The effect of Ukrainian refugees on the local labor markets: the case of Czech Republic

Agnieszka Postepska* Anastasiia Voloshyna †

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Abstract

Following the Russian Federation's invasion of Ukraine on February $24^{th}, 2022$, over a quarter of the Ukrainian population became displaced. Due to their geographical and cultural proximity, the Visegrad Group countries served as a primary refuge, and the Czech Republic emerged as a key destination for Ukrainians fleeing the conflict. Due to its small size, the Czech Republic experienced the largest per capita inflow of refugees. Such a sudden and large influx of refugees brought considerable demographic changes to the Czech labour market. Using individual micro-level data from sixteen waves of the Labour Force Sample Survey (LFSS), collected between 1Q 2019 and 4Q 2022, we aim to examine the short-term effects of the 2022 Ukrainian refugee influx on the local labour market. In absence of a randomized experiment, we employ several empirical strategies, including a two-way fixed effects model and extensions to the canonical difference in differences estimator. Our very preliminary results suggest that the influx of refugees barely affected the local workers across different demographic groups (defined by gender and educational achievement). However, we observe that the effects increase in magnitude across the quarters, suggesting that more recent data is needed to corroborate the economic significance of our results.

JEL Classification: F22, J15, J21

Keywords: Ukrainian refugees, immigrants, local labour market, labour supply

Note: data for the last quarter of 2022 is not yet available. Therefore, the current analysis below is done for 1Q 2019 - 3Q 2022. When the last quarter is available, the analysis will be extended.

*Corresponding author: Faculty of Economics and Business, Department of Economics, Econometrics & Finance, University of Groningen P.O. Box 800 9700 AV Groningen, The Netherlands, a.postepska@rug.nl

†University of Groningen, a.o.voloshyna@student.rug.nl

1 Introduction

Following the Russian Federation's invasion of Ukraine on February 24^{th}, 2022, over a quarter of the Ukrainian population became displaced [IOM, 2023b, UNHCR, 2023b]. By December 2022, the United Nations High Commissioner for Refugees (UNHCR) reported that nearly eight million individuals, mainly women of working age and children, had scattered across Europe, with about five million registering for Temporary Protection or equivalent national protection programs [UNHCR, 2023c]. This refugee crisis is the largest in Europe since World War II, exceeding the displacement caused by the Yugoslav Wars of the 1990s and the Syrian Civil War[1].

Due to their geographical and cultural proximity, the Visegrad Group (V4) countries[2] served as a primary refuge, and the Czech Republic emerged as a key destination for Ukrainians fleeing the conflict [GLOBSEC, 2023]. By the end of 2022, this mid-sized European country, with 10.5 million inhabitants, granted Temporary Protection to approximately 433 thousand individuals[3] [MVCR, 2023d]. As a result, the Czech Republic shelters the highest per capita number of Ukrainian refugees worldwide[MoLSA, 2022].

The sudden influx of refugees brought about considerable demographic changes within the Czech Republic. By the end of 2022, many districts experienced at least a 1% increase in their working-age populations, with a spike reaching as high as 13% in certain areas. Furthermore, with the enactment of the Lex Ukraine law by the EU states in March 2022, the refugees were given full access to the labour market, alongside other social benefits. Hence, not only did the refugees contribute to population growth, but they also had the opportunity to participate actively in the host country's workforce.

In this paper, we aim to examine the short-term effects of the 2022 Ukrainian refugee influx on the labour market outcomes of locals.[4] Theoretical frameworks offer varied predictions concerning the impacts of a large-scale immigration event, such as the Ukrainian refugee influx. First, if labour force is considered homogeneous, the standard competition framework suggests that an increase in immigrants could enhance overall welfare, despite potentially lowering wages due to the heightened labour supply. However, if wages do not adjust freely (perhaps due to union influences) it may lead to unemployment increases.

If we consider labour as heterogeneous, outcomes depend on whether foreign workers are seen as substitutes or complements to native workers. Typically, we can simplify labour into skilled and unskilled workers, with the former often seen as complementary to immigrant labour and the latter as substitute labour. If this assumption holds, an increase in unskilled immigration lowers wages

[1]The Yugoslav Wars in the 1990s resulted in approximately 2 million people fleeing Bosnia, 500 thousand from Croatia, 100 thousand from Serbia, and 30 thousand from Slovenia [USCRI, 1998]. The Syrian Civil War displaced around 6.6 million Syrians, with European countries hosting just over 1 million [UNHCR, 2023a].

[2]The Czech Republic, Hungary, Poland, and Slovakia.

[3]This count only includes individuals who secured Temporary Protection status; the actual number of refugees in the Czech Republic may be higher or lower.

[4]Locals refer to both Czech nationals and foreign nationals residing under permanent status, excluding Ukrainians. The age range for this demographic extends from 18 to 65 years. We use terms like locals, refugees, diaspora, and immigrants interchangeably. See Section 8.1 for their precise definition.

and raises unemployment rates among unskilled native workers, while the opposite occurs for skilled natives. This understanding aligns with the skill-cell approach, suggesting that immigration impacts vary by skill level and that the interplay between immigrant and native workers within these skill segments is key in determining immigration's influence on native wages and employment. However, it's important to note that these predicted effects are generally anticipated to be short-term in nature, according to most theoretical models.

Empirical research, however, generally finds immigration to have only a minimal impact on employment outcomes and a mild effect on wages[5]. More pronounced adverse effects are sometimes observed within specific demographic segments like 'low-skilled' males and minorities [Borjas, 1994, Card, 2001a, Borjas, 2003, Dustmann et al., 2005a, Borjas and Katz, 2007, Lemos and Portes, 2008, Ottaviano and Peri, 2011, Nickell and Saleheen, 2015].

The limited impact on employment outcomes could be partially due to the various barriers newcomers encounter, including legal obstacles [International Labour Organization (ILO), 2017, UN2, 2017], or difficulties in transferring their skills to the new economy, which can lead to struggles in securing work or accepting underemployment[6]. This underemployment makes them less effective substitutes for native workers of the same demographic profile. Language proficiency, an important factor for refugees' successful societal integration, has also been previously identified as a significant barrier to employment, further undermining their labour market outcomes[7].

Other studies, however, have identified positive immigration effects on local workers. Some of these effects were isolated to specific demographic groups and market conditions. For example, the presence of female immigrant labour has been linked to affordable household services, encouraging locals with household duties and high potential market salaries to (re-)enter the workforce [Cortés and Tessada, 2011, Farre et al., 2011, Cortés and Pan, 2013]. Additionally, another set of studies using a general approach to analyze immigration impacts has identified several beneficial secondary effects. These include boosted capital markets in host countries [LaLonde and Topel, 1997, Ottaviano and Peri, 2011], decreased prices of non-traded goods and services that require low-skilled labour [Borjas and Katz, 2007], and improved industry efficiency [Ottaviano et al., 2013].

To summarize, the effects of immigration can be viewed through the lens of complementarity or substitutability with natives. The degree to which they are substitutes or complements depends on factors such as the education levels of the immigrants, pre-immigration work experience, transferability of immigrants' human capital, legal and language barriers, demographic similarity with the locals, and others, which are examined in the next section of this paper. Determining the extent to which

[5] See, for example, [Altonji and Card, 1991, Friedberg and Hunt, 1995, Borjas et al., 1996b, Pischke and Velling, 1997, Angrist and Kugler, 2003, Card, 2009].

[6] See, for example, [Borjas et al., 1996a, Friedberg, 2000, Schaafsma and Sweetman, 2001, Bevelander and Nielsen, 2001, Weiss et al., 2003, Warman and Worswick, 2004, Aydemir and Skuterud, 2005, Dustmann and Fabbri, 2005, Lemaitre and Liebig, 2007, Lubotsky, 2007, Chiswick and Miller, 2008, Borjas and Friedberg, 2009, Chiswick and Miller, 2009, Warman, 2010, Cohen-Goldner and Paserman, 2011, Sharaf, 2013].

[7] See, for example, [Tip et al., 2019, Chiswick and Miller, 1995, Ferrer et al., 2006, Skuterud, 2011, Chiswick and Miller, 2012, Chiswick and Miller, 2013, Adsera and Ferrer, 2015, Gazzola, 2017].

Ukrainian immigrants act as complements or substitutes for native Czech workers is crucial to this analysis and next section proved an extensive discussion.

One common challenge in most immigration impact studies is the self-selection bias. Immigrants tend not to distribute randomly but are drawn to regions with favourable demand conditions [Borjas, 1987, Borjas, 1991, Jaeger, 2007]. Therefore, a straightforward comparison of high- and low-immigration areas may produce biased estimates of the immigration effect. Researchers often employ the Shift-Share Instrument to overcome this endogeneity problem [8]. However, as noted by [Jaeger et al., 2018], if the spatial distribution of immigrant inflows remains consistent over time, the instrument may correlate with lingering responses to previous supply shocks.

In contrast, the forced nature of the immigration shock caused by the Russian invasion of Ukraine allows us to analyze its impact on the local labour market in the context of a "natural experiment." Previous studies have used substantial immigration waves caused by civil wars or political unrest to establish causal relationships[Card, 1990, Hunt, 1992, Carrington and de Lima, 1996, Friedberg, 2001, Mansour, 2010, Glitz, 2012, Maystadt and Verwimp, 2014, Ceritoglu et al., 2017, Aydemir and Kırdar, 2017], eliminating the need for traditional selection-correction methods.

We use individual micro-level data from sixteen waves of the Labour Force Sample Survey (LFSS), collected by the Czech Statistical Office (CZSO) between 1Q 2019 and 4Q 2022. We limit our scope to working-age individuals (18-65 years), resulting in a sample of 425,503 observations.

Our identification strategy unfolds in several stages. Firstly, a two-way fixed effects (2WFE) model is estimated without distinguishing between the pre-war and post-war periods. We regress the labour market outcome—either an extensive margin (employment, unemployment, inactivity, labour force participation) or an intensive margin (hours usually worked)—on the immigrant-local ratio for all districts and time periods. This captures the relationship between fluctuations in these variables.

Next, we explore the impact of the Ukrainian influx in 2022 on local labour market outcomes. We shift the focus from the immigrant-local ratio to the refugee-local ratio by the end of 2022, a metric we label as "Treatment Doses" (TD_j). Essentially, this "treatment" represents the population surge from the refugee influx by the fourth quarter of 2022, which translates to the total "shock" each district experienced. The “treatment” variable is discrete with ten categories, with the first category corresponding to a 1% increase in the district population, the second to a 2% increase, and so forth, up to the tenth category, which corresponds to a 10% or more increase. We also introduce a dummy variable, War_t, which takes the value of 1 from the beginning of the 2022 Ukrainian refugee influx (1Q 2022), and 0 otherwise. We then interact this "treatment period" variable with our "treatment".

Designed to vary by district but not over time, our treatment did not employ a staggered adoption design. This is justified as the primary wave of refugees had already arrived by the end of 1Q 2022, a situation akin to being treated at $T = 1Q$ 2022, with the treatment continuing subsequently. Moreover, the majority of the districts experienced simultaneous impacts.

Conceptually, this extension of the 2WFE model estimates the effect of a treatment on an outcome

[8] See, for example, [Altonji and Card, 1991, Card and DiNardo, 2000, Card, 2001b, Fairlie and Meyer, 2003, Dustmann et al., 2005b, Cortés and Tessada, 2011, Farré et al., 2011, Facchini et al., 2013, Romiti, 2017].

by comparing, over time, groups experiencing different intensities of the treatment. Having reasons to believe that the treatment effects from the refugee influx are heterogeneous in nature,[9] we estimate the DiD Estimators with Discrete Treatment(s) with Heterogeneous Treatment Effects, following the theoretical work of [de Chaisemartin and D'Haultfœuille, 2020a]. This forms our baseline DiD model.

Given the ongoing nature of the refugee influx (our treatment), we anticipate that earlier treatments could affect future labour market outcomes. Thus, we extend our baseline DiD model by incorporating dynamic treatment effects as in [de Chaisemartin and D'Haultfœuille, 2020b].

Finally, given that we also have data on the increase in employment in the Czech Republic, we repeat the analysis, but this time we define our "treatment variable" as the increase in the employed population due to the refugees who found jobs by 4Q2022.

An advantage of our approach and the forced nature of the refugee influx is that we bypass the 'self-selection problem' often seen in migration economics literature. However, in turn, we are required to satisfy the common trends assumption. This assumption, given the discrete nature of the treatment, requires that in the absence of any treatment, the trends across all groups would be the same. In other words, we would need to see parallel trends in labour market outcomes across all districts, irrespective of their economic stability, labour demand, or refugee count. Admittedly, this assumption is a strong one. Therefore, as a part of our robustness check, we:

i. Re-estimate the DiD model, conditioned on the proportion of Ukrainian diaspora in each district just prior to the treatment period (4Q 2021). We group districts by the size of their respective diasporas (7 groups: from 0% up to 6% or more ratio of the diaspora to the locals) and estimate the model separately for each group. This approach aids in upholding the parallel trend assumption by allowing us to compare districts that showed similar levels of attractiveness to earlier immigration waves. However, it results in a reduced sample size for each evaluation.

ii. Re-estimate the DiD model, ensuring unbiased estimators even if groups experience differential trends, by matching observations on the relevant covariates.

Our preliminary results are based on estimating the Difference-in-Difference (DID) with Discrete Treatment and Heterogeneous Dynamic Effects. This method allowed us to assess how the 2022 Ukrainian refugee influx affected local employment among three groups: the total population, females, and males. These effects were measured dynamically across three distinct periods: the first, second, and third quarters of 2022. We focused on local employment as the key labour market outcome. Moving forward, we plan to extend this focus to include hours usually worked, unemployment, inactivity, and labour force participation outcomes.

Upon examining the total population, we observed negative coefficients across all periods following the refugee influx, though these were not statistically significant. This suggests that the influx did not substantially affect overall employment.

[9] We estimated weights for the two-way fixed effects regressions, as suggested by de Chaisemartin and D'Haultfoeuille (2020a), and with many weights being non-negative and the ratio not large, we concluded that the treatment effects are heterogeneous.

Our analysis of female employment yielded a similar pattern. The average effect across all three periods was negative and significant at -0.0025, but only narrowly excluded zero in its lower confidence limit. It's important to note that we employed bootstrap replications to estimate standard errors. At this stage, using only the default 50 bootstraps provided us with a preliminary approximation of results while limiting computational intensity. For a more reliable estimate of standard errors, we will increase the number of replications, which could potentially alter the confidence limits. The results for males mirrored these patterns, revealing negative but statistically insignificant treatment effects.

Of particular interest is the growing size of the effect across the quarters, peaking in the third quarter, as mirrored in the dynamic treatment effect coefficients. This underlines the importance of incorporating data from the final quarter of 2022, which we plan to do shortly, to corroborate these findings and better understand the dynamic effects across the year.

We would like to highlight that the current stage of our analysis is still preliminary, with the identification strategy subject to potential revisions. We intend to maintain our Difference-in-Difference (DiD) with a Discrete Treatment design. However, we are considering refining the specifics of this design to better accommodate the complexity of the effects we aim to measure.

In summary, our preliminary results indicate that the 2022 Ukrainian refugee influx had a negligible impact on employment among locals. Although a slight negative effect on female employment was estimated, there is no substantial evidence to suggest a change in the labour market structure in the short run.

This is a welcomed finding. European Union member states, including the Czech Republic, welcomed Ukrainian refugees on humanitarian grounds. However, the introduction of large numbers of refugees into their societies, granting them unfettered access to the labour market, has sparked worries about possible negative impacts on local populations. These concerns were layered atop existing economic pressures intensified by war and other macroeconomic factors.

Our findings of no substantial change in the labour market structure and no significant adverse effects on local inhabitants cautiously suggest that there wasn't a direct trade-off between aiding Ukrainians fleeing for safety and maintaining stable local labour market conditions.

However, we recognize the need to consider the potential secondary effects of the 2022 refugee influx. The interconnectedness of local labour markets may generate spillover effects. For instance, a large influx of immigrants could trigger a reactive adjustment among the local population. Faced with such an immigrant supply shock, locals might opt to move their labour or capital to other cities, contributing to stabilizing the national economy. We examine data on local population movements to explore whether this phenomenon could explain our minimal effects.

The remainder of the paper is organized as follows. The next section outlines the background information about the 2022 refugee wave, detailing settlement patterns, demographic characteristics, and labour market conditions within the Czech Republic. Section 3 discusses the data, while Section 4 explains the empirical strategy strategy, followed by results and robustness checks in Sections 5 and 6, respectively. Section 7 concludes. Additional details regarding definitions and variables used in the analysis can be found in Appendix 8.1, while all tables and figures are presented in Appendix ??.

2 Contextual Details

2.1 Settlement Patterns of Refugees

By the end of 2022, the Czech Republic had welcomed approximately 433,000 Ukrainian refugees [MVCR, 2023d] as documented in Figure.1. This population influx was not distributed evenly across the country, but rather exhibited distinct clustering in certain areas. The capital city of Prague, along with Středočeský kraj and Jihomoravský kraj, received 24%, 14%, and 10% of the refugee population, respectively. Collectively, they attracted almost half of the displaced Ukrainians. Given that these regions are characterized by high economic productivity and rank among the top in per capita GDP, the pattern suggests that regional economic performance may have influenced the refugees' settlement choices [CZSO, 2023a].

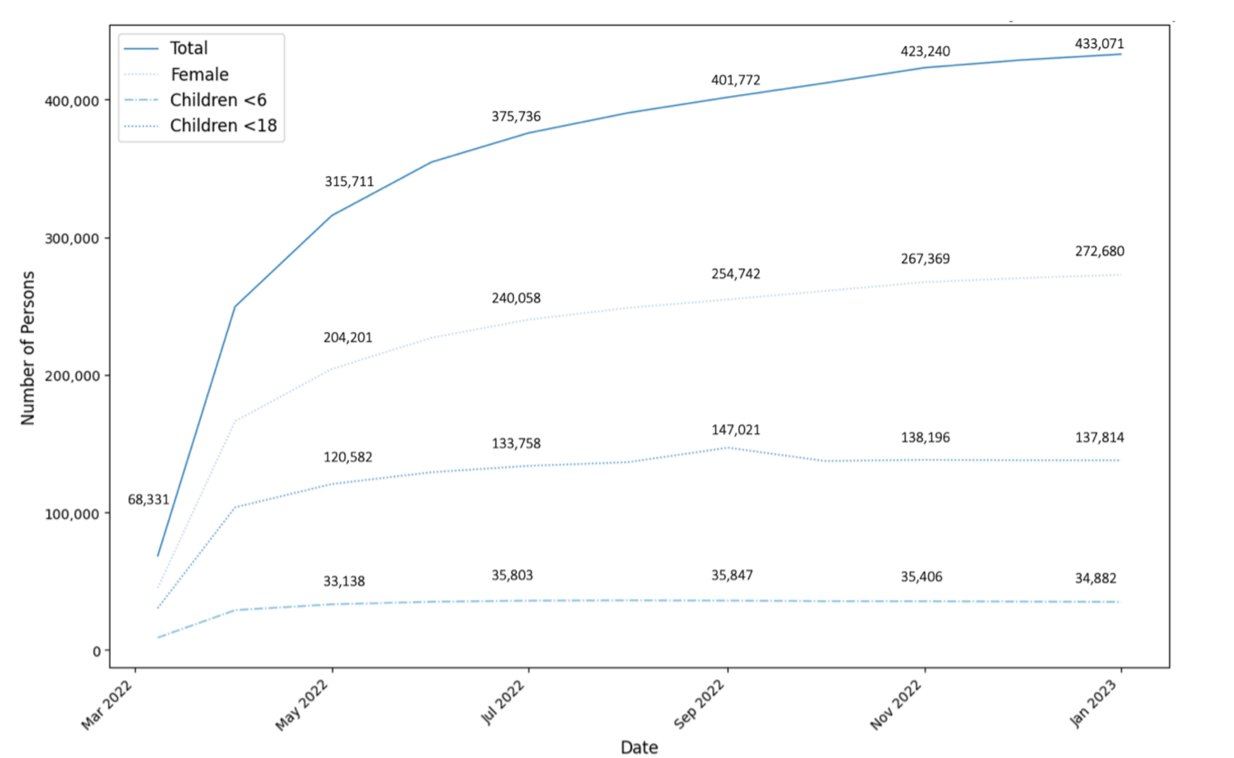


Figure 1: Registration Timeline for Refugees Seeking Temporary Protection in the Czech Republic

Note: data sourced from Ministry of the Interior of the Czech Republic [MVCR, 2023d]

Even before the conflict, some regions had substantial Ukrainian diasporas. As of the last quarter of 2021, nearly 197,000 Ukrainians resided in the Czech Republic [MVCR, 2023b]. It constituted the largest group of foreign nationals and the incoming refugees located in the areas where the existing Ukrainian diaspora was already present, as indicated by the correlations in Tab.1 and the 2022 UNHCR survey according to which 23% of respondents cited the presence of family or friends as their primary reason for selecting the Czech Republic as their destination country [UNHCR, 2022]. This aligns with established migration and network theories, which suggest that migrants often choose regions with pre-existing diasporas [Hatton and Williamson, 1998, Woodruff and Zenteno, 2007, Patel and Vella, 2013, Stuart and Taylor, 2021].

In response to the crisis, the Czech Republic established 14 Regional Centres for Help and Assistance to Ukraine (KACPUs) in populous districts, which correspondingly saw an uptick in refugee registrations [MVCR, 2023c]. However, attributing specific influences on refugee settlement patterns to economic performance, pre-existing diaspora, or the presence of KACPUs is complex due to the considerable correlation among these factors.

Variables	(1)	(2)	(3)	(4)
(1) Diaspora	1.000			
(2) Refugees	0.993	1.000		
(3) Employed diaspora	0.992	0.985	1.000	
(4) Employed refugees	0.882	0.912	0.876	1.000

Table 1: Matrix of Correlations Between the Ukrainian Diaspora and Refugee Settlemets

The sudden arrival of refugees led to significant demographic changes in some districts. Places such as Tachov, Plzeň-město, Prague, Cheb, Mladá Boleslav, and Karlovy Vary experienced increases in their working-age population (18-65 y.o.) ranging from 7% to 13% by the end of 2022 (see Fig.2). A considerable influx of female refugees led to a distinct rise in the female population, averaging an additional 2% to 5%. Conversely, districts like Karvina, Decin, Prostejov, Kromeriz, Bruntal, and Opava saw a growth of no more than 1% in their working-age populations, indicating a significant variation in the degree to which districts were impacted. We will explore this variation in our identification strategy.

2.2 Demographics Comparison between Locals and Refugees

To gain insights into whether the Ukrainians should be seen as substitutes or complements to the local labour force, we turn to the demographics of the incoming refugees. The 2022 Ukrainian refugee wave was predominantly composed of working-age women and children, a demographic profile distinct from typical migration patterns.[10] Women constituted 63% of the total, and this percentage

[10] Data on the socio-economic profiles of Ukrainian refugees comes primarily from two 2022 surveys: one conducted by the Czech Ministry of Labour and Social Affairs in July with 50,236 respondents[MoLSA, 2022], and another by the same ministry, in collaboration with PAQ Research and the Institute of Sociology of the Czech Academy of Sciences, running from February to November with 1,246 respondents[MoLSA et al., 2023]. Supplemental data was derived from a 2023 IOM survey[IOM, 2023a], conducted from June to December 2022 with 4,284 responses across all Czech regions, and a 2022 UNHCR survey[UNHCR, 2022], conducted from May to September 2022, yielding 4,800 global responses and 721 responses specific to the Czech Republic. The non-representative nature of the last two surveys suggests that their results are indicative rather than conclusive. Please refer to the original reports for detailed

rose to 69% for the age group 18-65. This gender imbalance can likely be traced back to Ukraine's wartime regulations restricting many males of combat age from leaving the country.

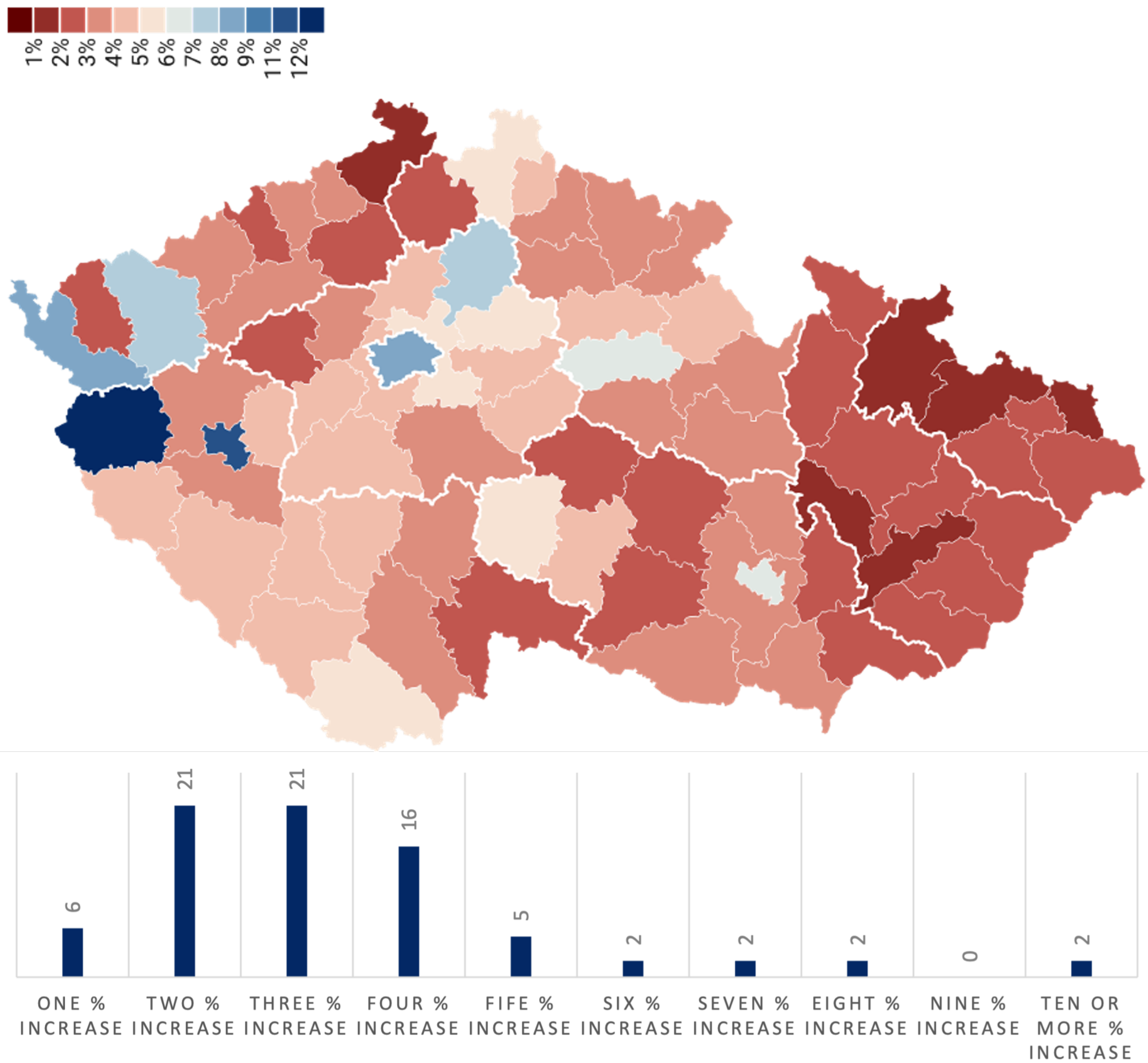


Figure 2: Refugee-Induced Population Increase in the Czech Republic by District (as of December, 2022

Note: data sourced from Ministry of the Interior of the Czech Republic [MVCR, 2023d]

Table 2 reveals that approximately 64% of the refugees were of working age (18-65 y.o.). The age distribution among migrants mirrored that of the native Czech population [MVCR, 2023d, CZSO, 2023c], with one exception: only 4% of refugees were elderly (65+ years old), contrasting with the 20% observed locally.

methodologies.

	Refugees (31st of December, 2022)							Natives (census of 2021)						
	Overall	Largest Increase			Largest Relative Increase			Overall	Largest Increase			Largest Relative Increase		
		Prague	Brno-město	Plzeň-město	Tachov	Cheb	Mladá Boleslav		Prague	Brno-město	Plzeň-město	Tachov	Cheb	Mladá Boleslav
Gender														
Female	(63%)	(64%)	(63%)	(63%)	(69%)	(66%)	(62%)	(51%)	(51%)	(51%)	(51%)	(50%)	(51%)	(50%)
Male	(37%)	(36%)	(37%)	(37%)	(31%)	(34%)	(38%)	(49%)	(49%)	(49%)	(49%)	(50%)	(49%)	(50%)
Age														
0-5y.o.	(8%)	(8%)	(7%)	(6%)	(4%)	(7%)	(9%)	(5%)	(5%)	(6%)	(5%)	(5%)	(5%)	(6%)
6-14y.o.	(18%)	(17%)	(16%)	(14%)	(11%)	(16%)	(23%)	(11%)	(10%)	(10%)	(10%)	(11%)	(11%)	(11%)
15-17y.o.	(6%)	(6%)	(6%)	(5%)	(4%)	(5%)	(6%)	(5%)	(4%)	(4%)	(4%)	(5%)	(5%)	(5%)
18-64y.o.	(64%)	(65%)	(67%)	(72%)	(79%)	(67%)	(60%)	(59%)	(62%)	(61%)	(60%)	(61%)	(58%)	(60%)
65+y.o.	(4%)	(4%)	(3%)	(3%)	(2%)	(5%)	(3%)	(20%)	(18%)	(20%)	(21%)	(19%)	(21%)	(19%)

Table 2: Comparative Demographics by Age and Gender

*Note:*data sourced from the Ministry of the Interior of the Czech Republic [MVCR, 2023d] and the 2021 Census [CZSO, 2023c].

Table 3 reveals that the refugees generally held higher qualifications than both the local Czech population and the pre-conflict Ukrainian diaspora in Czechia [MPI, 2023, CZSO, 2023c]. Depending on the source, the percentage of those with tertiary education was estimated to be between 35% and 49%, noticeably exceeding the 18% rate among Czech locals [MoLSA, 2022, IOM, 2023a, UNHCR, 2022]. This education gap narrowed in urban districts like Prague and Brno-město, where local tertiary education rates were 34% and 32% respectively, but it widened in other highly affected regions such as Tachov, Cheb, and Mladá Boleslav.

	Refugees			Natives (census of 2021)						
Education Attainment	MoLSA (a)	IOM (b)	UNHCR (c)	Overall	Largest Increase			Largest Relative Increase		
					Prague	Brno-město	Plzeň-město	Tachov	Cheb	Mladá Boleslav
Tertiary	(35%)	(49%)	(44%)	(18%)	(34%)	(32%)	(21%)	(8%)	(9%)	(14%)
Post-Secondary	(14%)	(5%)	(21%)	(32%)	(35%)	(33%)	(35%)	(29%)	(30%)	(33%)
Secondary	(39%)	(30%)	(20%)	(31%)	(17%)	(20%)	(26%)	(37%)	(34%)	(33%)
Primary/Basic	(7%)	(15%)	(3%)	(13%)	(8%)	(9%)	(11%)	(17%)	(17%)	(12%)
No Education	(5%)	-	(13%)	(1%)	(0%)	(0%)	(1%)	(1%)	(1%)	(1%)
Not Identified	-	-	(1%)	(6%)	(6%)	(5%)	(6%)	(9%)	(9%)	(7%)

Table 3: Comparative Demographics by Education

Note: data sourced from the 2021 Census [CZSO, 2023c] and the surveys [MoLSA, 2022, IOM, 2023a, UNHCR, 2022].

However, the degree to which human capital can be transferred, especially in the short run, remains uncertain. Past research indicates that immigrants often face difficulties utilizing their academic qualifications and work experience to secure equivalent positions in their host countries' labour markets. This can lead to less favourable initial outcomes[11].

[11] See, for example, [Borjas et al., 1996a, Friedberg, 2000, Schaafsma and Sweetman, 2001, Bevelander and Nielsen, 2001, Weiss et al., 2003, Warman and Worswick, 2004, Aydemir and Skuterud, 2005, Dustmann and Fabbri, 2005, Lemaitre and Liebig, 2007, Lubotsky, 2007, Chiswick and Miller, 2008, Borjas and Friedberg, 2009, Chiswick and Miller, 2009, Warman, 2010, Cohen-Goldner and Paserman, 2011, Sharaf, 2013].

Moreover, the literature identifies language proficiency as an important determinant for refugees' successful integration into host societies [Tip et al., 2019]. Empirical evidence suggests that a lack of language skills can be a significant employment barrier, negatively impacting labour market outcomes for migrants[12]. The lack of sufficient language skills is particularly pronounced for displaced Ukrainians. Between 60% and 87% of refugees, depending on the source, report not being able to speak English, and between 69% and 91% lacked any Czech language skills [MoLSA, 2022, UNHCR, 2022]. However, a more recent survey, by tracing the same individuals over time, shows that Czech skills among adults had been steadily increasing throughout the year [MoLSA et al., 2023].

Finally, data from the 2022 UNHCR survey suggested that despite consistent age distribution across host countries, a higher percentage of tertiary-educated Ukrainians opted to settle in Poland and Germany (63% and 79% respectively) rather than in the Czech Republic [UNHCR, 2022]. This trend implies that more educated Ukrainians might be drawn to destinations offering better labour market opportunities. While this observation isn't the central focus of the present study, it nonetheless warrants future cross-country comparative research.

2.3 Workforce Integration

In March 2022, shortly after the initial wave of refugees began arriving in Europe, the Czech government and other EU nations enacted the Lex Ukraine law [EC, 2022]. This legislative framework extended benefits usually reserved for permanent residents, including full access to the labour market, retraining programs, self-employment opportunities, and a variety of social benefits, to the refugees.

Subsequently, the employment rate of Ukrainians in the Czech Republic began to climb steadily. By the final quarter of 2022, an additional 75,000 Ukrainians[13] had found work compared to the previous year [MoLSA, 2023a]. This constituted nearly one-third of all Ukrainians who arrived during the same period. Women made up 79% of this increase in employment.

The capital city, Prague, saw the most significant rise in employment, with one in ten employees being Ukrainian by the end of 2022. The proportion of Ukrainian workers was even higher in smaller districts, such as Tachov, where they accounted for one-third of all employees. A contributing factor was the considerable Ukrainian workforce, approximately 195,000, already present before the conflict. Employment patterns, similar to settlement patterns, displayed a substantial correlation of 0.876 between the employed Ukrainian diaspora and refugees across districts (see Table 1). This suggests that refugees potentially had a higher chance of securing employment in districts where the diaspora was already established in the workforce. Alternatively, it could imply that these districts historically had a greater demand for foreign workers.

Despite the lack of comprehensive data on labour market outcomes for refugees, some insights

[12] has demonstrated this citechiswick1995, ferrer2006, skuterud2011, chiswick2012, chiswick2013, adsera2015, gazzola2017.

[13] Considering the way data are reported, it is challenging to ascertain whether all of these employed individuals are refugees, Ukrainians who arrived on a different visa, or Ukrainians already residing in Czechia who have just entered or re-entered the labour market. However, the significant increase, coupled with 8,965 Ukrainians of working age entering the country under various types of legal protection/visas compared to 278,436 refugees, implies that many of them are likely refugees.

can be gleaned from smaller, population-representative surveys carried out by the Czech Ministry of Labour and Social Affairs [MoLSA, 2022]. By the end of 2022, it was estimated that half of the economically active Ukrainian refugees had found local jobs, while a significant number worked part-time or remotely in Ukraine. However, the newly secured jobs often paid less and required fewer qualifications than their previous roles in Ukraine. This change was particularly pronounced among highly educated individuals (49%) and women (of whom only 29% retained equivalent qualifications). Irrespective of their qualifications, many refugees found themselves in low-wage manual and auxiliary positions, with those caring for preschool-aged children having a lower rate of workforce participation.

2.4 Labour Market Overview

Maintaining a consistently low unemployment rate relative to other European nations, the Czech Republic's labour market has proven to be one of the region's most stable. By the end of 2022, the unemployment rate stood at 2.22%, the lowest within the European Union [MPSV, 2023, Eurostat, 2023b]. This figure, though representing a slight increase from the 2.20% recorded in the previous year, remains significantly below the EU average of 6%.

Regional differences within the Czech Republic's labour market, however, are also present. The capital city, Prague, for instance, reported an unemployment rate of 1.35%, a contrast to the 4.08% recorded in the Moravian-Silesian Region. Generally, these statistics mirrored those from the previous year, with a few exceptions. The Plzeň Region, for example, saw unemployment approach an increase of 1%, while the Pardubice Region witnessed a slight decrease just above 1%. Unemployment rates also displayed a seasonal pattern, typically rising during winter months and falling in the spring.

Year-on-year alterations in unemployment rates revealed a mild correlation with the resettlement and subsequent employment of Ukrainian refugees, registering correlation coefficients of -0.141 and -0.176, respectively. This is indicative of either a mildly positive effect of refugees on unemployment rates or a tendency for incoming individuals to select regions offering more favourable employment opportunities.

Despite global challenges such as the COVID-19 pandemic, the stability of the Czech Republic's employment rate and economic activity has also been resilient. See Figure 3. The demand for labour has remained high, with the number of job vacancies often surpassing job seekers. As of February 2022, the country listed more than 364,000 open positions for a mere 267,076 job seekers, featuring supply shortages. Sectors absorbing the majority of job seekers included retail, construction, public administration, defense, social security, wholesale, and education [MoLSA, 2023c].

However, the labour market in the Czech Republic is not without challenges. Certain demographic groups, such as women (particularly those with young children), older workers, low-skilled labourers, and individuals with disabilities, have consistently demonstrated low employment rates [OECD, 2020]. Notably, employment rates for women have remained roughly 15% lower than for men. The country also grapples with a considerable gender pay gap [Eurostat, 2023a]. At 19%, this gap considerably exceeds the EU27 average of 14%, rendering it among the highest in the EU.

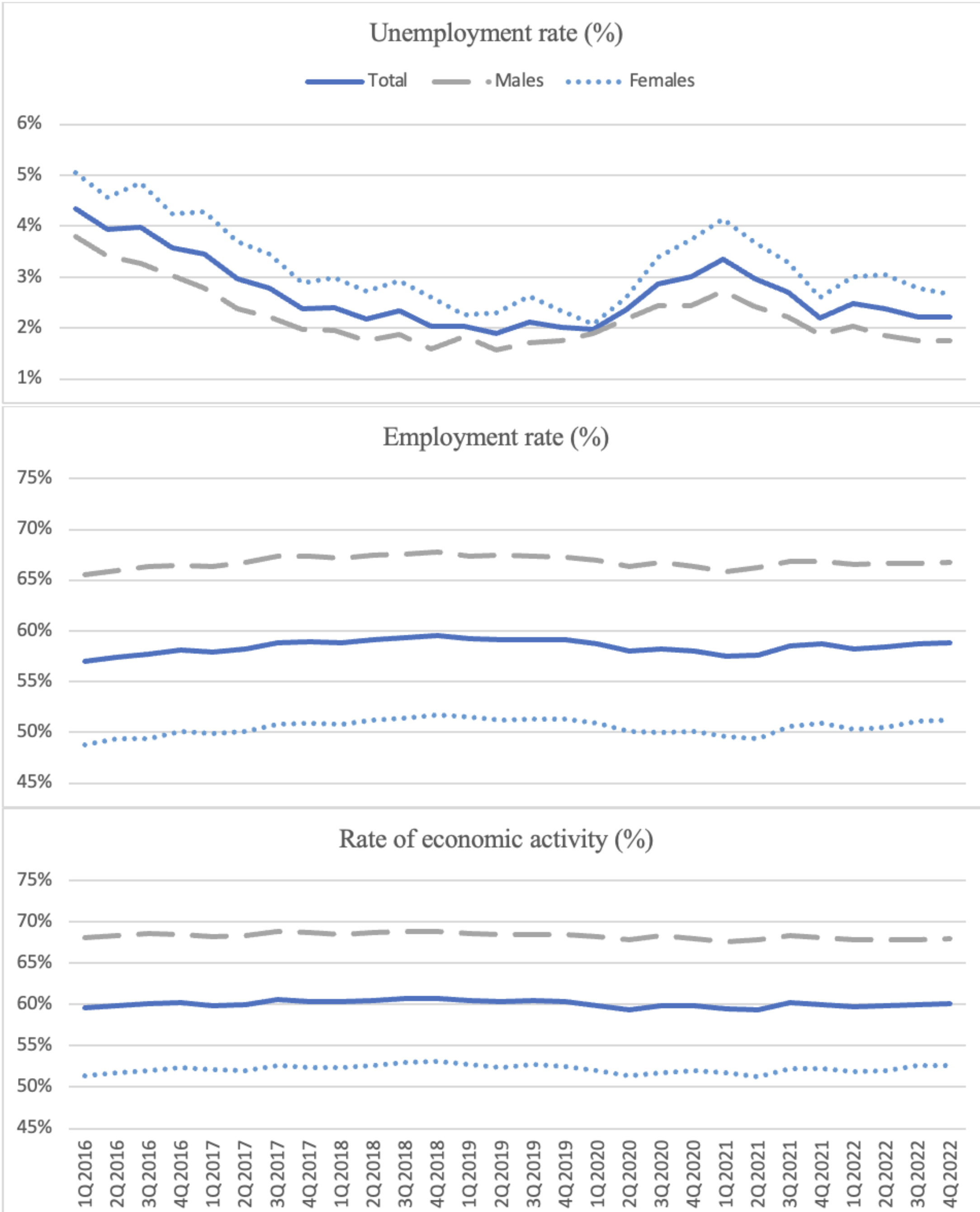


Figure 3: Snapshot of the Czech Republic's Labor Market

Note: data sourced from the Czech Statistical Office [MPSV, 2023].

2.5 Expectations

The theoretical predictions on immigration's labour market impacts are ambiguous, hinging on whether the labour inputs of refugees and locals are regarded as (im)perfect complements or substitutes. Additionally, the expected outcomes may differ greatly based on the degree of labour substitution elasticity. The fact that many refugees found some form of employment by the end of 2022, coupled with about 58% of refugees living below the poverty line, implying that even those who had not found work likely had been searching, suggests potential supply-side pressure on the labour market [MoLSA, 2022]. However, the tightness of the Czech labour market in 2021 and 2022, characterized by a greater number of vacancies than job seekers and low unemployment rates, may have offset this pressure without substantial disruption. Furthermore, the influx of refugees might have stimulated demand in certain sectors, leading to new employment opportunities. This demand increase may have originated from the consumption of goods and services and the potential need for additional labour in the education and healthcare sectors due to a high number of refugee children.

When considering the possible impacts, heterogeneity is a likely feature. The majority of incoming refugees were educated, working-age women. If we agree with prior studies that associate education levels with skills [Belot and Hatton, 2008], we will anticipate a significant increase in the pool of medium-to-highly skilled labour market participants. However, despite their skill levels, Ukrainians often found themselves in lower-skilled jobs due to language barriers and unfamiliarity with the local labour market, as observed from the actual outcomes. This situation suggests that refugees might compete with locals possessing lower education levels than themselves, potentially affecting local women with low to medium education levels more significantly since Ukrainian women are likely to enter sectors already dominated by local women.

On the other hand, an increase in available labour might result in affordable household services, motivating locals, especially those with household responsibilities and high expected market salaries, to (re-)enter the labour market [Cortés and Tessada, 2011, Farre et al., 2011, Cortés and Pan, 2013]. While the Czech Republic's employment rate was high overall, the rate for women consistently remained lower than for men; the gap for young women, especially mothers, was even more pronounced. However, it remains unclear whether such effects can be observed in the short run, or whether they only unfold in the long run.

3 Data and Descriptive Statistics

We employ two different data sets in our analysis. The Labour Force Sample Survey (LFSS), compiled and published by the Czech Statistical Office (CZSO), is our primary source of individual micro-level data on local labour force[CZSO, 2023b]. LFSS is a nationally-representative, rotating panel dataset administered quarterly across all Czech districts. Its large sample size and broad coverage make it a robust dataset for our purposes.

The dataset, made available upon request for scientific research purposes,[14] provides us with the socio-demographic profiles of locals (age, education, marital status) and their labor market characteristics (employment status, employment history, job preferences, industry and occupation,

[14] The Czech Statistical Office (CZSO) permits access to confidential statistical data specifically for scientific research, as detailed in Section 17 "Provision of confidential statistical data" of Act No. 89/1995 relating to the State Statistical Service. Additional conditions apply. For further details, consult the official CZSO data provision page [CZSO, 2023d]

hours worked, and unemployment duration). We employ data from sixteen successive waves of the LFSS, spanning 2019 to 2022. Our analysis focuses on individuals within the working-age bracket (18-65 years), resulting in a sample of 425,503 observations[15] across 77 districts.

The second data set concerns information on Ukrainian refugees. We rely on district-level aggregated data obtained from the Ministry of the Interior of the Czech Republic, which maintains a detailed record stratified by age and gender, updated monthly. We also accessed data on employment levels from the Ministry of Labour and Social Affairs, which maintains similar monthly records. We related these data points to the sizes of the local and employed local populations sourced from the Czech Statistical Office publications. All data regarding Ukrainians and locals was limited to individuals of working age.

Relying on the richness of the data, our analysis incorporates individual and district-level covariates. In addition to individual characteristics such as age, gender, marital and parental status, and education level, we factored in the population density at the municipal level (a finer measure than the district level), which served as an urbanization index. Furthermore, district-wise macroeconomic health and labour market conditions were proxied by the number of active and large companies, vacancies per working-age population, and average wage rate.

For descriptive statistics, see Table 4 and Table 5. A detailed list of the variables used, along with their definitions and associated data sources, is provided in Section 8.1.

[15] A methodological change by the CZSO in the final two quarters of 2022 prevented us from verifying the unique identifiers for individuals. However, we matched new observations with previous ones, prioritizing time-invariant variables.

	Diaspora of 0 %	Diaspora of 1 %	Diaspora of 2 %	Diaspora of 3 %	Diaspora of 4 %	Diaspora of 5 %	Diaspora of ≥6 %	Total
Labour Market Outcomes for locals								
Employed Status	.71	.73	.75	.78	.76	.78	.78	.75
Inactive Status	.25	.23	.23	.19	.21	.20	.19	.22
Unemployed Status	.03	.02	.01	.02	.01	.00	.01	.01
In Labour Force Status	.74	.76	.76	.80	.78	.79	.80	.77
Hours usually worked	39.2	39.8	40.0	40.5	39.8	40.7	39.5	39.9
Individual-level covariates								
Male	.48	.48	.49	.48	.48	.49	.47	.48
Age	44.4	44.2	44.4	44.7	43.5	44.0	42.5	44.1
Marital status	.52	.52	.53	.54	.53	.60	.47	.53
Foreign-born status	.99	.99	.99	.99	.99	.99	.99	.99
Pension or disability status	.15	.16	.16	.13	.13	.11	.10	.14
Parental status								
Child(ren) < 3y.o.	.09	.10	.09	.09	.11	.09	.10	.10
3y.o. ≤Child(ren) < 15y.o.	.18	.18	.19	.20	.19	.23	.17	.19
15y.o. ≤Child(ren) < 18y.o.	.13	.15	.15	.12	.14	.14	.10	.14
Education level								
No education	.00	.00	.00	.00	.00	.00	.00	.00
Basic education	.09	.09	.09	.07	.07	.06	.04	.08
Secondary without matriculation	.38	.37	.36	.34	.29	.29	.15	.34
Secondary with matriculation	.35	.35	.36	.36	.36	.39	.39	.36
University	.16	.17	.17	.20	.25	.23	.39	.20
Population dencity								
Dense population	.15	.13	.13	.17	.44	.52	.97	.24
Medium settlement	.52	.41	.36	.40	.23	.47	.02	.35
Sparsely populated	.32	.44	.49	.41	.31	-	-	.39
District-level covariates								
# active companies	190	176	149	166	329	232	294	427
# active large companies	283	271	187	200	562	302	572	773
# vacancies per population	.01	.02	.04	.04	.07	.08	.03	.03
Average wage rate (1,000)	33.2	33.8	34.5	35.5	35.5	37.5	43.7	35.3
Unemployment rate	.04	.03	.02	.03	.03	.02	.02	.03
Immigration patterns								
# of Locals pre-2022	113,505.7	86,597.86	68,779.45	69,779.27	12,0921.4	88,272.77	669,265.3	138,912
# of Locals post-2022	111,860.2	84,896.83	68,028.1	69,017.56	12,1614.2	88,498.38	661,637	138,833
# of Ukrainians pre-2022	247.77	583.43	1,111.74	1,756.55	3,627.46	3,437.95	37,682.31	4,581.4
# of Ukrainians post-2022	1,928.24	2,377.54	3,273.3	4,752.30	10,159.73	7,905.838	88,547.49	11,783.1
# of observations	31,567	140,535	126,269	29,105	48,627	10,635	38,765	425,503

Table 4: Descriptive Statistics by Diaspora

Note: This table presents descriptive statistics for local labour market outcomes ($y_{i,j,t}$), individual-level ($\mathbf{X}$), and district-level ($\mathbf{Z}$) covariates, as well as immigration patterns, all categorized by the percentage of the Ukrainian diaspora in 4Q2021. 'Diaspora of %' refers to districts where the proportion of Ukrainian immigrants to locals was % in 4Q 2021. The age range considered is 18-65 years. Mean values are provided for each variable; for continuous variables such as 'Hours Usually Worked,' 'Age,' 'Active Companies,' 'Active Large Companies,' 'Vacancies per Population (of working age),' 'Average Wage,' and all variables under 'Immigration Patterns,' the mean of these variables are reported. All other variables are presented as percentages.

	TD of 1%	TD of 2%	TD of 3%	TD of 4-5%	TD of 6-7%	TD of 8-9%	Total
Labour Market Outcomes for locals							
Employed Status	.73	.73	.75	.75	.76	.78	.75
Inactive Status	.24	.24	.23	.22	.21	.19	.22
Unemployed Status	.02	.02	.01	.01	.02	.01	.01
In Labour Force Status	.75	.75	.76	.77	.78	.80	.77
Hours usually worked	39.6	39.5	40.1	40.2	39.5	39.6	39.9
Individual-level covariates							
Male	.47	.48	.48	.49	.47	.47	.48
Age	45.0	44.2	44.1	44.5	43.5	42.6	44.1
Marital status	.57	.52	.53	.55	.50	.47	.53
Foreign-born status	.99	.99	.99	.99	.99	.99	.99
Pension or disability status	.15	.15	.15	.15	.14	.10	.14
Parental status							
Child(ren) < 3y.o.	.10	.10	.10	.09	.11	.10	.56
3y.o. ≤Child(ren) < 15y.o.	.17	.18	.19	.19	.20	.17	.10
15y.o. ≤Child(ren) < 18y.o.	.12	.15	.15	.15	.12	.10	.19
Education level							
No education	.00	.00	.00	.00	.00	.00	.00
Basic education	.10	.09	.09	.08	.08	.05	.08
Secondary without matriculation	.39	.37	.36	.36	.27	.17	.34
Secondary with matriculation	.33	.35	.36	.36	.35	.39	.36
University	.16	.18	.18	.18	.27	.37	.20
Population dencity							
Dense population	.47	.16	.17	.11	.52	.90	.24
Medium settlement	.52	.44	.35	.39	.26	.02	.35
Sparsely populated	-	.39	.47	.48	.20	.06	.39
District-level covariates							
# active companies	170	193	167	152	413	272	427
# active large companies	235	310	224	192	712	531	773
# vacancies per population	.01	.02	.03	.05	.06	.05	.03
Average wage rate (1,000)	332	335	346	351	346	431	35.3
Unemployment rate	.03	.03	.03	.02	.03	.02	.03
Immigration patterns							
# of Locals pre-2022	89,662.26	100,224	79,904.17	66,128.77	141,094.3	622,376.0	138,912
# of Locals post-2022	88,859.53	98,422.15	78,945.41	65,825.5	144,978.5	615,426.2	138,833
# of Ukrainians pre-2022	197.46	507.70	1,103.02	1,496.64	4,179.03	34,977.98	4,581.4
# of Ukrainians post-2022	1,326.94	2,340.13	3,184.06	4,225.29	12,482.31	82,339.38	11,783.1
# of observations	9,825	112,449	104,875	126,116	30,389	41,849	425,503

Table 5: Descriptive Statistics Stratified by Treatment Dose (TD)

Note: The table provides descriptive statistics on locals' labour market outcomes ($y_{i,j,t}$), individual-level covariates ($\mathbf{X}$), and district-level covariates ($\mathbf{Z}$), all conditioned on Ukrainian diaspora percentages in 4Q2021. 'Treatment Dose (TD) of %' refers to a % population increase in a district by 4Q 2022 due to the refugee wave. Data are split accordingly. Age is restricted to 18-65 years. Reported values are mean statistics for respective variables. For the variables 'Hours Usually Worked', 'Age', 'Active Companies', 'Active Large Companies', 'Vacancies per Population (of working age)', 'Average Wage', and all under 'Immigration Patterns', means of continuous variables are reported. Other variables are presented in percentages.

4 Empirical Analysis

We unfold our identification strategy in several steps, beginning with a two-way fixed effects (2WFE) model without distinguishing between the "treated" (1Q2022-4Q2022) and "untreated" (1Q2019-4Q2021) periods. We then differentiate these periods and estimate two extensions of the canonical Difference-in-Difference (DiD) model. Specifically, we adopt the DiD Estimators for Treatments Discretely Distributed across Groups and Time, based on works of[16] [de Chaisemartin and D'Haultfœuille, 2020a, de Chaisemartin and D'Haultfœuille, 2020b]. Lastly, we discuss the identification of Average Treatment Effects (ATEs) under the adapted versions of the DiD model.

4.1 Two-way Fixed Effects (2WFE)

We start by estimating the following 2WFE model:

$$y_{i,j,t} = \alpha + \beta \frac{Ukrainian\ Immigrants_{j,t}}{Locals_{j,t}} + \boldsymbol{\theta}'\mathbf{X}i,j,t + \kappa'\mathbf{Z}j,t + f_j + f_t + \epsilon_{i,j,t}, \tag{1}$$

where i, j, and t index individuals, districts, and time, respectively. The dependent variable, $y_{i,j,t}$, is the labour market outcome of interest. We consider both the extensive margin by looking at employment, unemployment, inactivity, or labour force participation and the intensive margin by considering the hours worked. The primary independent variable of interest is the ratio of working-age Ukrainian immigrants to locals of the same age group within a given district j and time t. Immigrants include both the Ukrainian diaspora and refugees. To account for the varying impact of immigration on districts of different sizes, we use relative-to-population immigration rates rather than absolute immigrant counts.

The matrices $\mathbf{X}$ and $\mathbf{Z}$ include individual- and district-level covariates.[17] The error term, ϵ, is clustered at the district level. The model accounts for district f_j and time-fixed effects f_t, effectively reducing confounding risks by controlling for district-specific (but time-invariant) and time-specific (but district-invariant) unobserved confounders under the assumption of linear additive effects [Allison, 2009, Wooldridge, 2010]. Section 8.1 provides detailed descriptions of control variables.

[16] This is also related to the broader sector of non-canonical difference-in-differences (DiD) estimators. In recent years, DiD has received substantial attention, with several alternative DiD estimators robust to heterogeneous effects proposed. Some apply to binary treatments following a staggered design, which means that once units receive the treatment, they cannot switch out of it [Sun and Abraham, 2020, Callaway and Sant'Anna, 2020, Borusyak et al., 2021]. Others apply to binary or discrete treatments that may not follow a staggered design [de Chaisemartin and D'Haultfœuille, 2020b]. Lastly, some estimators apply to continuous treatments following a staggered design. In this case, all units start with treatment equal to 0, and may then get treated at different dates with varying intensities, but once a unit receives treatment, its treatment intensity never changes [de Chaisemartin and D'Haultfœuille, 2020a, **?**].

[17] **X**: age, age squared, gender, marital status, parental status, education level, country of birth, pension or disability status, population density by municipality; **Z**: number of active companies, number of large active companies, average wage rate, number of vacancies per working-age population.

4.1.1 Causal Inference with the 2WFE Model

Our approach involves regressing the labour market outcome of interest on the ratio of immigrants to locals in each district while including relevant controls. This approach aligns with traditional methods in immigration economics research. We employ this strategy to evaluate the impact of immigration on local labour market outcomes, captured by β. The identification relies mainly on the variations in immigrant shares across regions and over time. Nonetheless, we confront the primary identification challenge common in migration literature: the self-selection problem. Immigrants tend not to distribute randomly across locations but are instead drawn to regions with favourable demand conditions [Borjas, 1987, Borjas, 1991, Jaeger, 2007].

This pattern holds true for the Czech Republic, where more than half of the Ukrainian immigrants before 2022 resided in five districts, each of which had among the highest GDP per capita in the country, higher levels of average wages, higher levels of education of locals and lower levels of unemployment. See Table 4 and Figure ??. This self-selection trend continued into 2022. Consequently, a direct comparison of high- and low-immigration areas may yield a biased estimate of the impact of immigration. The Shift-Share Instrument[18] is often used to address this endogeneity problem. However, [Jaeger et al., 2018] demonstrated that if the spatial distribution of immigrant inflows remains stable over a long period (as is the case with Ukrainian immigration to the Czech Republic), the instrument could correlate with lingering responses to previous supply shocks. Hence, we refrain from using the Shift-Share Instrument.

The panel data structure and 2WFE model we employ partly alleviate this endogeneity concern. The individual and time-fixed effects in our model adjust for time-invariant potential confounders like the economic conditions of a district or local labour demand. Considering the relatively short period from 2019 to 2022, it is reasonable to assume these factors remained stable, allowing our fixed effects model to average them out.

Variable: $\frac{\textit{Ukranian immigrants}}{\textit{Locals}}$	2019-2021		2022	
	VIF	1/VIF	VIF	1/VIF
Number of active businesses per district	191.1	.005	665.7	.002
Number of large active businesses per district	175.1	.006	607.2	.002
Average employment rate	18.4	.054	15.6	.064
Average labour force participation rate	15.9	.063	13.6	.074
Average of vacancies posted per district population	14.2	.071	13.5	.074
Average monthly wage	2.1	.471	4.5	.223
Average unemployment rate	1.7	.58	1.6	.623
Mean VIF	59.8	.	188.8	.

Table 6: Variance Inflation Factor (VIF)

However, this brief timespan presents its own set of challenges. In the pre-war period from 2019

[18] See, for example, [Altonji and Card, 1991, Card and DiNardo, 2000, Card, 2001b, Fairlie and Meyer, 2003, Dustmann et al., 2005b, Cortés and Tessada, 2011, Farré et al., 2011, Facchini et al., 2013, Romiti, 2017].

to 2021, there was limited variation in immigration rates across districts, with immigration rising steadily but slowly (refer to Figure 4 and Figure 5.). This lack of significant variation complicates identification using fixed effects. Additionally, a high correlation is observed between the relative immigration rate and certain macroeconomic variables, such as the number of all companies in a district, the number of large companies only, the unemployment rate, the employment rate, and the average wage. See Table 6 and Figure ??. The former group serves as our control variables, and the latter as our dependent variables, raising concerns about multicollinearity and potential reverse causality. These are issues that the canonical TWFE model alone cannot adequately address without further extensions.

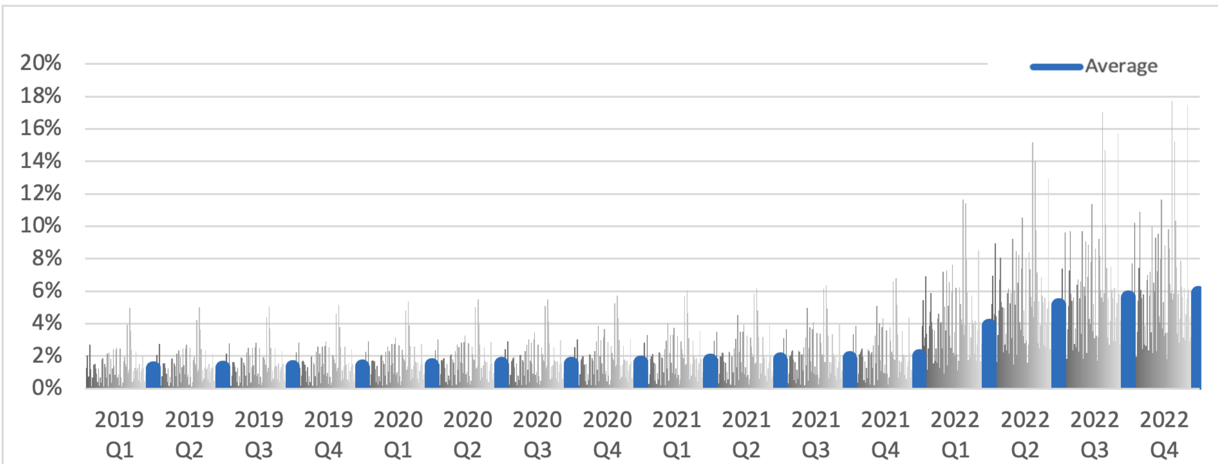


Figure 4: Ratio of Ukrainian Immigrants to Local Residents

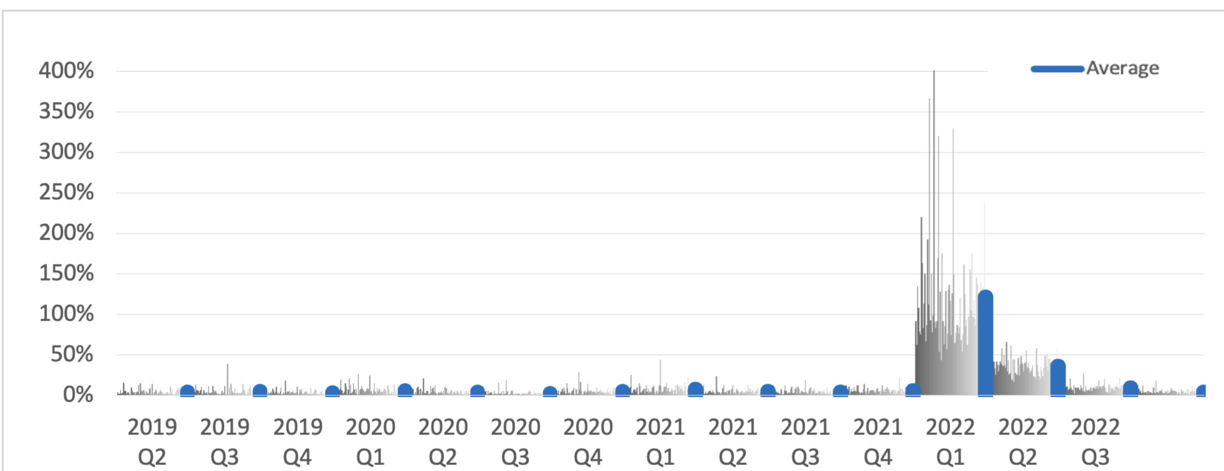


Figure 5: Quarter-on-Quarter Variation in Ukrainian Immigrant to Local Ratio

Note: data sourced from the Czech Statistical Office [CZSO, 2023c] and The Ministry of the Interior [MVCR, 2023b].

4.2 Difference-in-Difference with Discrete Treatment

The forced nature of the immigration shock caused by the Russian invasion of Ukraine allows us to analyze its impact on the local labour market in the context of a "natural experiment." Previous studies have used substantial immigration waves caused by civil wars or political unrest to establish causal relationships [Card, 1990, Hunt, 1992, Carrington and de Lima, 1996, Friedberg, 2001, Mansour, 2010, Glitz, 2012, Maystadt and Verwimp, 2014, Ceritoglu et al., 2017, Aydemir and Kırdar, 2017], eliminating the need for traditional selection-correction methods.

The Czech Republic's local labour market experienced an external shock, leading to a significant influx of refugees. This influx resulted in a variable population increase across Czech districts, ranging from 1% to 13% by the end of 2022.

We denote our "treatment period" with the dummy variable War_t, which takes the value of one starting from Q1 2022 onwards, zero otherwise. Our "treatment variable," denoted as TD_j, is defined as population surge from the refugee influx by the fourth quarter of 2022, which translates to the total "shock" each district experienced. Mathematically, it can be written as:

$$TD_j = \frac{Refugees_{j,4q2022}}{Locals_{j,4q2022}} \tag{2}$$

where TD_j is a discrete "treatment variable" with ten categories ("Treatment Doses"). The first category corresponds to a 1% increase in the district population as a result of immigration by the end of 2022, the second to a 2% increase, and so forth, up to the tenth category, which corresponds to a 10% or more increase. Each category groups individuals from their respective districts, creating a division of districts into those less affected and those more affected by population increases. This division is visualized in Figure 2.

Designed to vary by district but not over time, our treatment did not employ a staggered adoption design. This is justified as the primary wave of refugees had already arrived by the end of 1Q 2022, a situation akin to being treated at $T = 1Q$ 2022, with the treatment continuing subsequently. Moreover, the majority of the districts experienced simultaneous impacts.

The augmented 2WFE model we estimate is:

$$y_{i,j,t} = \alpha + \beta'(TD_j \times War_t) + \theta' X_{i,j,t} + \kappa' Z_{j,t} + f_j + f_t + \varepsilon_{i,j,t} \tag{3}$$

The model explores the impact of varying intensities of a given treatment on the outcome over time. In this context, our treatment - the influx of refugees - is presumed to have heterogeneous effects, as confirmed by our weight estimations based on the approach suggested by [de Chaisemartin and D'Haultfœuille, 2020a]. Consequently, we make use of their method for estimating Difference-in-Differences (DiD) with discrete treatment(s) under heterogeneous treatment effects. We refer to this as our 'parsimonious' DiD model.

Given the ongoing nature of the refugee influx (our treatment), we anticipate that earlier treatments could affect future labour market outcomes. Thus, we extend our baseline Difference-in-Differences (DiD) model by incorporating dynamic treatment effects, based on the framework suggested by [de Chaisemartin and D'Haultfœuille, 2020b].

Our analysis adheres to the notation proposed by de [de Chaisemartin and D'Haultfœuille, 2020a, de Chaisemartin and d'Haultfoeuille, 2023]. We track a single unit, specifically an individual from the Labor Force Survey, across multiple quarters ($T > 2$), from 1Q 2019 to 4Q 2022. Our data is segmented into G groups (with each group g representing an individual) and T periods (representing quarters).

For each group and time pair (g, t) within the set $1, ..., G \times 1, ..., T$, we denote $N_{g,t}$ as the number of observations for group g at time t. The total observations in our study are denoted by $N = \sum_{g,t} N_{g,t}$.

The refined Difference-in-Differences (DiD) approach measures the effect of a treatment, TD_j, on the outcome $y_{i,j,t}$ for each individual. For each observation (i, g, t) in the set $1, ..., N_{g,t} \times 1, ..., G \times 1, ..., T$, $D_{i,g,t}$ signifies the treatment status. Here, $(Y_{i,g,t}(0), Y_{i,g,t}(1))$ express potential outcomes without and with the treatment, respectively. The treatment variable, $D_{i,g,t}$, can assume a finite sequence of ordered values such as $0, 1, ..., d$.

'Stayers' are individuals who consistently do not receive treatment, so their $D_{i,g,t}$ value remains zero. Conversely, 'movers' initiate treatment, altering their $D_{i,g,t}$ value from 0 to another number.

By contrasting these groups, we can discern the treatment effect. If the outcome $y_{i,j,t}$ for 'movers' substantially differs from 'stayers', we can attribute this difference to the treatment.

Under specific assumptions (S5 - S8), that are mean independence, strong exogeneity, common trends, and the existence of "stable" groups (as discussed in [de Chaisemartin and D'Haultfœuille, 2020a]), we can estimate the causal effect of the treatment. These estimates produce Average Treatment Effects (ATE) that are robust to heterogeneity in treatment effects.

When translating this setting into more traditional DiD language, we categorize units based on their initial treatment levels, denoted by D_1. These levels may vary across units and might even start as non-zero values, resulting in the creation of multiple groups. We refer to periods with constant initial treatment levels D_1 as the "pre-treatment" periods, which occur prior to 1Q 2022. At $T = 1Q$ 2022, units whose treatment remains unchanged (the "stayers") comprise the control group, while those experiencing a treatment change (the "movers") constitute the treatment group(s). In our context, the 'stayers' are districts without a population increase, and the 'movers' are districts experiencing a population increase.

Since all districts experienced at least an 11% population increase, which we define as treatment, it implies that we don't have any 'stayers'—groups unaffected by the treatment—in our analysis. However, we circumvent this issue by employing a design with quasi-stayers, as suggested by [de Chaisemartin and D'Haultfœuille, 2020a, de Chaisemartin and d'Haultfoeuille, 2023].

Our analysis incorporates two versions of the initial treatment, D_1 and ${D_1}^*$:

1. For
$$D_1 = \frac{\text{Refugees}_{j,t}}{\text{Locals}_{j,t}} \tag{4}$$

, we consider the initial treatment as the refugee-to-local-population ratio, rendering all units equivalent, with an initial treatment value of zero before $T = 1Q$ 2022. This means that all the districts in our sample belong to the same group with $D_1 = 0$, and we compare them simultaneously across movers and stayers (see Figure 6). This approach offers the advantage of incorporating data from all districts simultaneously, thus enhancing our statistical power. However, it does not account for substantial pre-existing diasporas across districts, a factor closely correlated with local labour demand. Given that the refugees tended to settle non-randomly in districts with high GDP per capita and sizable pre-existing Ukrainian diasporas, suggesting that pre-existing diaspora communities influenced refugee settlement patterns and labour demand conditions, it becomes challenging to uphold the parallel trends assumption. This assumption requires $Y_t(d) - Y_{t-1}(d)$ to be mean-independent of treatments, with a consistent evolution of the treatment effect among movers and stayers. This motivates our second initial treatment estimator, ${D_1}^*$.

2. For

$$D_1^* = \frac{\text{Ukrainian Immigrants}j, 4q2021}{\text{Locals}j, 4q2021} \tag{5}$$

, the initial treatment refers to the proportion of Ukrainian diaspora in a district one quarter before the treatment period (4Q 2021). Units are grouped into seven separate groups (see Fig. 1) based on the initial immigration level in 4Q 2021: zero% (group 1), one% (group 2), and so on, up to seven% (group 8). (see Figure 7)) Based on D_1^* specification, we calculate Average Treatment Effects (ATEs) separately for each group. This approach is appealing as it facilitates defending the parallel trend assumption; we are comparing districts with similar initial attractiveness to earlier immigration waves. However, it narrows the sample size for each estimation.

The evaluation of both versions of initial treatments — D_1 and ${D_1}^*$ — will enable us to verify the consistency of results, both conditional and non-conditional on the pre-existing diaspora. It is important to note that both initial treatments remain constant over time for $T < 1Q$ 2022. In the case of D_1, this is a natural outcome, resulting from the specification of our treatment variable: the percentage of Ukrainian refugees to locals before 2022 rounds up to zero for all periods. For ${D_1}^*$, however, the treatment was intentionally held constant at the 4Q 2021 level. We chose not to incorporate the slight variation present in the data throughout 1Q 2019 - 4Q 2021. The rationale for this decision is our focus on the impact of the 2022 refugee wave, rather than the effects of immigration across the entire data period. By keeping ${D_1}^*$ constant, we simplify our model without sacrificing the accuracy of our core estimation—the impact of the refugee wave. Moreover, no anticipation of the refugee wave makes the distribution of Ukrainian immigrants in 4Q 2021 consistent with all previous periods.

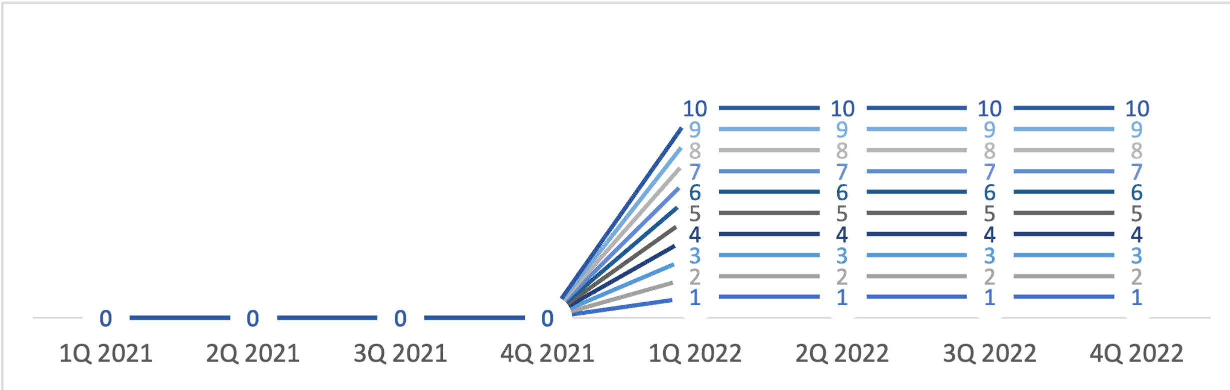


Figure 6: Initial treatment represented by the refugee-to-local-population ratio (D_1)

Note: This figure depicts the initial treatment D_1 (refer to Eq. 4), demonstrating the ratio of working-age Ukrainian refugees to locals of the same age. By design, this ratio is zero before 1Q 2022, with all districts consequently pooled together. From 1Q 2022, districts are assessed based on their respective "Treatment Doses" (see Eq. 2). Here, $\delta = TD$ distinguishes *stayers* (districts without refugee-induced population growth, TD $=$ 0%) and *quasi-stayers* (districts with a slight population increase, i.e., $\delta = \min\{TD\}$). In this instance, $\delta = 1\%$.

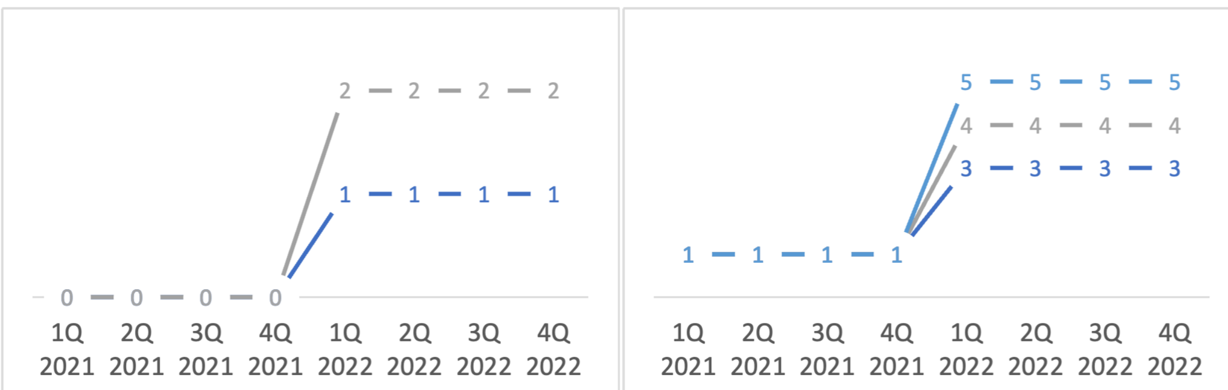


Figure 7: Initial treatment as the Ukrainian diaspora-to-local-population ratio (${D_1}^*$)

Note: The figure(s) portray the initial treatment ${D_1}^*$ (see Eq. 5), highlighting the ratio of working-age Ukrainian immigrants (i.e., Diaspora) to locals of the same age in 4Q 2021. This ratio varies among districts prior to 1Q 2022. Each district is grouped separately based on their pre-treatment Diaspora levels. The left figure represents districts with 0% Diaspora, while the right figure represents those with 1% Diaspora. From 1Q 2022, comparisons are made within each group separately based on their respective "Treatment Doses" (refer to Eq. 2). $\delta = TD$ differentiates *stayers* (districts with no refugee-induced population increase, TD $=$ 0%) from *quasi-stayers* (districts with slight population growth, i.e., $\delta = \min\{TD\}$). Here, $\delta = \min TD_{inc,j}$.

4.3 Employment Data Extension

In this section, we extend our analysis by incorporating employment data from the Czech Republic. We redefine our "treatment variable" to represent the growth in employment attributable to refugees who secured jobs by the end of 4Q 2022. Our analysis then repeats using this new treatment variable.

5 Results and Discussion

5.1 Two-way Fixed Effects (2WFE)

Table 7. reports the results of our two-way fixed effects (2WFE) model. Our analysis reveals that the ratio of Ukrainian immigrants to locals in the Czech Republic doesn't exhibit significant correlations with employment status, unemployment status, inactivity status, or labour force participation. However, we observe a negative influence on the typical number of hours worked per week.

Variable	Employed Status		Inactive Status		Unemployed Status		In Labour Force Status		Hours usually worked	
A) Estimating equation (1) with and without district level controls for macroeconomic and labour market health										
$\frac{Ukranian\ immigrants}{Locals}$	**0.0028**	**0.0036**	**0.0532**	**0.0777**	**-0.0560***	**-0.0814***	**-0.0532**	**-0.0777**	**7.439****	**6.758***
	(0.0617)	**(0.0790)**	**(0.0689)**	**(0.0849)**	**(0.0336)**	**(0.0424)**	**(0.0689)**	**(0.0849)**	**-3.556**	**-3.565**
Time and Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proxy for economic act.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.205***	0.139**	0.813***	0.869***	-0.0173	-0.0075	0.187***	0.131**	31.31***	33.60***
	(0.0533)	(0.0576)	(0.0548)	(0.0618)	(0.0274)	(0.0275)	(0.0548)	(0.0618)	-1.496	-1.993
Overall R^2	0.027	0.028	0.036	0.037	0.002	0.002	0.036	0.037	0.008	0.008
# of Obs.	482,589	480,234	482,589	480,234	482,589	480,234	482,589	480,234	324,144	322,413
Number of groups	130,833	130,824	130,833	130,824	130,833	130,824	130,833	130,824	89,949	89,93
B) Estimating equation (1) by gender: Male (M) and Female (F)										
	M	F	M	F	M	F	M	F	M	F
$\frac{Ukranian\ immigrants}{Locals}$	**0.0799**	**-0.0704**	**0.0098**	**0.145**	**-0.0897***	**-0.0747**	**-0.0098**	**-0.145**	**7.665**	**5.810****
	(0.0963)	**(0.0800)**	**(0.0981)**	**(0.0927)**	**(0.0536)**	**(0.0512)**	**(0.0981)**	**(0.0927)**	**-5.056**	**-2.682**
Intercept	-0.0272	0.380***	0.970***	0.690***	0.0570	-0.0701	0.0299	0.310***	30.60***	31.34***
	(0.0835)	(0.0805)	(0.0804)	(0.0867)	(0.0453)	(0.0531)	(0.0804)	(0.0867)	-4.687	-3.106
Overall R^2	0.043	0.020	0.061	0.025	0.002	0.002	0.061	0.025	0.012	0.006
# of Obs.	233,224	247,01	233,224	247,01	233,224	247,01	233,224	247,01	171,792	150,621
Number of groups	63,58	67,244	63,58	67,244	63,58	67,244	63,58	67,244	47,379	42,551
D) Estimating equation (1) by education level: Low education (L) and Medium-to-High education (M-H)										
	L	M-H	L	M-H	L	M-H	L	M-H	L	M-H
$\frac{Ukranian\ immigrants}{Locals}$	**-0.359***	**-0.0123**	**0.172**	**0.0784**	**-0.434****	**-0.0375**	**-0.172**	**-0.0784**	**22.84*****	**6.034**
	(0.200)	**(0.135)**	**(0.212)**	**(0.0720)**	**(0.165)**	**(0.0463)**	**(0.212)**	**(0.0720)**	**-7.469**	**-3.730**
Intercept	0.261	0.291**	1.064***	0.842***	-0.0771	0.0568	-0.0639	0.158*	33.08***	33.13***
	(0.239)	(0.120)	(0.0908)	(0.0851)	(0.0766)	(0.0394)	(0.0908)	(0.0851)	-6.298	-2.022
Overall R^2	0.008	0.025	0.017	0.034	0.002	0.001	0.017	0.034	0.005	0.007
# of Obs.	51,615	171,028	61,708	418,526	61,708	418,526	61,708	418,526	14,604	307,809
Number of groups	14,152	46,57	18,186	113,664	18,186	113,664	18,186	113,664	4,406	85,573

Table 7: 2WFE estimator results

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The variable of interest is the ratio of working-age (18-65y) Ukrainian immigrants to locals of the same age. M refers to males, F refers to females. L refers to low education (none or primary), M-H refers to medium to high education (secondary to tertiary).

When we separate the data by gender, males show no significant changes in any labour market outcomes. Females, on the other hand, appear to work more hours when the immigrant-to-local ratio increases.

The effects differ when we look at education levels. For individuals with low education, the ratio correlates negatively with employment and unemployment but positively with the number of hours worked. For those with medium-to-high education, no significant relationships surface.

We acknowledge potential complications, such as endogeneity due to self-selection, reverse causality, and multicollinearity. Therefore, we avoid interpreting these results as a causal relationship, but rather as associations which require further investigation.

5.2 Difference-in-Difference with Discrete Treatment and Heterogeneous Dynamic Effects

We explore the influence of the 2022 Ukrainian refugee influx on the employment outcomes of locals among three groups: the total population, females, and males. We measure the dynamic treatment effects on these demographics in three different time periods: the first quarter of 2022 (Effect_0), the second (Effect_1), and the third quarter (Effect_2).

In addition, we estimate the placebo effects. These counterfactual scenarios allow us to cross-check our methodology's assumptions. We apply a methodology introduced by de Chaisemartin and D'Haultfœuille (2020) to examine pre-treatment employment trends, ensuring that any trend variations between switchers and stayers reflect our assumptions, not treatment changes.

Our main findings, reported in the Table 8 and visualised in Figure 8, include the estimated effect, standard error, confidence interval bounds, total number of observations, count of switchers, and a joint hypothesis test p-value. This last measure confirms the statistical insignificance of all placebo effects.

The results for the total population (a) show negative coefficients across all periods subsequent to the refugee influx. Nevertheless, these results are statistically insignificant, suggesting the influx did not have a significant impact on overall employment. The non-significant placebo effects and a p-value of 0.2534 from the joint placebo test corroborate this assertion.

The findings for females(b) depict a similar pattern, with negative coefficients hinting at a potential decrease in the likelihood of female employment. These results, however, are statistically insignificant, with the exception of the Average effect which barely excludes zero in its lower confidence limit. Notably, we have employed bootstrap replications to estimate standard errors. At this stage, we use only the default 50 bootstraps to provide a preliminary approximation of results and to reduce computational intensity. For more reliable standard error estimates, a greater number of replications would be advisable, implying potential changes to the confidence limits. The joint placebo test yields a p-value of 0.4577, further supporting this group's insignificance of placebo effects.

The results for males (c), likewise, indicate negative but statistically insignificant treatment effects. The joint placebo test's p-value of 0.6321 aligns with our broader findings.

Table 8: Heterogeneous Dynamic Effects of Treatment on Local Employment, by gender

(a) Local Population

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0032	0.0024	-0.0079	0.0015	19999	13859
Effect_1	-0.0036	0.0026	-0.0088	0.0015	14487	10060
Effect_2	-0.0065	0.0042	-0.0148	0.0018	9248	6416
Average	-0.0017	0.0011	-0.0038	0.0003	43734	30335
Placebo_1	0.0011	0.0027	-0.0042	0.0065	14755	10236
Placebo_2	-0.0093	0.0063	-0.0217	0.0030	4569	3232
$e(p\_\text{jointplacebo}) = 0.2534$						

(b) Local Women

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0043	0.0028	-0.0097	0.0011	10206	7100
Effect_1	-0.0061	0.0036	-0.0131	0.0010	7420	5177
Effect_2	-0.0085	0.0076	-0.0233	0.0064	4726	3299
Average	-0.0025	0.0013	-0.0049	-0.0000	22352	15576
Placebo_1	0.0033	0.0041	-0.0048	0.0113	7502	5222
Placebo_2	-0.0118	0.0130	-0.0372	0.0136	2335	1654
$e(p\_\text{jointplacebo}) = 0.4577$						

(c) Local Men

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0021	0.0025	-0.0070	0.0029	9793	6759
Effect_1	-0.0011	0.0033	-0.0074	0.0053	7067	4883
Effect_2	-0.0046	0.0048	-0.0141	0.0049	4522	3117
Average	-0.0010	0.0012	-0.0034	0.0014	21382	14759
Placebo_1	-0.0011	0.0031	-0.0072	0.0050	7253	5014
Placebo_2	-0.0065	0.0068	-0.0198	0.0068	2234	1578
$e(p\_\text{jointplacebo}) = 0.6321$						

Interestingly, the size of the effect appears to increase over the quarters, reaching the highest values in the third quarter, as reflected in the dynamic treatment effects coefficients. Hence, including data from the final quarter of 2022, which we will do shortly, is important to corroborate these findings and better understand the progression of dynamic effects throughout the year.

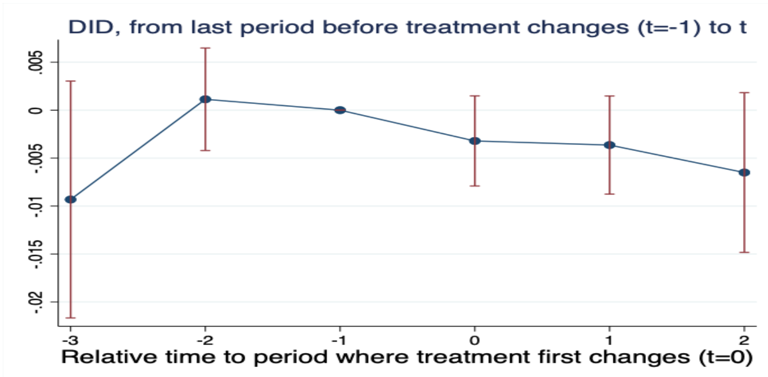
When we extend our analysis to educational subgroups, the results maintain the same pattern.

Females with only basic education or less display minor negative effects that are statistically insignificant. See Table 9 and Figure 9. A similar trend appears in the group with secondary education, although the effects are slightly more pronounced. For university-educated females, the effects shift in the opposite direction and become positive, although they remain insignificant.

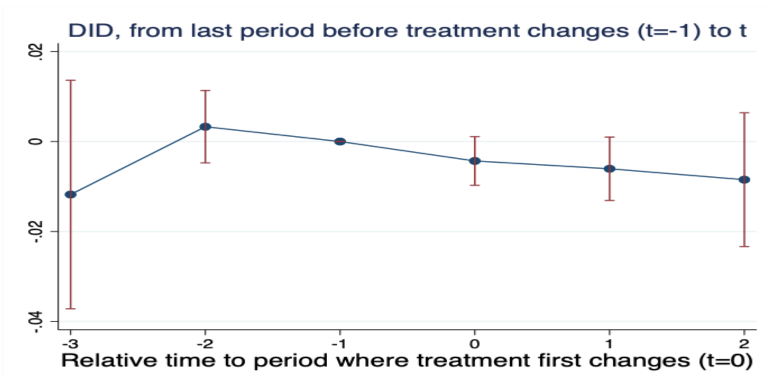
For males, across all educational strata - basic, secondary, and university - we observe slightly negative employment effects, all of which lack statistical significance. See Table 10 and Figure 10.

In summary, our results suggest that the 2022 Ukrainian refugee influx didn't significantly impact the employment rates of the examined groups. While there's a slightly negative effect on female employment, there's no major evidence of change in the labour market structure.

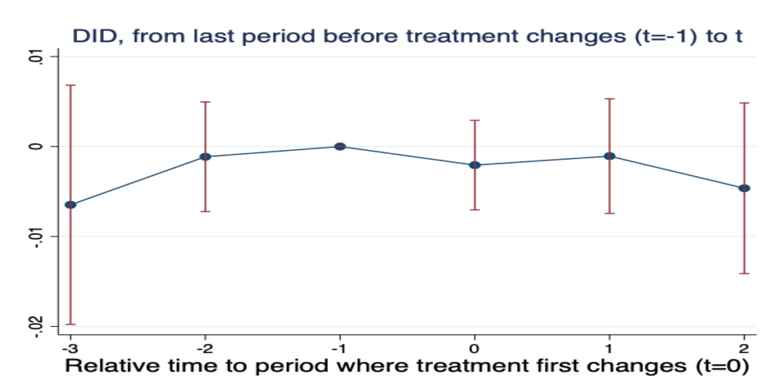
Figure 8: Heterogeneous Dynamic Effects of Treatment on Local Employment



(a) Local Population



(b) Local Women



(c) Local Men

Table 9: Heterogeneous Dynamic Effects of Treatment on Local Female Employment, by education

(a) ISCED (0-2): No Education or Basic Education

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0079	0.0237	-0.0544	0.0386	927	627
Effect_1	0.0015	0.0313	-0.0598	0.0627	665	454
Effect_2	-0.0380	0.0538	-0.1435	0.0675	362	239
Average	-0.0043	0.0127	-0.0291	0.0206	1954	1320
Placebo_1	0.0112	0.0112	-0.0108	0.0331	663	444
Placebo_2	0.0190	0.0439	-0.0671	0.1051	209	156

Note: $e(p\_jointplacebo) = 0.5730$

(b) ISCED (3-4): Secondary Education without or with Matriculation

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0066	0.0030	-0.0126	-0.0007	6976	4855
Effect_1	-0.0112	0.0041	-0.0193	-0.0031	5065	3538
Effect_2	-0.0036	0.0077	-0.0187	0.0116	3245	2267
Average	-0.0033	0.0015	-0.0063	-0.0003	15286	10660
Placebo_1	-0.0070	0.0047	-0.0162	0.0022	5131	3586
Placebo_2	-0.0218	0.0142	-0.0497	0.0060	1574	1119

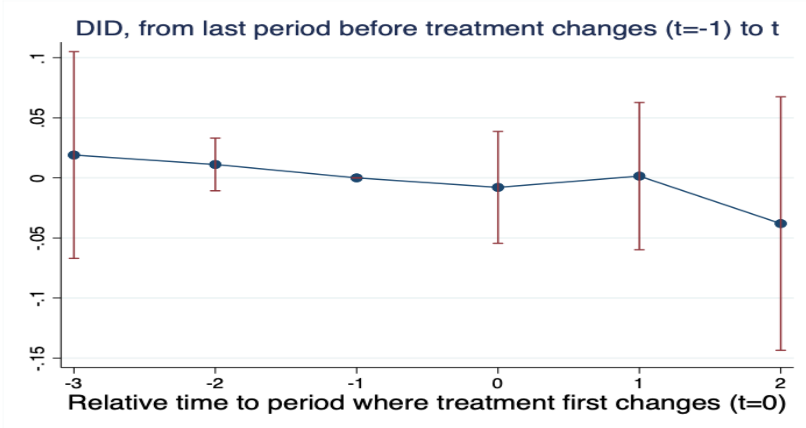
Note: $e(p\_jointplacebo) = 0.1538$

(c) ISCED (5-6): Tertiary Education

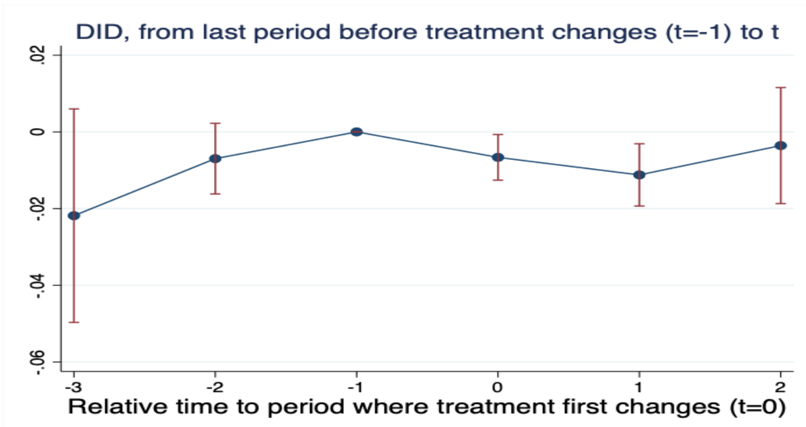
	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	0.0030	0.0090	-0.0147	0.0206	2295	1614
Effect_1	0.0070	0.0098	-0.0123	0.0262	1665	1170
Effect_2	0.0024	0.0151	-0.0272	0.0319	1061	758
Average	0.0016	0.0030	-0.0042	0.0075	5021	3542
Placebo_1	0.0298	0.0081	0.0139	0.0456	1687	1180
Placebo_2	0.0065	0.0308	-0.0538	0.0669	519	358

Note: $e(p\_jointplacebo) = 0.0010$

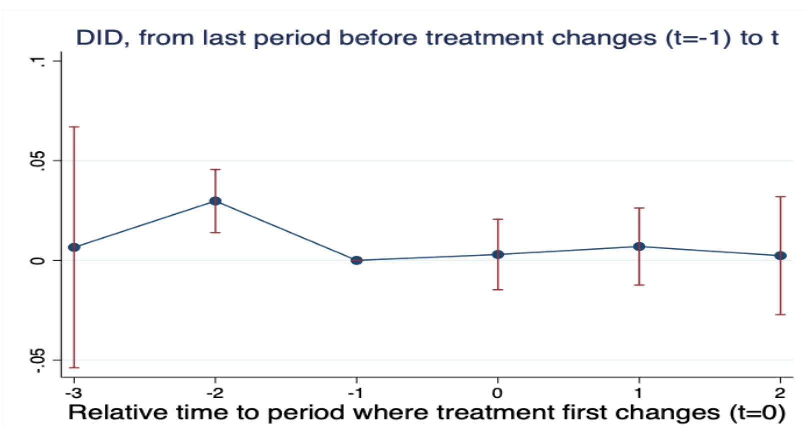
Figure 9: Heterogeneous Dynamic Effects of Treatment on Local Female Employment



(a) ISCED (0-2): No Education or Basic Education



(b) ISCED (3-4): Secondary Education without or with Matriculation



(c) ISCED (5-6): Tertiary Education

Table 10: Heterogeneous Dynamic Effects of Treatment on Local Male Employment, by education

(a) ISCED (0-2): No Education or Basic Education

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0059	0.0163	-0.0379	0.0261	706	465
Effect_1	-0.0003	0.0202	-0.0398	0.0392	480	321
Effect_2	0.0017	0.0341	-0.0652	0.0686	294	193
Average	-0.0011	0.0083	-0.0173	0.0151	1480	979
Placebo_1	0.0096	0.0175	-0.0247	0.0439	494	322
Placebo_2	-0.0369	0.0417	-0.1186	0.0449	122	91
Note: $e(p\_jointplacebo) = 0.2741$						

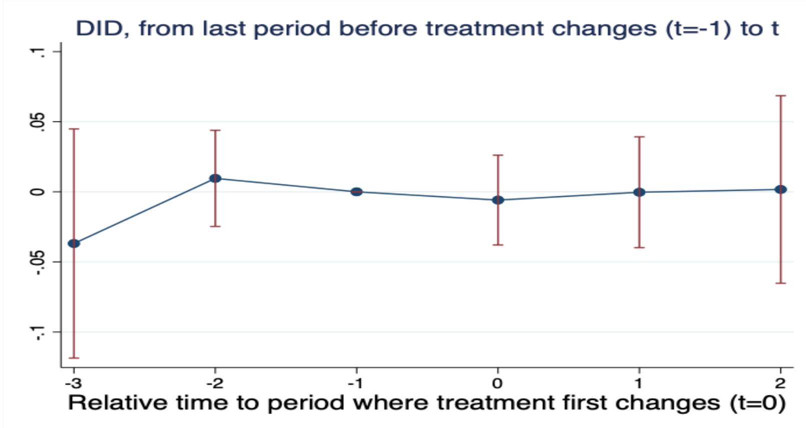
(b) ISCED (3-4): Secondary Education without or with Matriculation

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	0.0006	0.0045	-0.0083	0.0095	7309	5046
Effect_1	0.0005	0.0075	-0.0143	0.0152	5285	3647
Effect_2	-0.0059	0.0083	-0.0221	0.0103	3379	2327
Average	-0.0004	0.0026	-0.0055	0.0048	15973	11020
Placebo_1	-0.0013	0.0033	-0.0078	0.0051	5429	3769
Placebo_2	-0.0066	0.0076	-0.0216	0.0083	1658	1165
Note: $e(p\_jointplacebo) = 0.6569$						

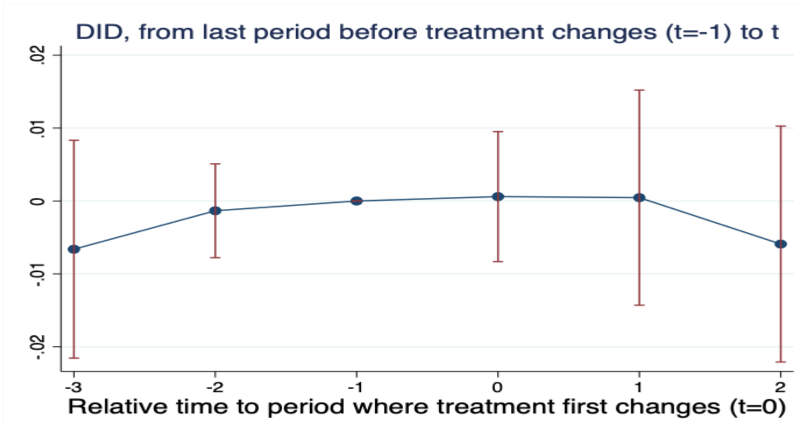
(c) ISCED (5-6): Tertiary Education

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.0097	0.0053	-0.0202	0.0008	1774	1245
Effect_1	-0.0096	0.0082	-0.0257	0.0064	1283	901
Effect_2	-0.0058	0.0093	-0.0240	0.0125	801	561
Average	-0.0035	0.0025	-0.0084	0.0014	3858	2707
Placebo_1	0.0000	0.0036	-0.0070	0.0071	1302	907
Placebo_2	-0.0023	0.0090	-0.0198	0.0153	418	298
Note: $e(p\_jointplacebo) = 0.9680$						

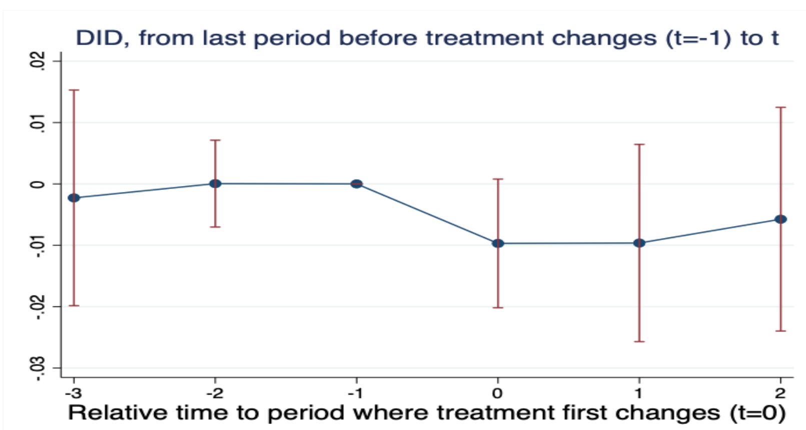
Figure 10: Heterogeneous Dynamic Effects of Treatment on Local Male Employment



(a) ISCED (0-2): No Education or Basic Education



(b) ISCED (3-4): Secondary Education without or with Matriculation



(c) ISCED (5-6): Tertiary Education

6 Robustness check

To ensure the robustness of our findings, we apply various checks. Among these, one significant method is relaxing the parallel trends assumption through non-parametric outcome regression.

6.1 Imperfect Parallel Trends: Non-Parametric Outcome Regression

In our scenario, we acknowledge that groups might experience differential trends. To address this issue, we reestimate our results using non-parametric outcome regression. This method serves to relax the stringent parallel trends assumption that is typically enforced in a Difference-in-Differences framework.

The use of non-parametric outcome regression is based on the methodology proposed by Heckman et al. (1997), which provides an unbiased estimator even under the condition of differential trends across groups. However, this estimator relies on the crucial condition that groups sharing the same category, as defined by a specified variable, should experience parallel trends.

6.2 Secondary Effects of the 2022 Refugee Influx

In considering the robustness of our findings, we must account for potential spillover effects. These arise from the interconnected nature of local labour markets. Specifically, the influx of immigrants could prompt a reactive shift amongst the local population. In response to such an immigrant supply shock, locals may reallocate their labour or capital to other cities in an effort to stabilize the national economy.

We plan to examine data on population movements between districts.

7 Conclusions

To be completed when all the analysis is done.

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8 Appendix

8.1 Appendix A: Variables description

In this appendix, we elaborate on the various definitions and variables use in the analysis. All the variables, excluding those categorized under the section "Additionally Created Using Aggregate Data Variables," are sourced from the Labour Force Sample Survey (LFSS) [CZSO, 2023b].

General Definitions:

Local population – This group comprises both Czech nationals and foreign nationals residing under permanent status, excluding Ukrainians. The age range for this demographic extends from 18 to 65 years. The choice of the upper limit is determined by the retirement age applicable to the majority of individuals in the Czech Republic, a figure that may fluctuate based on factors such as gender, birth year, and other contributing elements [MoLSA, 2023b].

Refugees – Individuals who were forced to leave Ukraine in the aftermath of the Russian Federation's invasion of Ukraine on February 24th, 2022. Includes everyone safeguarded under the Temporary Protection scheme. The age range for this group also spans from 18 to 65 years.

Diaspora – Individuals of Ukrainian nationality living in the Czech Republic under temporary or permanent legal statuses. Notably, Ukrainians who have naturalized and acquired Czech passports are not included in this classification but are instead considered part of the local population. This is because citizenship application necessitates a ten-year period of permanent residence in the country[MVCR, 2023a].

Immigrants – This category consists of both the Ukrainian diaspora and refugees. Therefore, it includes individuals under permanent or temporary visas/statuses, as well as those under the Temporary Protection scheme. The age range for this demographic of interest extends from 18 to 65 years.

Table 11: Description of Independent Variables

Variable	**Description**
Employed Status	Binary: 1 if the worker is employed, 0 otherwise
Inactive Status	Binary: 1 if the worker is not actively involved in job search or employment, 0 otherwise
Unemployed Status	Binary: 1 if the worker is without work but actively seeking employment, 0 otherwise
In Labour Force Status	Binary: 1 if the individual is either employed or actively seeking employment (unemployed), 0 otherwise
Hours usually worked	Continuous: Total hours worked in a typical week
Individual-level covariates	
Age and age squared	Discrete variable, ranges from 18 to 65
Gender	Binary: 1 if male, 0 if female
Marital status	Binary: 1 if married, 0 otherwise
Foreign-born status	Binary: 1 if the individual was born outside of the Czech Republic, 0 otherwise
Pension or disability status	Binary: 1 if the individual is a pensioner or disabled, 0 otherwise
Parental status	Categorical: 1 if at least one child <3; 2 if at least one child >2 and <15; 3 if at least one child >14 and <19, 0 otherwise
Education level	Categorical: 1 for no education (ISCED 0); 2 for basic education (ISCED 1,2); 3 for secondary without matriculation (ISCED 3b); 4 for secondary with matriculation (ISCED 3a); 5 for university (ISCED 5,6)
Sectorial industry of employment	NACE Rev. 2, 21 sections
Population density by municipality	Categorical: 1 for dense population; 2 for medium settlement; 3 for sparsely populated
District-level covariates	
# of active companies	Discrete: Total number of active firms in the district
# of large companies	Discrete: Total number of firms in the district with more than 250 employees
# of vacancies per working age population	Continuous: Number of job vacancies divided by the population of working age (15-64 years)
Average wage rate	Continuous: Average gross monthly earnings in the district
Additionally Created Using Aggregate Data Variables	
$\frac{Ukrainian\ Immigrants_{j,t}}{Locals_{j,t}}$	Ratio: Number of Ukrainian immigrants to the number of locals in each district at time t
$D_1 = \frac{Refugees_{j,t}}{Locals_{j,t}}$	Ratio: Number of refugees to the number of locals in each district at time t
$\frac{Employed\ Ukrainian\ Immigrants_{j,t}}{Employed\ Locals_{j,t}}$	Ratio: Number of employed Ukrainian immigrants to the number of employed locals in each district at time t
$D_2 = \frac{Working\ refugees_{j,t}}{Working\ locals_{j,t}}$	Ratio: Number of employed refugees to the number of employed locals in each district at time t