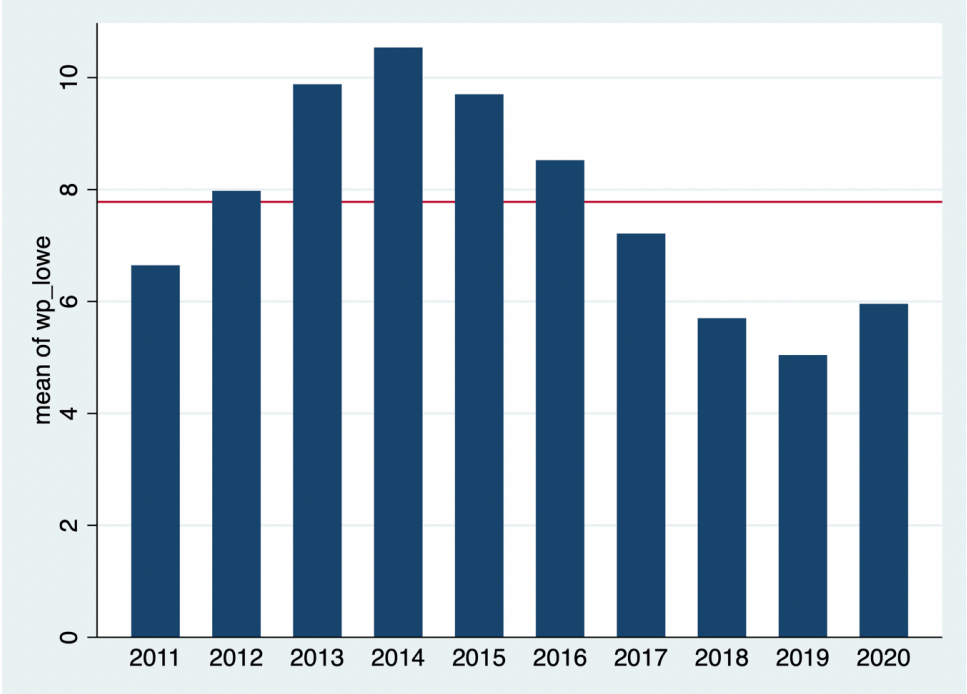

Figure A.2. The average unemployment rate of the LE population between 2011 and 2020, including the overall average unemployment rate (red line).

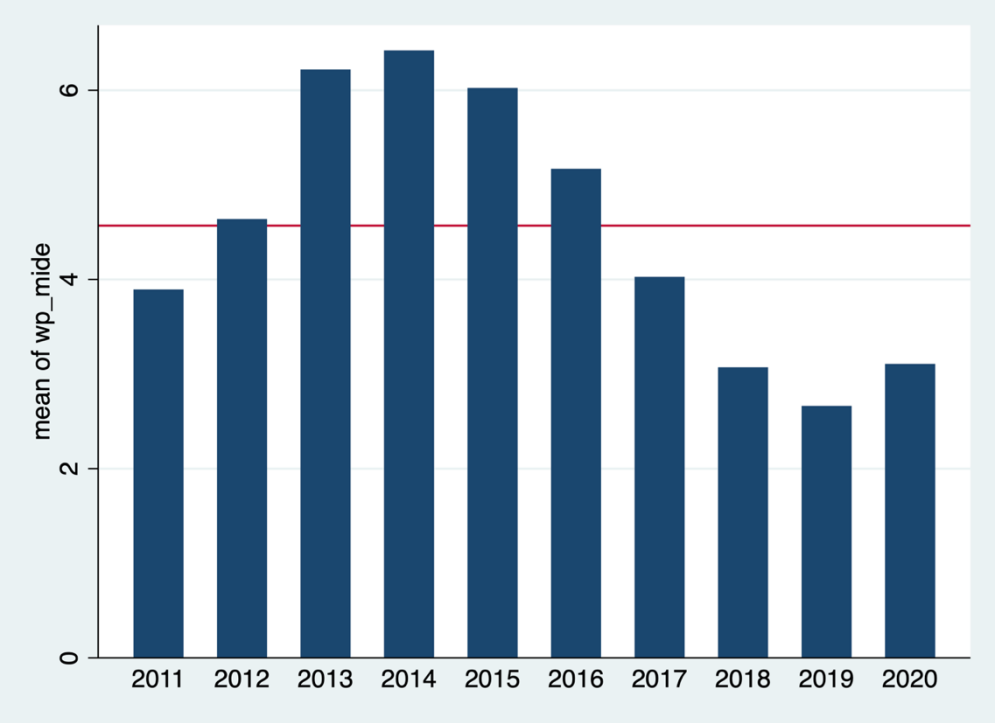

Figure A.3. The average unemployment rate of the ME population between 2011 and 2020, including the overall average unemployment rate (red line).

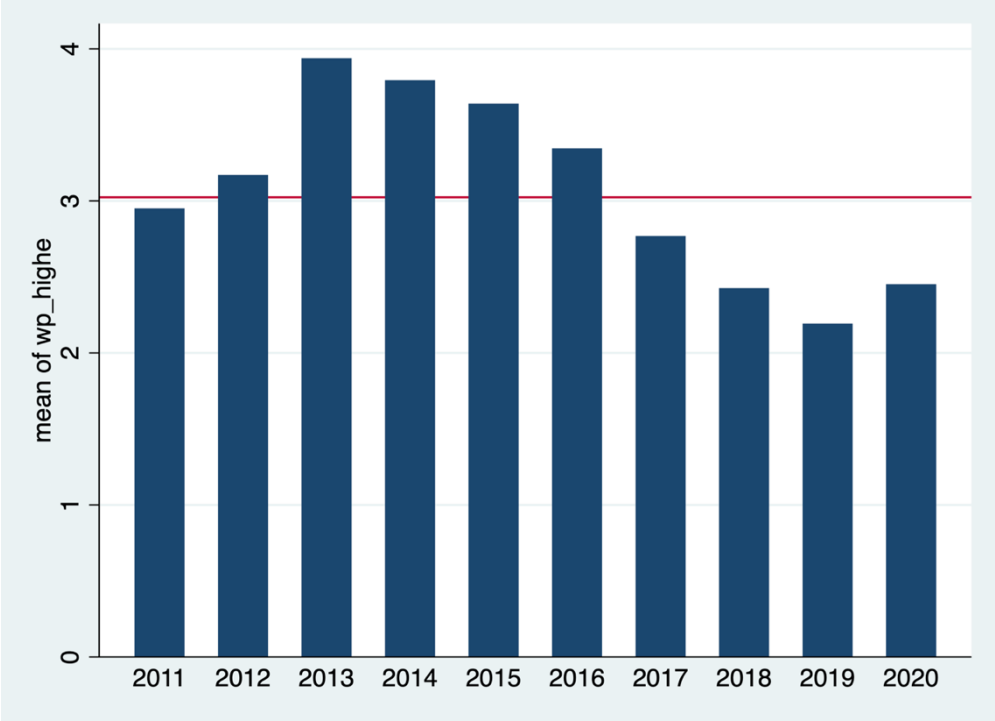

Figure A.4. The average unemployment rate of the HE population between 2011 and 2020, including the overall average unemployment rate (red line).

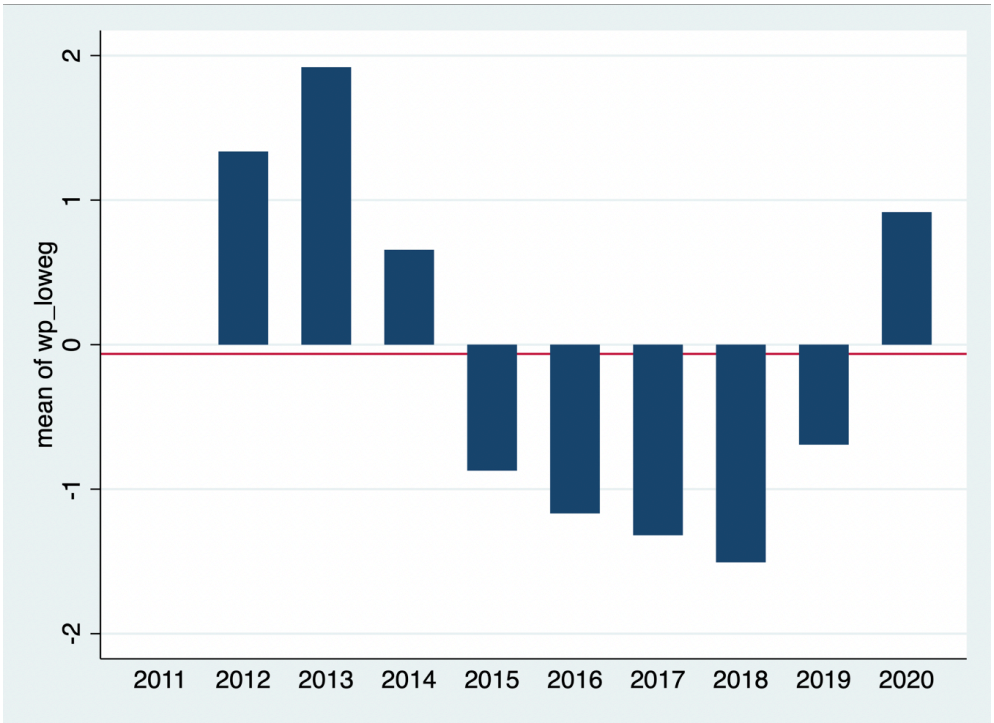

Figure A.5. The average growth of the unemployment rate for the LE population between 2011 and 2020, including the overall average growth of the unemployment rate (red line).

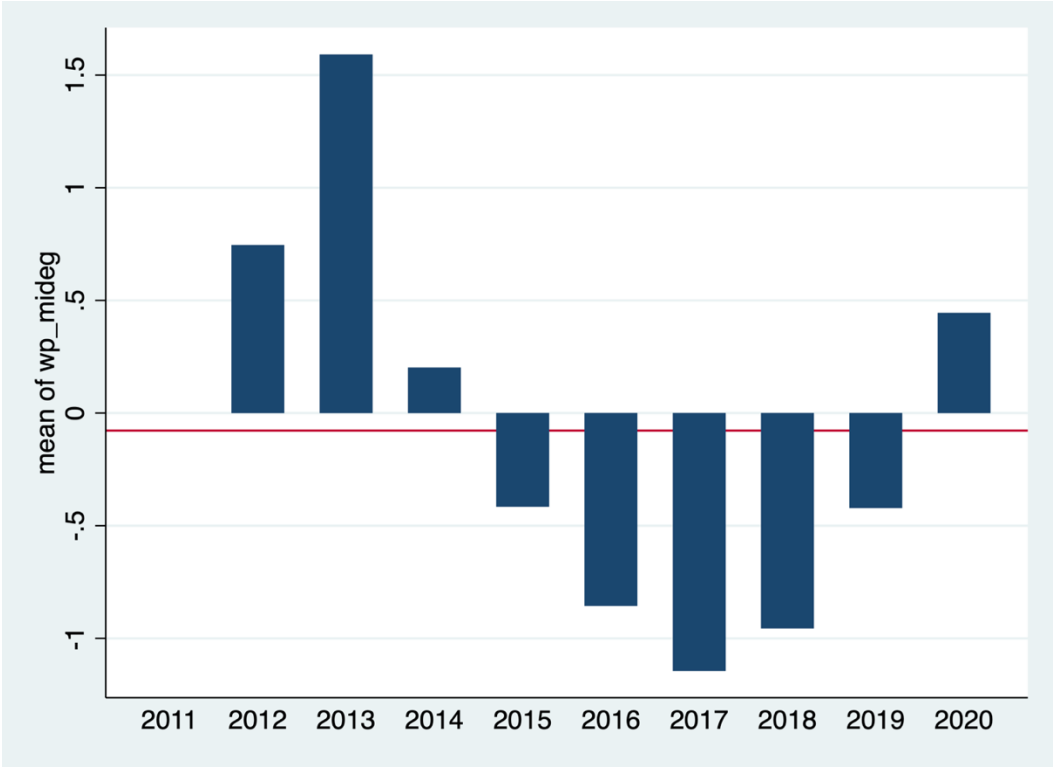

Figure A.6. The average growth of the unemployment rate for the ME population between 2011 and 2020, including the overall average growth of the unemployment rate (red line).

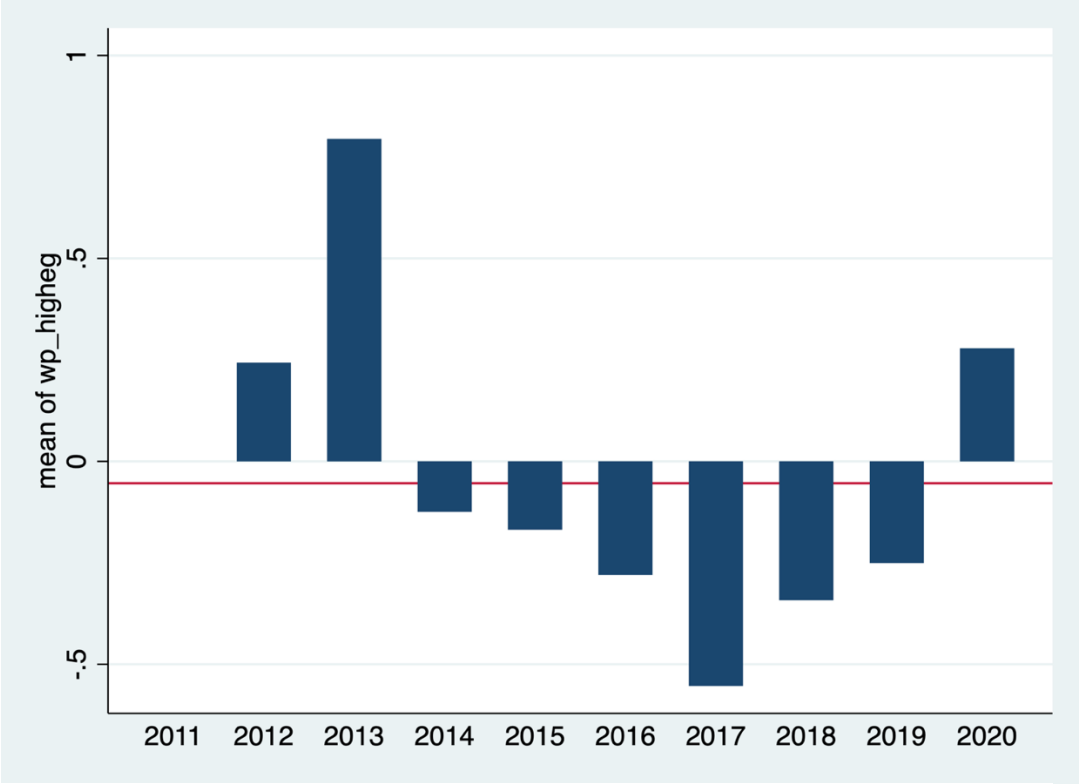

Figure A.7. The average growth of the unemployment rate for the ME population between 2011 and 2020, including the overall average growth of the unemployment rate (red line).

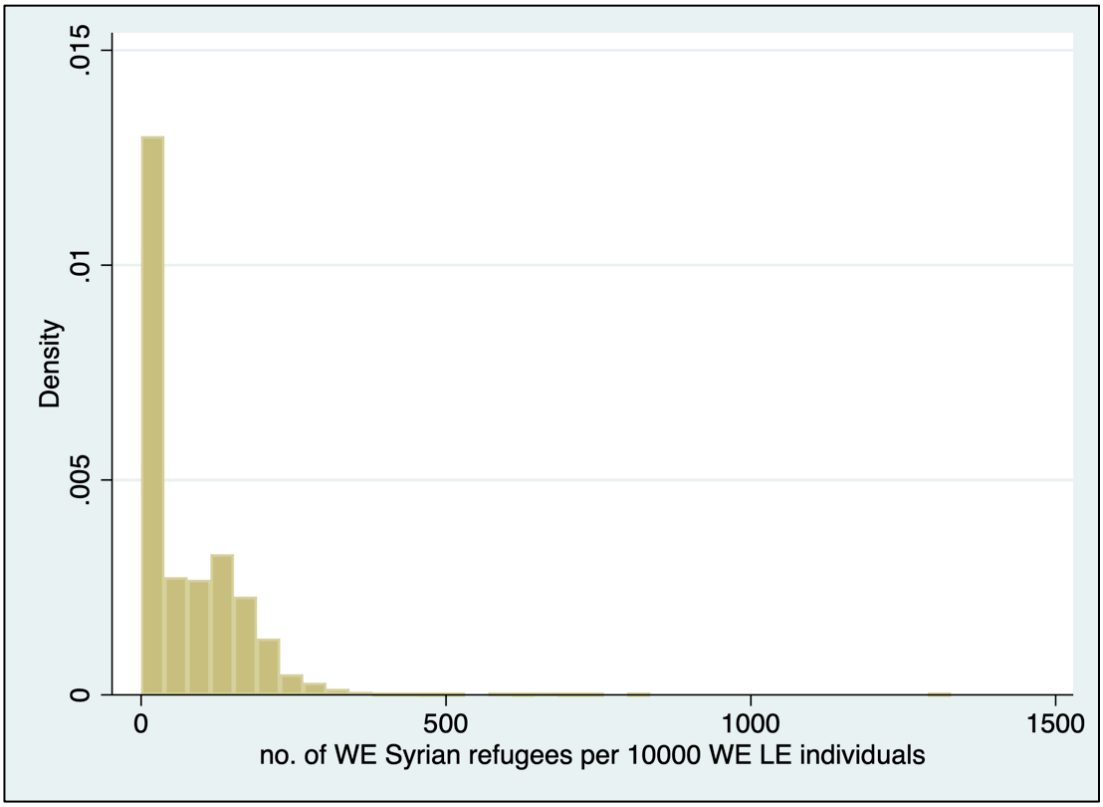

Figure A.8. Histogram of the main independent variable (low-educated)

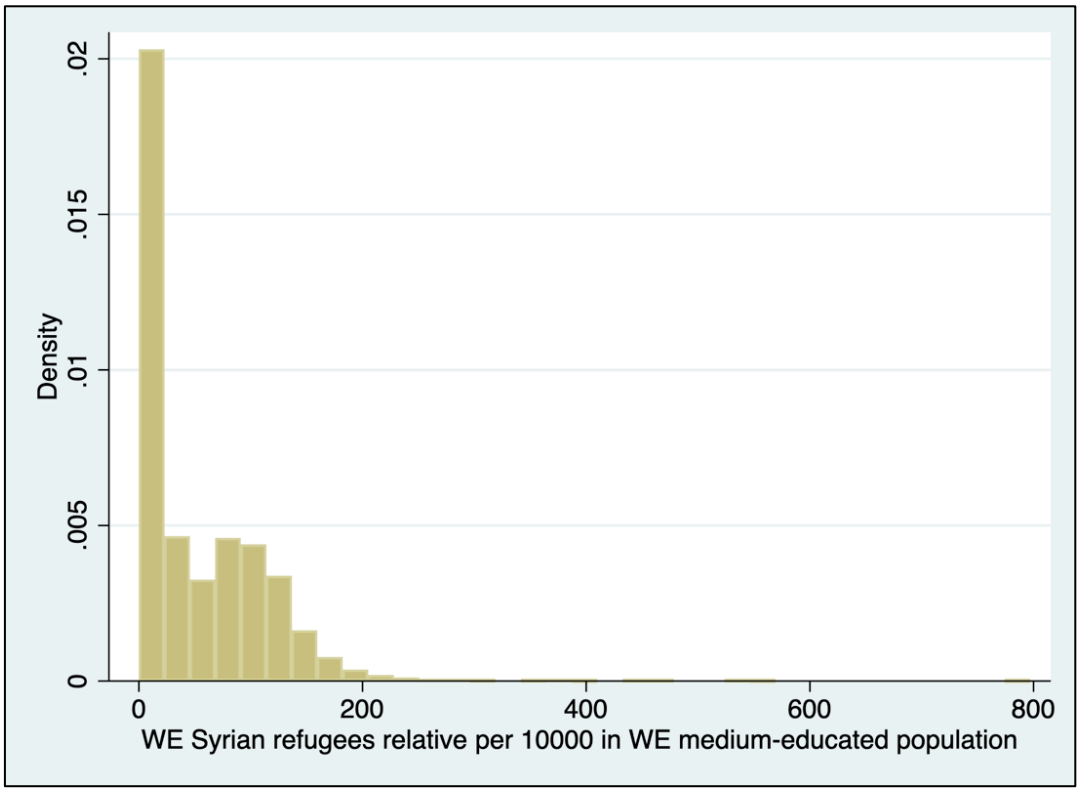

Figure A.9. Histogram of the main independent variable (medium-educated)

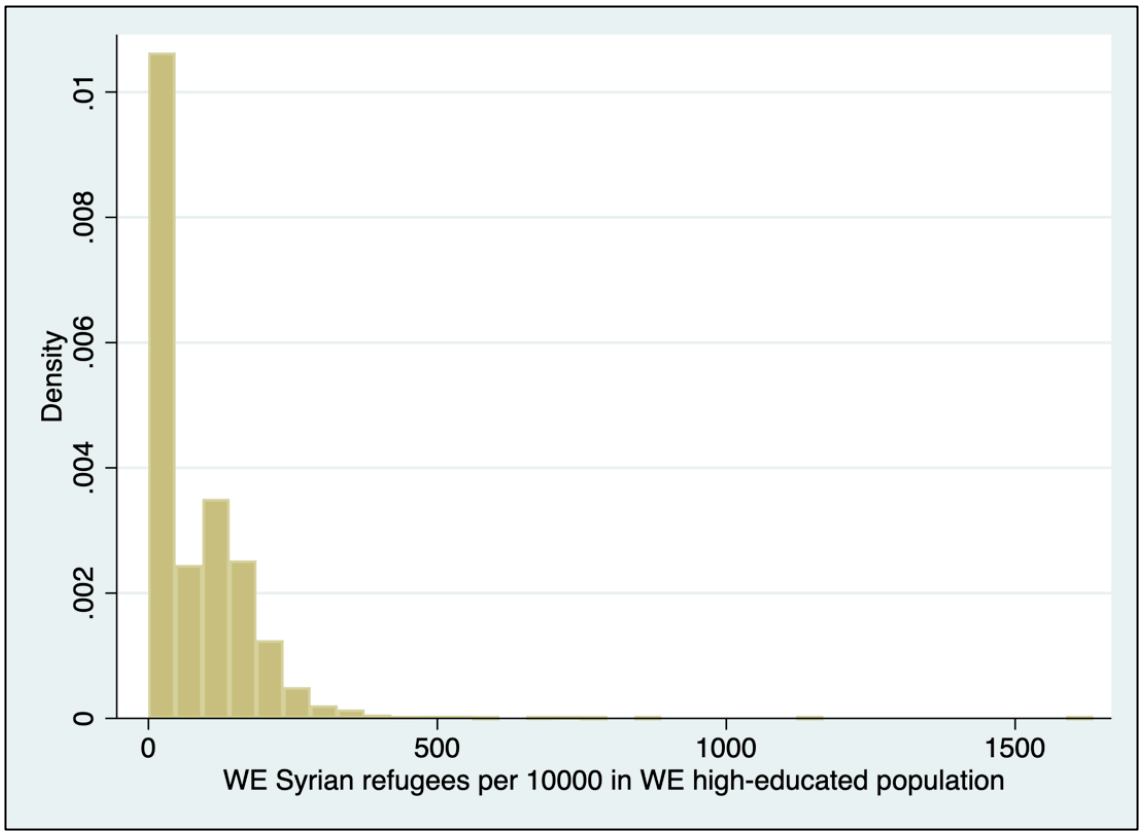

Figure A.10. Histogram of the main independent variable (high-educated)

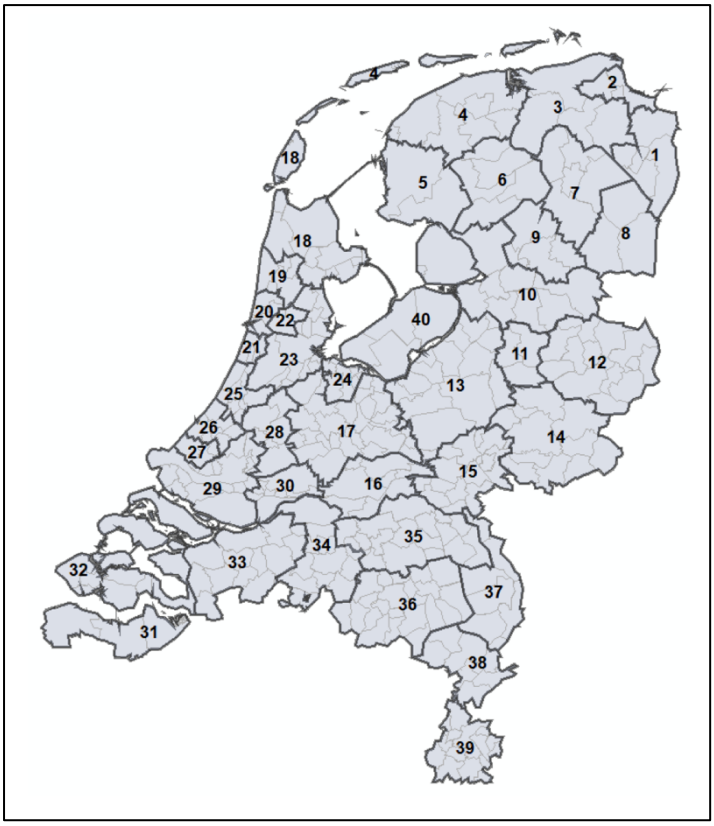

Figure A.11. The 40 COROP-areas in the Netherlands.

```
 regio1:  1, 2, ..., 422                                    n =        417
   year:  2011, 2012, ..., 2020                             T =         10
          Delta(year) = 1 year
          Span(year)  = 10 periods
          (regio1*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%      95%      max
                         2       4      10        10        10       10       10

    Freq.  Percent    Cum.  |  Pattern
-----------------------------+----------
      331    79.38   79.38  |  1111111111
       33     7.91   87.29  |  11111111..
       12     2.88   90.17  |  1111......
       11     2.64   92.81  |  1111111...
        9     2.16   94.96  |  ........11
        5     1.20   96.16  |  11111.....
        3     0.72   96.88  |  .......111
        3     0.72   97.60  |  .....11111
        3     0.72   98.32  |  111111....
        7     1.68  100.00  |  (other patterns)
-----------------------------+----------
      417   100.00          |  XXXXXXXXXX
```

Figure A.12. Number of municipalities and their data coverage for each year.

11.3 Summary Interview with COA[14]

1. As soon as refugees receive a residence permit, they are linked to a labor market region, how does this happen?

Not completely. The labor market region connection has more to do with that if somebody has a very specific job, working in a harbor for example, we try to place this individual in a municipality where there is harbor work. Important is here that this only applies to those individuals who have legal documents that they have worked in a harbor.

2. You are responsible for linking refugees to municipalities in the Overijssel/Gelderland region, can you explain how this link works?

Yes, I am indeed responsible for the municipalities in Overijssel and Gelderland. The answer is quite short, it solely depends on which municipalities are below target. Each six months, municipalities receive a target number on how many permit holders they need to house. When I need to link permit holders to a municipality, I check which municipalities are below target and consequently I place more permit holders there.

3. What are the soft and hard criteria?

Soft criteria of permit holders: education and work experience in the country of origin, ambitions, and social network. Hard criteria of permit holders: first-degree family, medical details, work, and education in the Netherlands.

4. Do refugees have any voice when they are linked to a municipality?

They do have a voice in the sense that legal documents can result in permit holders being placed in the municipality they desire. This number in reality is very small and it is too difficult to place all permit holders in preferred municipalities, everybody wants to go to a big city. So, in the end, their voice is very small.

5. Do all municipalities get an equal number of refugees? How is this decided?

Relatively yes, based on the number of inhabitants in a municipality.

[14] All questions and corresponding answers can be verified with Cornélie Polderman from the COA. E-mail: corneliepolderman@coa.nl.

6. Did any changes occur after the 2014-2016 Syrian refugee wave in terms of connection to municipalities?

No, it did not.

7. Are certain demographics clustered in certain areas? For example: are Syrian mothers mostly placed in Amsterdam?

Normally not. Sometimes specific projects are created for very specific individuals such as single Somalian mothers in the Hague. But this is very rare, in the end there is no clustering if specific demographics.

8. For Syrians specifically, are they evenly distributed among all municipalities in the Netherlands?

Yes.

9. More specifically, are there municipalities where many Syrians are deliberately deported and municipalities where they are less likely to be deported?

No.

10. For Enschede, for example, the number of Syrian refugees is very high, why is this?

Due to an orthodox church which attracts Syrian refugees.

11. Is there enough time to link everyone properly given the high number of residence permits requested?

It is very busy, and the number of permit holders and refugees is very high. It is therefore sometimes difficult to make an optimal connection. In the end, we always make sure that all permit holders are connected in a good manner.

12. The website of the COA talks about 'linking based on best integration options', what is meant by integration options? At what level?

This mostly has to do with education, family, and work. If somebody has family here for example, we want to make sure that they can help each other integrate and thus we try to place this permit holder close to their family. Same goes for individuals with legal documents for education or work.

13. Is there documentation that summarizes the distribution of permit holders?

On the website of the COA is all the publicly available information. The rest is restricted information.

Table 11.3.1. Key take-aways from the interview with Cornélie from the COA.

Interview with Cornélie from the COA
The province of the refugee center in which the refugee is randomly placed is highly determinative for the municipality they will be connected to once their residence permit is granted.
There is no grouping of certain demographics in certain municipalities. Each municipality receives an equal number of men, women, young people, old people, low educated, highly educated etc.
While the main task of Cornélie is to make a good connection, the high amount of permit holders sometimes makes it difficult to have enough time to make the perfect connection.
Even though someone might have all reasons to be placed in Rotterdam (for study or work), it is also possible that this person ends up in a municipality bordering Rotterdam.
There are many refugees who enter the Netherlands '*blanco'*. In other words, they have no preference at all and are completely random distributed across the Netherlands.