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

Agnieszka Postepska* Anastasiia Voloshyna †

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Abstract

Following the invasion of Ukraine by the Russian Federation on February 24^{th}, 2022, over a quarter of the Ukrainian population became displaced, with many seeking refuge across Europe. The Visegrad Group (V4) countries, and in particular the Czech Republic, emerged as key destinations. By the end of 2022, the Czech Republic had granted Temporary Protection to around 433 thousand Ukrainians, sheltering the highest per capita number of Ukrainian refugees worldwide. Following the enactment of the Lex Ukraine law, these refugees were granted benefits typically reserved for permanent residents, such as unrestricted access to the labour market, retraining programmes, and opportunities for self-employment. This resulted in a notable rise in the number of Ukrainians officially employed, subsequently expanding the Czech Republic's workforce. Using individual micro-level data from sixteen waves of the Labour Force Sample Survey (LFSS), collected between the 1^{st} quarter of 2019 and the 4^{th} quarter of 2022, we aim to examine *"the short-term effects of these higher-than-usual levels of Ukrainian official employment on the labour market outcomes of locals in the Czech Republic"*. In the absence of a randomised experiment, we employ several empirical strategies, including a two-way fixed effects model (TWFE) and extensions to the canonical difference in differences (DiD) estimator. Our preliminary results suggest that the influx of refugees into the workforce had no impact on local unemployment. Local females in districts with increased Ukrainian employment initially faced a brief drop in employment likelihood, but this effect was transient, with the market rapidly adjusting. Furthermore, there is consistent evidence pointing to an increase in the number of hours typically worked by local females as a result of the refugee influx. However, such patterns were not observed for the local males.

JEL Classification: F22, J15, J21

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

Note: The Labour Force Survey data for the 4^{th} quarter of 2022 is preliminary.

*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 invasion of Ukraine by the Russian Federation on February 24^{th}, 2022, over a quarter of the Ukrainian population became displaced (IOM, 2023b; UNHCR, 2023). By December 2022, the United Nations High Commissioner for Refugees reported that nearly 8 million individuals, mainly women of working age and children, had sought refuge across Europe, with about 5 million registering for Temporary Protection or equivalent national protection programs. 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 served as a primary refuge.[2] The Czech Republic, in particular, 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] As a result, the Czech Republic shelters the highest per capita number of Ukrainian refugees worldwide (MoLSA, 2022).

Unlike other unexpected, large-scale migration waves instigated by wars or political upheavals, Ukrainian refugees not only contributed to the Czech Republic's population growth but also had the opportunity to actively participate in the country's workforce. In March 2022, as refugees began arriving in Europe, the Czech government, alongside other EU countries, enacted the Lex Ukraine law (EC, 2022). This legislative framework extended to these migrants the benefits typically reserved for permanent residents, such as unrestricted access to the labour market, retraining programmes, and self-employment opportunities. As a result, by year's end, there was a marked surge in the official employment of Ukrainians, equating to nearly one-third of all registered refugees of working age (18-65 y.o.). This influx significantly expanded the Czech Republic's workforce, with marked variations across districts that we explore for our identification strategy.

This paper examines *"the short-term effects of these higher-than-usual levels of Ukrainian official employment on the labour market outcomes of locals in the Czech Republic"*.[4] Our focus is on inferring the potential consequences of the employment surge in 2022, rather than of the overall increase in the Ukrainian population or of Ukrainian employment on the labour market outcomes of locals over the entire panel duration.

Theoretical frameworks offer varied predictions concerning impacts of a large-scale immigration event, such as the Ukrainian refugee influx. First, if we treat the labour force as homogeneous, the standard competition framework suggests that an influx of immigrants might exert downward

[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 (for Refugees , UNHCR).

[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] Local workers refer to both Czech nationals and foreign nationals with permanent resident status excluding Ukrainians, aged 15 years and above. Throughout the paper we use terms like locals, refugees, diaspora, and immigrants. See Section A.1 for definitions.

pressure on wages due to the increased labour supply. If wages are sticky — perhaps due to union influences — this can result in rising unemployment. Alternatively, when considering labour as heterogeneous, outcomes depend on whether foreign workers are viewed as substitutes or complements to native workers. Assuming most immigrants are either unskilled or find it challenging to transfer their skill sets to the new market, as with many prior migration waves and in line with the skill-cell approach, skilled natives can be seen as complements to immigrant labour, while unskilled natives may find themselves in more direct competition.

Earlier empirical research often found little to no impact of immigration on the overall employment or wages of locals.[5] However, when the analysis is narrowed down to specific demographic groups, particularly those with demographics akin to the immigrants, more pronounced effects have been observed. For example, adverse effects of immigration have been pinpointed for local low-skilled males and minorities[6] or the influx of female immigrant labour, providing affordable household services, has been linked with incentivising locals engaged in household duties and those with high potential market salaries to (re-)enter the workforce.[7] Additionally, studies adopting a more general approach and looking at secondary effects of immigration have identified boosted capital markets in host countries (LaLonde and Topel, 1997; Ottaviano and Peri, 2011), reduced prices for non-traded goods and services requiring low-skilled labour (Borjas and Katz, 2007), and increased industry efficiency (Ottaviano et al., 2013).

Turning to the findings of our paper, we find little evidence consistent across the used models and their respective extensions that the increase in the workforce as a result of the 2022 Ukrainian refugee influx had an effect on local 'unemployment'. As for 'employment', we identify a semi-consistent pattern of local females from districts where more Ukrainians secured official work experiencing a temporary decline in employment likelihood. The adverse effect is short-lived, lasting for only one period since the impact — one quarter — and then reversing to positive and non-significant coefficients, potentially signalling that the labour market quickly adjusted to the inflow of refugees. This pattern is not observed for males; given that a significant number of employed Ukrainian refugees were female and were likely in competition with local women in similar roles with matching demographics, this reinforces the reliability of the finding that local females have faced a short-term adverse effect.

The limited impact on employment and unemployment outcomes that we have identified could be partially due to the various barriers refugees encountered, such as difficulties in transferring their skills to the new economy, lack of language proficiency, or potential movement of locals away from the most affected areas. In the main section of the paper, we analyse and discuss the above-mentioned concerns.

Another outcome of interest, 'hours usually worked', is the variable for which we find the most

[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 (1994); Card (2001); Borjas (2003); Dustmann et al. (2005a); Borjas and Katz (2007); Lemos and Portes (2008); Ottaviano and Peri (2011); Nickell and Saleheen (2015).

[7] See, for example, Cortés and Tessada (2011); Farre et al. (2011a); Cortés and Pan (2013).

consistent estimated effects. The body of evidence suggests that the treatment — i.e., the increase in the workforce as a result of the 2022 Ukrainian refugee influx — had a positive effect on the hours usually worked by local females. This effect increased in magnitude over time and retained significance for at least the first two periods since the beginning of the treatment, with variation depending on the model used. The evidence for males is less consistent; hence, we refrain from drawing any conclusions for them.

We note that these results are very much still in their preliminary stage, as the data for the 4th quarter of 2022 is still being finalized. Once we obtain the final data set, we will extend the analysis to other outcome variables of interest such as job separation, job acquisition, inactivity, or labour force participation.

For the analysis, we use individual micro-level data from sixteen waves of the Labour Force Sample Survey (LFSS), collected by the Czech Statistical Office (CZSO), spanning from 2019 to 2022. We limit our analysis to locals who are 15+ years old and exclude individuals of Ukrainian descent and/or nationality, resulting in a sample of 671,778 observations across 77 districts. For statistics on the Ukrainian refugees and diaspora, residing and/or working in the Czech Republic, we rely on aggregated district-level data sets provided by the Ministry of the Interior (2023) and the Ministry of Labour and Social Affairs (2023).

Our identification strategy unfolds in several steps. We implement a two-way fixed effects (TWFE) regression. Recognising the regression's potential shortcomings, we turn to the estimators proposed by de Chaisemartin and D'Haultfoeuille (2022) and Callaway and Sant'Anna (2021). Both are comparable under our design and aim to address some of the limitations of the TWFE regression. We then introduce extensions to the models, matching on selected individual characteristics and labour market conditions. Finally, moving to what we consider the most interesting stage of our identification strategy, we condition the estimator by de Chaisemartin and D'Haultfoeuille (2022) on the pre-2022 Ukrainian diaspora's employment levels. This allows us to relax a restrictive assumption upon which earlier estimators depended and check the validity of our results.

The remainder of the paper is organised as follows. The next section provides background information about the 2022 Ukrainian refugee influx, detailing settlement patterns, demographic characteristics, and labour market conditions within the Czech Republic. Section 3 discusses the data and descriptive statistics, while Section 4 outlines the identification strategy. Results and robustness checks are presented in Sections 5 and 6, respectively. Section 7 concludes. Additional details regarding definitions and variables used in the analysis can be found in Appendix A.1, while all tables and figures are presented in Appendix A.2.

2 Contextual Details

Settlement Patterns of Refugees. By 31 December 2022, the Czech Republic had welcomed approximately 433 thousand Ukrainian refugees, as documented in Figure 1. Upon arrival, Ukrainians were encouraged to apply for Temporary Protection status, with the address provided on their application, and any subsequent changes to it, serving as the primary source of information about their residential location.

The distribution of the refugee population across the country was not uniform, with pronounced clustering in certain regions. The capital, Prague, along with the Středočeský and Jihomoravský, accommodated 24%, 14%, and 10% of the refugee population, respectively. These regions, with some of the country's highest GDP per capita, also consistently report higher average wages, higher levels of educational attainment among locals, and lower unemployment rates (CZSO, 2023a). The pattern mirrors findings from earlier migration studies, suggesting that refugees might have self-selected into areas with favourable economic and/or labour demand conditions (Borjas, 1987; Jaeger, 2007).

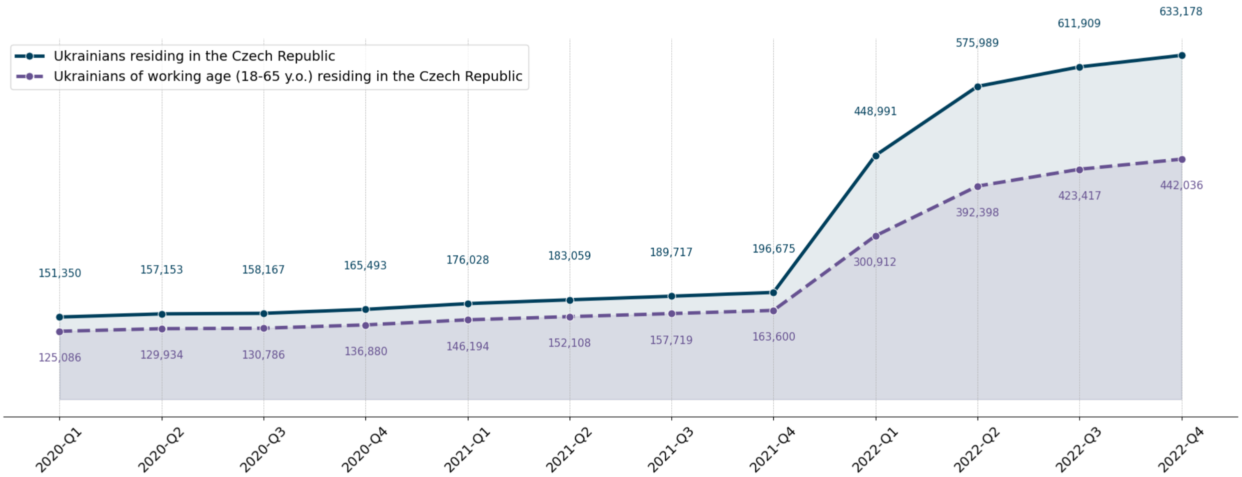

Figure 1: Timeline of refugee registrations for temporary protection in CZ

Note: Data sourced from the Ministry of the Interior (2023) of the Czech Republic.

A significant Ukrainian diaspora had already been established in the Czech Republic before the 2022 Ukrainian refugee influx — with nearly 197 thousand residents and around 195 thousand formally employed as of 31 December 2021— making up the largest foreign demographic in the country (MVCR, 2023b). Analogous to the pattern observed for the refugees, the Ukrainian diasporas also tended to settle in the country's economically advantageous areas.

Interestingly, when the distribution of refugees by district is expressed as a percentage of the total, it correlates strongly with the 2021 distribution of the Ukrainian diaspora, with a correlation coefficient of 0.99 (refer to Table 1.). Districts with an established Ukrainian presence might have been more appealing for refugees to settle/register in, aligning with prevailing migration and network theories (Hatton and Williamson, 1998; Woodruff and Zenteno, 2007; Patel and Vella, 2013; Stuart and Taylor, 2021). Further supporting this hypothesis, a 2022 UNHCR survey reports that 23% of respondents cited the presence of family or friends — the most commonly chosen option — as their main reason for selecting the Czech Republic as their destination country (UNHCR, 2022).

The sudden influx of refugees led to demographic changes all across the country, impacting every district. While all districts experienced a minimum increase of 1% in their working-age population

(18-65 y.o.), places such as Tachov, Plzeň-město, Prague, Cheb, Mladá Boleslav, and Karlovy Vary saw rises between 7% and up to 13% by the end of 2022 (refer to Figure 2(a)).

Variables	(1)	(2)	(3)	(4)
(1) Diaspora in 2021	1.00			
(2) Refugees in 2022	0.99	1.00		
(3) Employed diaspora in 2021	0.98	0.97	1.00	
(4) Employed refugees in 2022	0.80	0.81	0.81	1.00
(5) # active companies	0.85	0.99	0.79	0.80
(6) # active large companies	0.98	0.99	0.96	0.81
(7) # vacancies per working age population	0.89	0.91	0.92	0.82
(8) Unemployment rate	-0.05	-0.07	-0.10	-0.12
(9) Average wage rate (1,000)	0.50	0.47	0.50	0.37

Table 1: Matrix of correlations

Note: For the years 2021 and 2022, the figures for the diaspora and employed diaspora in 2021, as well as refugees in both years, are calculated monthly as a percentage of the district's total. Data sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

Workforce Integration and Labour Market Conditions. Contrary to many past, unexpected and large-scale migration waves instigated by wars or political upheavals, Ukrainian refugees not only contributed to Czechia's population growth, but also had the opportunity to actively participate in the country's workforce. In March 2022, as refugees began arriving in Europe, the Czech government, alongside other EU countries, enacted the Lex Ukraine law (EC, 2022). This legislative framework extended to these migrants benefits usually reserved for permanent residents, such as full access to the labour market, retraining programmes, and self-employment opportunities.

Subsequently, there was a marked surge in the employment of Ukrainians in the Czech Republic. By the 4$^{\text{th}}$ quarter of 2022, an additional 75 thousand had secured formal employment, of which 79% were women (MoLSA, 2023a). Another 5 thousand obtained valid trade licences, enabling entrepreneurial activity (MPO, 2023). Altogether, this increase in employment equated to nearly one-third of all registered refugees of working age (18-65 y.o.).[8]

This influx led to a notable enlargement of Czechia's workforce, with significant variations across districts (refer to Figure 2(b)). Districts such as Tachov, Mladá Boleslav, and the capital, Prague, experienced marked increases, with every 3$^{\text{rd}}$, 9$^{\text{th}}$, and 10$^{\text{th}}$ employed individual being Ukrainian by the year's end, respectively. In contrast, districts like Chomutov or Děčín saw little to no changes.

[8] Employment data are reported by citizenship but not by the type of stay permit. Thus, we cannot assert with certainty whether all Ukrainians who joined the Czech workforce in 2022 were refugees, or perhaps part of the existing diaspora in the country (re-)entering the workforce. However, considering that most Ukrainians in Czechia who relocated there before 2022 were already employed, it's highly probable that a very large majority are refugees.

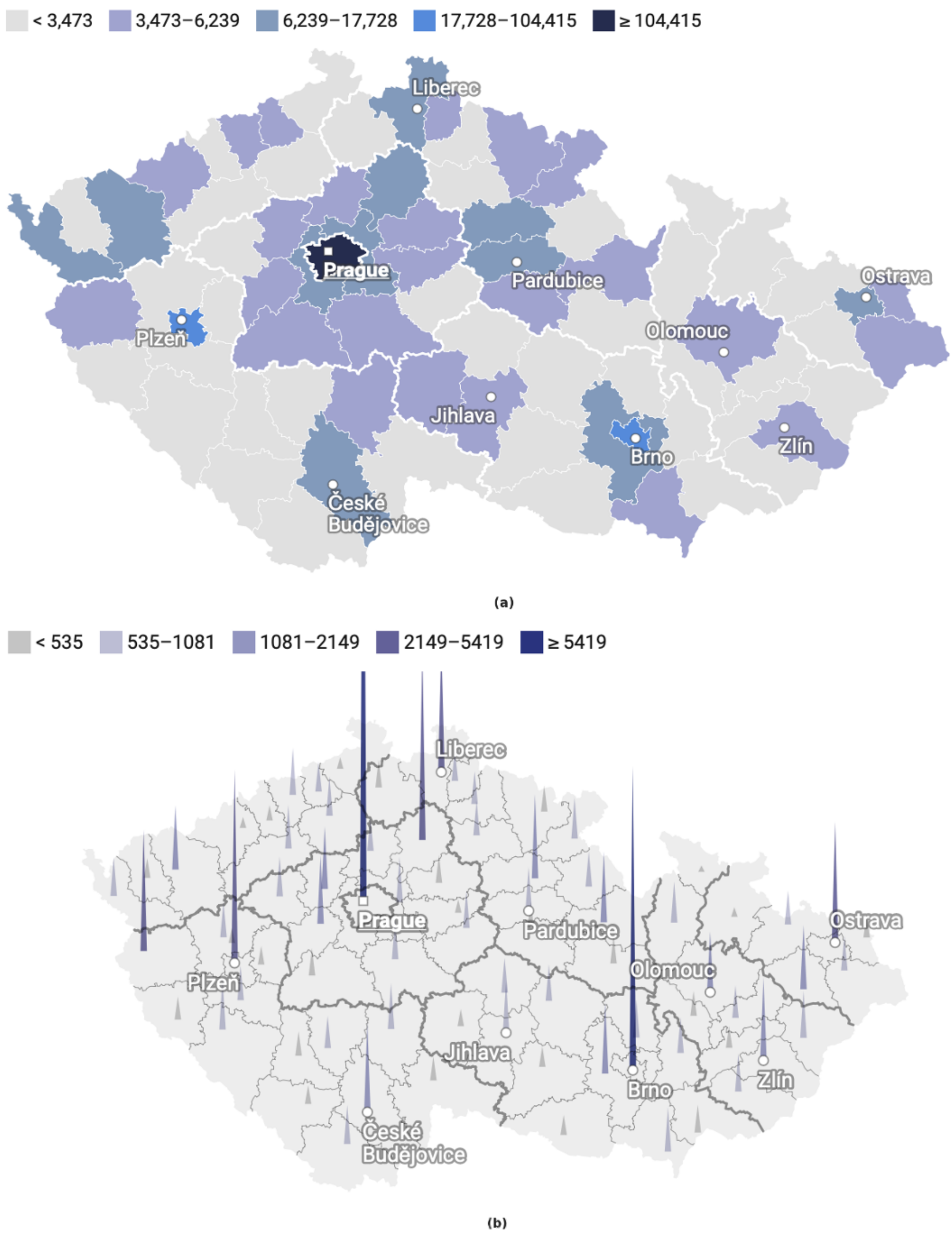

Figure 2: Map of registrations and employment.

Note: Panel(a): settlement patterns of refugees; Panel(b): workforce integration. Data sourced from Ministry of the Interior (2023) and Ministry of Labour and Social Affairs (2023) of the Czech Republic.

The distribution of employed refugees by district, when expressed as a percentage of the total, correlated strongly with the distribution of employed Ukrainian diaspora in 2021, with a correlation coefficient of 0.81, echoing the pattern we observed earlier for residency locations (refer to Table 1). The refugees might have preferred or found it easier to secure jobs in districts where Ukrainians had been established before 2022, or these districts may also have historically had a higher demand for foreign labour; it's quite plausible that both factors played a role. We will explore both the variation in workforce enlargement by district and the correlation with the pre-2022 diaspora employment patterns in our identification strategy.

The refugees entered one of Europe's tightest and most resilient labour markets. By the end of 2022, the unemployment rate in the Czech Republic, although marginally up from the previous year's 2.20%, stood at 2.22% — the lowest within the European Union (with the average recorded at 6%) (MPSV, 2023; Eurostat, 2023). Naturally, there were some district-level differences, especially between central and more peripheral districts: the unemployment rate peaked in Karviná at 8.47% in 2021 and in Bruntál at 6.89% in 2022 during the years 2019-2022.

The demand for labour had remained high in the years leading up to and including 2022, with the number of job vacancies often surpassing job seekers (refer to Figure 3(c)). As of January 2022, just before the refugee crisis began, the country listed around 352 thousand open positions against about 267 thousand job seekers, indicating supply shortages (MoLSA, 2023c).

Despite global economic challenges, such as the COVID-19 pandemic, the Czech Republic maintained a relatively stable employment rate and economic activity rate throughout these years (refer to Figure 3(b)). Although the employment data from 2020, registering at 5,235 thousand, reveal a dip — likely a consequence of the COVID-19 pandemic — the 2021 census data, standing at 5,290 thousand, resembles the figures from the pre-pandemic years, 2019 and 2018, signalling recovery. These stood at 5,303 thousand and 5,293 thousand, respectively (CZSO, 2022, 2021).

However, the labour market in the Czech Republic is not without its challenges. Certain demographic groups, such as women (particularly those with young children), older workers, low-skilled labourers, and individuals with disabilities, consistently show low employment rates (OECD, 2020). Notably, employment rates for women have remained roughly 15% lower than for men.

Demographic Characteristics of Refugees and Expectations as for their Impact on the Labour Market. Predicting the impact on a host country's labour market of a significant immigration event, such as the Ukrainian refugee influx, is not straightforward. Many factors come into play. How do refugees compare with the local workforce? Are refugees and the local workforce substitutes, i.e., competing for the same roles, or are they (im-)perfect complements, offering different skill sets? What is the extent of labour elasticity? How resilient is the labour market?

If we treat the labour force as homogeneous, the standard competition framework suggests that an influx of immigrants might exert downward pressure on wages due to the increased labour supply. If wages are sticky — perhaps due to union influences — this can result in rising unemployment.

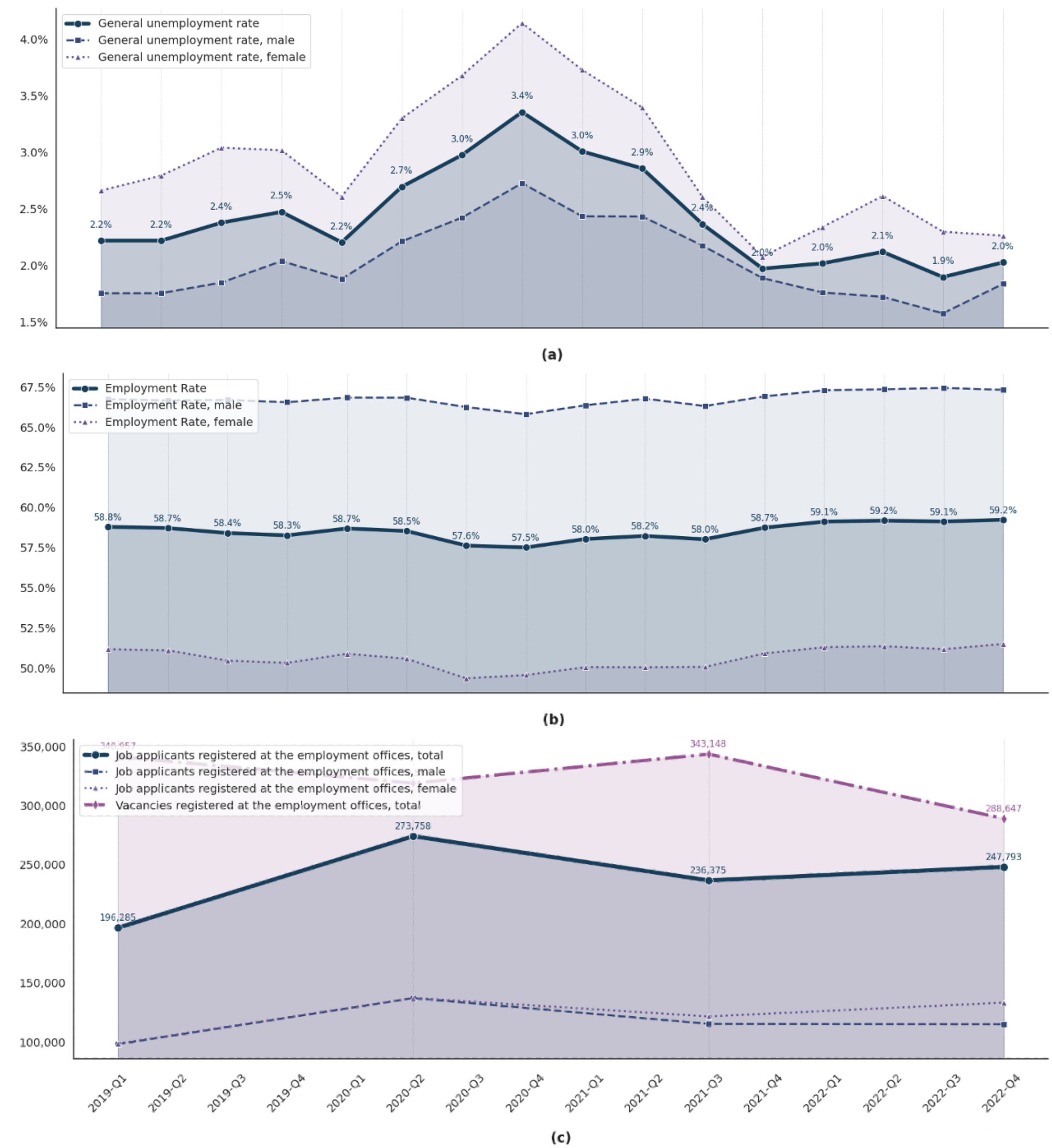

Figure 3: Snapshot of the Czech Republic's Labour Market

Note: Data sourced from the Czech Statistical Office (MPSV, 2023).

Alternatively, when we consider labour as heterogeneous, outcomes depend on whether foreign workers are viewed as substitutes or complements to native workers. This makes the demographic characteristics of both refugees and locals relevant and worth comparing. For the sake of this example, and in line with many previous migration waves, let's assume that the majority of immigrants are either unskilled or find it challenging to transfer their skill sets to the new market. In line with the skill-cell approach, if we categorise local labour into "skilled" and "unskilled", skilled natives can be seen as complements to immigrant labour. Conversely, unskilled natives may find themselves in more direct competition.

To better understand where the Ukrainian refugees fit in, we can examine their demographics. However, we do know that the 2022 Ukrainian refugee influx was predominantly composed of working-age women and children, a demographic profile distinct from typical migration patterns.[9] Women constituted 63% of the total refugee population, and this percentage rose to 69% within the age group 18-65 y.o. This gender imbalance can likely be traced back to Ukraine's wartime regulations restricting many males of combat age from leaving the country.

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

Table 2: Age and gender distribution: Ukrainian refugees vs. local Czech population

Note: Data sourced from the Ministry of the Interior of the Czech Republic (Ministry of the Interior, 2023) and the 2021 Census (CZSO, 2023b).

Around 64% of the refugees were of working age (18-65 y.o.). The age distribution among migrants mirrored that of the native Czech population (Ministry of the Interior, 2023; CZSO, 2023b), with one exception: only 4% of refugees were elderly (65+ y.o.), contrasting with the Czech 20% (refer to Table 2). In terms of education, the refugees generally had higher educational attainment levels than both the local Czech population and the Ukrainians who migrated before 2022 (refer to Table 3)[10] (MPI, 2023; CZSO, 2023b). Depending on the source, the percentage of those with

[9]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). Supplementary data were 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 methodologies.

[10]Table 3: To compare educational attainment across the surveys, some categories were merged. "No Education" remains unchanged. "Primary/Basic" combines "Primary" (UNHCR), "Basic" (MoLSA), "Lower Secondary" (IOM), and "Lower secondary/primary education" (CR). "Secondary" encompasses "Secondary" (UNHCR), "High school without diploma" (MoLSA), "High school with high school diploma" (MoLSA), "Upper secondary/Vocational" (IOM), and "Secondary, incl. vocational (no graduation)" (CR). "Post-Secondary" merges "Technical/Vocational" (UNHCR), "Post/Upper secondary/Vocational" (IOM), "Higher Professional" (MoLSA), "Upper/post-secondary

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 typically smaller, peripheral regions such as Tachov and Cheb.

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

Table 3: Educational attainment: Ukrainian refugees vs. local Czech population

Note: Data sourced from the 2021 Census (CZSO, 2021), and the surveys conducted by MoLSA (2022); IOM (2023a); UNHCR (2022).

Given that the majority of incoming refugees were educated, working-age women, and if we proxy the skills they have by their level of educational attainment, as done in earlier studies such as Belot and Hatton (2008), we could infer that there was a significant increase in the Czech Republic's pool of medium-to-highly skilled labour market participants. However, the actual transferability of refugees' human capital, especially in the short term, remains a challenge. Past studies have pointed out that immigrants often encounter difficulties in utilising their qualifications and past work experience in their host countries' labour markets.[11] This can lead to less favourable initial outcomes, such as underemployment.

According to several, albeit small-scale, surveys conducted by the Czech Ministry of Labour and Social Affairs, by the end of 2022, around half of the economically active Ukrainian refugees had found local employment (MoLSA, 2022). Yet, many of them took on roles that paid less and were below their qualifications compared to what they held in Ukraine. This was especially true for highly educated refugees and for women; only 49% and 29% respectively found jobs in line with their qualifications. Most refugees, irrespective of their qualifications, landed in low-wage manual or auxiliary positions. Moreover, those caring for preschool-aged children also had a lower workforce participation rate.

Language was yet another barrier. Literature identifies language proficiency as a key determinant for refugees' successful integration into host societies (Tip et al., 2019). Without strong language

education", and "Post-secondary professional education, Conservatoire" (CR). "Tertiary" includes "Doctorate", "Master", "Bachelor" (UNHCR), "PhD", "Tertiary" (IOM), "University"(MoLSA), and "Tertiary education" (CR). "Not Identified" comprises "Prefer not to answer" (UNHCR) and "Not identified" (CR).

[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).

skills, refugees can find themselves at a disadvantage in the labour market[12].This was a clear challenge for the Ukrainians; depending on the source, between 60%-87% self-reported as not being able to speak English, and 69%-91% had no Czech skills (MoLSA, 2022; UNHCR, 2022). However, a follow-up panel study reported that Czech skills among adults increased steadily throughout the year (MoLSA et al., 2023).

With these challenges in mind—language barriers, unfamiliarity with the Czech job market, and difficulties in transferring their skills—it is likely that Ukrainian refugees often found themselves competing for roles traditionally filled by locals with a lower educational background than themselves. In particular, local women with low to medium education might find themselves competing with Ukrainian women, especially in sectors already dominated by them.

On the flip side, a surge in the available labour force could make household services more affordable, potentially motivating locals, especially those with household responsibilities and high market salary expectations, to (re-)enter the labour market (Cortés and Tessada, 2011; Farre et al., 2011a; Cortés and Pan, 2013). Even though the Czech Republic enjoyed a high employment rate, it was consistently lower for women than for men, more so for young mothers. However, it remains unclear whether such effects can be observed in the short run or if they only unfold in the long run.

Finally, the tight Czech labour market, with more job vacancies than seekers and low unemployment rates, might have cushioned any potential disruptions from the refugee influx. The arrival of the refugees might even have stimulated demand in certain sectors, such as education and healthcare, due to the increased number of refugee children.

3 Data and Descriptive Statistics

We use three different data sets in our analysis. The primary source of individual micro-level data on the local labour force is the Labour Force Sample Survey (LFSS), compiled and published by the Czech Statistical Office (2023a). The LFSS is a nationally representative data set, administered quarterly across all Czech districts[13]. Importantly, it operates as rotating panel data, where individuals can be tracked across up to five sequential time periods. Its large sample size and detailed queries on labour market outcomes make it particularly suitable for our study.

The data set, made available upon request for scientific research purposes,[14] provides us with socio-demographic profiles of locals (age, education, marital status) as well as their labour market outcomes (employment status, employment history, industry and occupation, hours usually worked, and unemployment duration).

We utilise data from sixteen consecutive waves of the LFSS spanning from 2019 to 2022 and limit

[12] As reported by Chiswick and Miller (1995); Ferrer et al. (2006); Skuterud (2011); Chiswick and Miller (2012, 2013); Adsera and Ferrer (2015); Gazzola (2017).

[13] For the LFSS, the Czech Republic uses a stratified two-stage cluster sampling design.

[14] The Czech Statistical Office allows 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 more information, refer to the official CZSO data provision page (CZSO, 2023c).

our analysis to locals that are 15+ years old and exclude individuals of Ukrainian descent and/or nationality (0.7% of the data), resulting in a sample of 671,778 observations across 77 districts.[15]

	2019	2020	2021	Q4 2021	2022	Q4 2022
Labour Market Outcomes for locals						
Employed Status	0.53	0.52	0.52	0.52	0.52	0.51
Inactive Status	0.46	0.47	0.47	0.47	0.47	0.47
Unemployed Status	0.01	0.01	0.01	0.01	0.01	0.01
In Labour Force Status	0.54	0.53	0.53	0.53	0.53	0.53
Hours usually worked	39.76	39.67	39.19	39.14	39.20	39.13
Individual-level covariates						
Male	0.47	0.47	0.47	0.47	0.47	0.47
Age	52.44	52.94	53.26	53.48	53.81	54.00
Marital status	0.54	0.53	0.53	0.53	0.52	0.52
Pension or disability status	0.41	0.41	0.38	0.40	0.42	0.43
Foreigner	0.01	0.01	0.01	0.01	0.01	0.01
Parental status						
Child(ren) < 3y.o.	0.07	0.07	0.07	0.07	0.07	0.08
3y.o. ≤Child(ren) < 15y.o.	0.13	0.13	0.13	0.13	0.13	0.15
15y.o. ≤Child(ren) < 18y.o.	0.14	0.14	0.13	0.13	0.13	0.13
Education level						
No education	0.00	0.00	0.00	0.00	0.00	0.00
Basic education	0.14	0.13	0.13	0.12	0.13	0.13
Secondary without matriculation	0.36	0.35	0.35	0.35	0.35	0.35
Secondary with matriculation	0.34	0.34	0.34	0.34	0.34	0.34
University	0.17	0.17	0.18	0.18	0.18	0.18
Population density						
Dense population	0.25	0.25	0.25	0.25	0.25	0.25
Medium settlement	0.36	0.35	0.36	0.36	0.36	0.36
Sparsely populated	0.40	0.40	0.39	0.39	0.39	0.39
District-level covariates						
# active companies	43,414	45,972	40,174	19,336	47,176	48,240
# active large companies	80	77	80	82.10	82	83.52
# vacancies per population	0.05	0.05	0.06	0.06	0.05	0.05
Average wage rate (1,000)	33,133	34,690	36,741	39,091	38,569	41,638.36
Immigration patterns						
# of Ukrainians of working age	4,112	4,659	5,492	5,744	12,543	14,029
# of employed Ukrainians	4,944	5,244	6,181	6,513	7,870	8,249
# of locals of working age	140,169	141,650	142,434	139,690	140,302	140,403
# of employed local	114,207	114,646	115,141	115,043	113,947	113,444
# of observations	172,537	165,895	167,505	41,860	165,841	41,146

Table 4: Descriptive statistics

Note: The table reports mean values for local labour market outcomes ($y_{i,d,r,t}$), individual-level ($\mathbf{X}$), district-level variables ($\mathbf{Z}$), based on LFSS data. Data is restricted to locals aged 15+ and excludes individuals of Ukrainian descent and/or nationality. The immigration patterns data are sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

For statistics on the Ukrainian refugees and diaspora, residing and/or working in the Czech

[15] Due to a change in methodology by the CZSO in the final two quarters of 2022, we didn't receive the unique identifiers for individuals. We initially matched new observations with previous ones using deterministic data linkage where feasible. Subsequently, the remaining individuals were matched using probabilistic data linkage, with larger weights put on time-invariant and infrequently changing variables. More details can be found in Section A.1.

Republic, we rely on the aggregated district-level data sets provided by the Ministry of the Interior (2023) and the Ministry of Labour and Social Affairs (2023). Both ministries maintain detailed records stratified by age and gender, updated monthly. Data on the local Czech population are sourced from the Czech Statistical Office (2023b) public database.

Descriptive statistics are presented in Table 4. A comprehensive list of the variables used for the analysis, along with their data sources, can be found in Section A.1.

4 Identification Strategy

A recurring challenge in migration research, when attempting to identify the effects of immigration on the labour markets of recipient countries, is the self-selection problem. Immigrants often choose to settle and find employment in areas with favourable economic and/or labour demand conditions, resulting in non-random distribution patterns across a host nation (Borjas, 1987; Abowd and Freeman, 1991; Jaeger, 2007).

This pattern holds true for the Czech Republic. From 2019 to 2021, more than half of the Ukrainian immigrants selected just five economically prosperous regions in which they chose to reside. Each of these regions had a GDP per capita among the highest in the country and was characterised by higher average wages, higher levels of educational attainment among locals, and lower unemployment rates (CZSO, 2023a). Thus, a direct comparison between high- and low-immigration areas might produce a biased estimate of immigration's impact. To address this endogeneity problem, the Shift-Share Instrument has been frequently used in the migration literature.[16] However, as Jaeger et al. (2018) has shown, if the spatial distribution of immigrant inflows remains consistent over a prolonged period, such as with Ukrainian immigration to the Czech Republic, the instrument might correlate with lingering responses to previous supply shocks.

Instead of relying on traditional selection-correction methods, we use the sudden Ukrainian refugee influx of 2022, circumstantially forced by the Russian invasion of Ukraine, as a "natural experiment." Previous research has leveraged similar large-scale migration waves triggered by wars or political upheavals to infer causality.[17] But in contrast to many of these, not only did the Ukrainian refugees contribute to Czechia's population growth, they also had the opportunity to actively participate in the country's workforce. By year's end, there was a marked surge in the official employment of Ukrainians in the Czech Republic, equating to nearly one-third of all registered refugees of working age (18-65 y.o.). This influx led to a notable enlargement of Czechia's workforce, with significant variations across districts that we explore for our identification strategy.

We aim, therefore, to examine *"the short-term effects of these higher-than-usual levels of Ukrainian official employment on the labour market outcomes of Czech locals"*.[18] Our focus is on inferring the

[16]See, for example,Altonji and Card (1991); Card and DiNardo (2000); Card (2001); Fairlie and Meyer (2003); Dustmann et al. (2005b); Cortés and Tessada (2011); Farre et al. (2011b); Facchini et al. (2021); Romiti (2018).

[17]See, for example, Card (1990); Hunt (1992); Carrington and de Lima (1996); Friedberg (2001); Mansour (2010); Glitz (2012); Maystadt and Verwimp (2014); Ceritoğlu et al. (2017); Aydemir and Kırdar (2017).

[18]Locals refer to both Czech nationals and foreign nationals with permanent resident status excluding Ukrainians, aged 15 years and older. We use terms like locals, refugees, diaspora, and immigrants interchangeably. See Section A.1

potential consequences of the employment surge rather than the overall increase in the Ukrainian population in Czechia. This is because employment data offers a clearer distinction between districts that remain unaffected (control) and those impacted to varying degrees (treated). Given the sheer magnitude of the refugee influx, focusing on the overall increase in the Ukrainian population residing in Czechia would render every district affected, leaving no districts for control. Furthermore, while refugee registration might be skewed by migrants returning to Ukraine, relocating to other countries without deregistering, or unreported stays, the legally mandated official employment figures offer offer greater accuracy.

Our identification strategy unfolds in several steps. We start by defining the "treatment" variables and then implement a two-way fixed effects (TWFE) regression. Recognising the regression's potential shortcomings, we turn to the estimators proposed by de Chaisemartin and D'Haultfoeuille (2022) and Callaway and Sant'Anna (2021). Both are comparable under our design and aim to address some of the limitations of the TWFE regression. Finally, moving to what we consider the most interesting stage of our identification strategy, by conditioning the estimator by de Chaisemartin and D'Haultfoeuille (2022) on the pre-2022 Ukrainian diaspora's employment patterns, we relax a restrictive assumption upon which earlier estimators depended and check the validity of our results. In this section, we also discuss the assumptions upon which the estimators rely, strategies for testing them, and extensions to the estimators.

4.1 Defining the Treatment Variables

By defining the treatment variable(s) appropriately, we identify districts within the Czech Republic that experienced higher-than-usual levels of Ukrainian employment due to the 2022 Ukrainian refugee influx. We should clarify that our aim is not to discern the effect of Ukrainian employment on labour market outcomes of the locals over the entire panel duration, but rather to identify the short-term consequences of the abnormal employment levels in 2022. Thus, all districts prior to 2022 are considered 'untreated' (or 'not yet treated'), while districts that recorded a surge in Ukrainian employment in 2022 are classified as 'treated'. Treatment is assigned to locals at the district level — the most granular level at which the LFSS reports individuals' places of residence.

Selecting the Benchmark for the 'Usual' Ukrainian Employment Levels. A straightforward approach would be to use the employment averages of the years leading up to 2022 as the 'usual' levels. However, this would inadvertently factor in the reduced foreign employment in 2020, a result of the COVID-19 pandemic and subsequent border lockdowns, thus inflating the magnitude of our treatment variable. We rely on the 2021 data, when the number of employed Ukrainians had rebounded, mirroring the pre-COVID levels (CZSO, 2023).

Considering the foreign employment dip observed in the 4^{th} quarter over several years up to and inclusive of 2021 — likely due to seasonal workers moving out of employment at the end of the harvesting season — we have chosen two benchmarks for the 'usual' Ukrainian employment levels:

for the definitions.

the average employment in 2021 by district (d), as in (1); and employment in the 4^{th} quarter of 2021 by district (d), as in (2).

$$\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,\text{average in 2021}} \tag{1}$$

$$\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,4^{\text{th}}\text{ quarter of 2021}} \tag{2}$$

Normalising the Treatment Variable to Districts' Labour Market Sizes. An influx of 10 thousand foreign employees, for instance, would likely have a more pronounced effect, if any, on a district with about 50 thousand workers than on Prague, which is home to over 700 thousand workers. Using absolute figures might overstate the intensity of treatment in larger districts, like Prague, while underrepresenting the impact on less densely populated districts. To circumvent this, we normalise the treatment variable by a proxy of labour market size, for which we use the number of locals employed in 2021, as in (3).

$$\text{Employed Locals}_{d,\text{average in 2021}} \tag{3}$$

where the variable is set to vary by district (d) but not by time (t); it is fixed at the 2021 values. By anchoring the variable at its 2021 values, we prevent the treatment variable from being contaminated by the subsequent realisations of our outcome variables of interest (dependent variables) in 2022, which include employment status among locals.

The employment data are sourced from the 2021 census, providing more reliability than those from other surveys with significantly smaller sample sizes, such as the LFSS (CZSO, 2021). To avoid double-counting, the number of officially employed Ukrainians was subtracted from the total number of employed locals.

The employment levels in 2021 are not abnormal. Local employment has remained stable on average from the 1^{st} quarter of 2019 to the 4^{th} quarter of 2021, with a coefficient of variation at 0.01. Although the employment data from 2020, registering at 5,235 thousand, reveal a dip — likely a consequence of the COVID-19 pandemic — the 2021 census data, standing at 5,290 thousand, resembles the figures from the pre-pandemic years, 2019 and 2018, signalling recovery. These stood at 5,303 thousand and 5,293 thousand, respectively (CZSO, 2022, 2021).

We note that the 2021 census data was collected in the first two quarters of the year, historically showing slightly lower employment levels, a sign of seasonality (see Figure 3(b)). In Section 6, as part of our sensitivity analysis, we re-estimate the results of the models using the number of working-age locals (18-65 y.o.) per district as a proxy for the district's labour market size to normalise the treatment variable instead.

Treatment Specifications. Therefore, to minimise the chance that the results we find are biased due to foreign employment seasonality, we employ two versions of the treatment variables, as in (4) and (5).

$$\text{Treatment}^{I}_{d,t} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,\text{average in 2021}}}{\text{Employed Locals}_{d,\text{average in 2021}}} & \text{if } t \geq 2022 \\ 0 & \text{if } t < 2022 \end{cases} \tag{4}$$

or

$$\text{Treatment}^{II}_{d,t} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,4^{\text{th}}\text{ quarter of 2021}}}{\text{Employed Locals}_{d,\text{average in 2021}}} & \text{if } t \geq 2022 \\ 0 & \text{if } t < 2022 \end{cases} \tag{5}$$

where $\text{Treatment}^{I}_{d,t}$ and $\text{Treatment}^{II}_{d,t}$ are discrete variables,[19] indexed by districts (d) and time (t), with # distinct categories ('doses'). Each dose represents a 1% change in Ukrainian employment in district d at time t relative to a baseline period, adjusted for the district's labour market size.

Prior to 2022, the 'Treatment' value for all districts is set to zero, but from 2022 onwards, districts follow varying treatment trajectories. Refer to Figure 8 for the example. Some districts like Bruntal maintain zero treatment levels. In contrast, Blansko consistently receives a positive treatment dose of 1%, while Praha's treatment doses are also positive and increase over time up to 3% by the 2[nd] quarter of 2022. Some districts, such as Pardubice and Praha-zapad, experience negative treatment doses. The treatment varies in intensity and onset, as, for example, district Prerov's treatment kicks in in the 2[nd] quarter of 2022. Furthermore, some districts, like Pelhrimov, switch in/out of treatment, meaning they don't consistently experience a non-zero treatment throughout 2022 but revert to zero treatment before the year's end.[20]

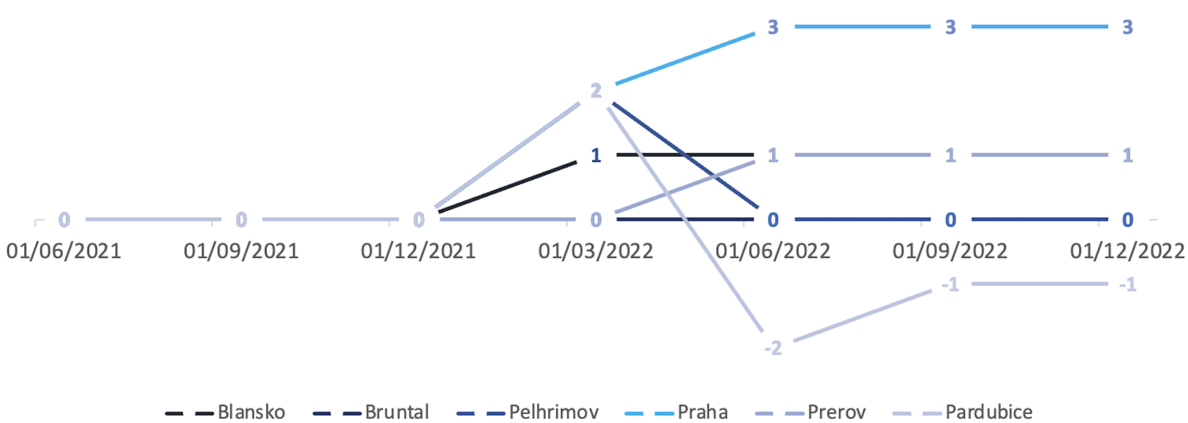

Table 5: Treatment I visualised: treatment trajectories for selected districts

[19]To ease the estimation process, values of Treatment^{I} and Treatment^{II} are rounded to the nearest integer. In Section 6, as part of our sensitivity analysis, we re-estimate the models using a continuous form of Treatment^{I} and Treatment^{II}.

[20]The variable Treatment^{II} in its form is identical to Treatment^{I} and differs only in that some districts are seen to experience a different dose of treatment or that the treatment kicks in earlier or later, all due to the difference in the selected baseline period for the "usual" employment level of Ukrainians.

The majority of the locals were residing in districts that experienced a positive dose ranging from 1% to 4%, corresponding to a rise in Ukrainian employment relative to the baseline period, due to the 2022 refugee influx, normalised by the district's labour market size. See Figure 6.

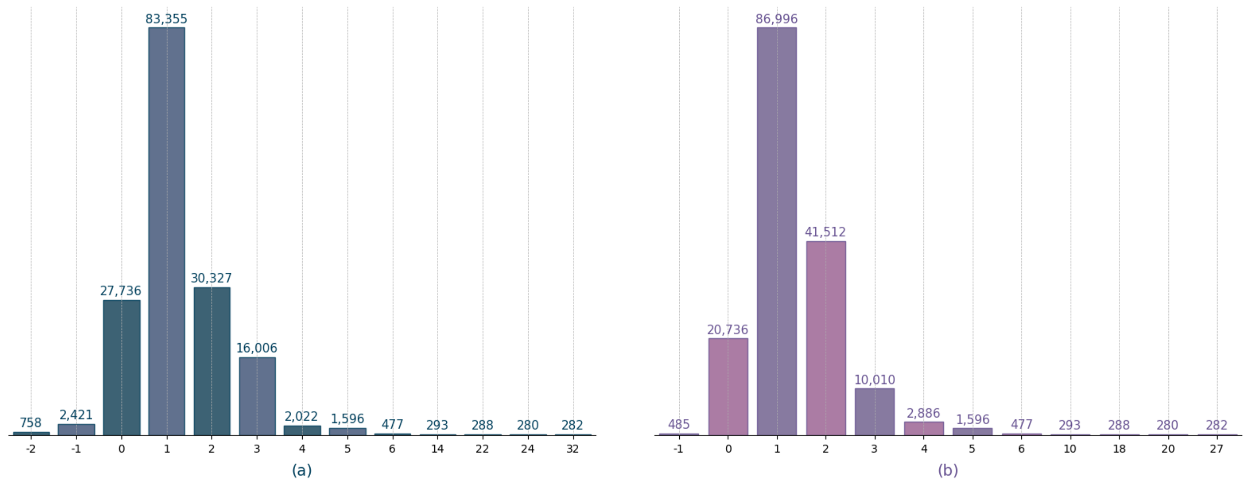

Table 6: Distribution of treatment doses I and II in 2022

Note: The histogram, based on the LFSS data, shows the counts of individuals receiving treatment doses in 2022. Panel a for (Treatment^I) and Panel b for (Treatment^{II}) depict distributions for the 1$^{\text{st}}$ to 4$^{\text{th}}$ quarters, respectively.

4.2 Static Two-Way Fixed Effects (TWFE)

We use the following static two-way fixed effects model (TWFE):

$$y_{i,d,r,t} = \alpha + \beta(\mathbf{Treatment}^{I \text{ or } II})_{d,r,t} + \boldsymbol{\theta}'\mathbf{X}_{i,d,r,t} + \kappa'\mathbf{Z}_{d,r,t} + f_i + f_t + (f_r \times f_t) + \epsilon_{i,d,r,t}, \quad (6)$$

where i, d, r, and t index individuals, districts, regions, and time, respectively. The dependent variable, $y_{i,d,r,t}$, represents the labour market outcome of interest. We explore both the extensive margin, considering employment, job separation, job acquisition, unemployment, inactivity, or labour force participation statuses, and the intensive margin by assessing the hours usually worked. The coefficients on the $\mathbf{Treatment}^I$ or $\mathbf{Treatment}^{II}$ variables, captured by β, are of primary interest. This model does not estimate the dynamic effects of the treatment.

Drawing on the richness of the LFSS data on locals, our analysis incorporates both individual-level characteristics ($\mathbf{X}$), and district-level characteristics ($\mathbf{Z}$).[21] At the district level, we include proxies that reflect the macroeconomic health and labour market conditions. Section A.1 provides detailed descriptions of control variables.

[21] $\mathbf{X}$: age, age squared, gender, marital status, parental status, foreigner status, education level, country of birth, pension or disability status, population density by a municipality, sector of employment (only included for hours usually worked); $\mathbf{Z}$: number of active companies, number of large active companies, average wage rate, number of vacancies per working-age population.

The error term, ϵ, when estimated, is clustered at the district level and is heteroskedasticity-robust for the binary dependent variables. The model accounts for individual f_i and time-fixed effects f_t, effectively minimising confounding risks by controlling for individual-specific (but time-invariant) and time-specific (but individual-invariant) unobserved confounders, assuming linear additive effects (Allison, 2009; Wooldridge, 2010).

The district fixed effects are multicollinear with individual fixed effects, as only around 111 individuals changed their district of residence over four years, making the district variable nearly constant. To account for unobserved confounders such as general economic health or long-term labour market demand, we introduce an interaction term $f_r \times f_t$ with region-fixed effects and time-fixed effects. Economic and labour market conditions vary sufficiently across regions (EURES, 2023), and by opting for regions over districts, we reduce the number of variables in the regression from 77×16 for districts to 13×16 for regions.

The specification of the "treatment" variable(s) results in a complex design, where districts may experience treatments that can be either: (i) negative or (ii) positive, (iii) positive and never-decreasing (meaning never switching out of treatment or having a treatment dose decrease), or (iv) a combination of strictly positive and negative treatments throughout 2022. We drop observations of the last type and re-estimate the TWFE model separately for each of the remaining three types.

4.2.1 Assumptions and Limitations of the TWFE Estimator

The two-way fixed effects (TWFE) regression, often seen as analogous to the difference-in-differences (DID) estimator, is frequently used in empirical research to assess the impact of a treatment on an outcome. The canonical DID model — comprising two periods, a binary treatment variable, and distinct treatment and control groups — allows for the identification of the average treatment effect on the treated (ATT), provided it satisfies several key assumptions. These include the "parallel trends" assumption, signifying that the average outcome among both the treated and non-treated populations would follow the same outcome evolution, and the "no anticipation" assumption, which requires that the treatment has no effect before its implementation. In this simple setting, given that the data provide a large number of independent clusters from both treated and untreated populations, the ATT can indeed be consistently estimated using the static TWFE regression.

However, the specification of our treatment variable(s), designed to capture the abnormal employment levels of Ukrainians in 2022 in a flexible and dynamic way, complicates the setting beyond the canonical DID model. Our design is not staggered. Some districts experienced changes in their treatment doses multiple times throughout 2022, as refugees continuously arrived in waves, rather than all at once. The treatment is not binary; converting it to such would prevent us from estimating the effects of different treatment intensities. Moreover, there is variation in the onset of treatment across districts; some became treated as early as in the 1st quarter of 2022, while for others, the treatment began later in the year.

For the TWFE estimator to remain unbiased for the ATT in our setting, we must impose an additional, rather stringent, assumption: the treatment effect should be constant both across individuals and over time. This effectively excludes the possibility of heterogeneous treatment effects, which, as the burgeoning literature indicates, is improbable in empirical applications[22].

The TWFE regression estimates the ATT as a weighted average of numerous treatment effects. Should we fail to satisfy the additional assumption, it may not identify a convex combination of these effects.[23] If some weights are negative, our estimator would not uphold the "no-sign reversal property", risking significant bias. The work by Roth et al. (2023) provides an overview of the discussion on the issue, summarising contributions from multiple authors.

Using the test proposed by de Chaisemartin and D'Haultfœuille (2020),[24] we evaluate the influence of negative weights on our treatment effects. For $Treatment^{I}$, restricted to positive doses only, the ATT for "employment status" is a weighted sum of 98 596 effects; 51 584 are positively weighted, while 47 012 received a negative weight. The total negative weight is -0.1389, influencing the overall ATT, given all weights sum to one. Similarly, for $Treatment^{II}$ for "employment status", out of 106 739 effects, 49 647 have positive weights and 57 092 are negatively weighted, with a total negative weight of -0.1746. Other variables of interest, such as "hours usually worked" ($Treatment^{I}$: sum of the negative weights is equal to -0.1451; $Treatment^{II}$: -0.1807), "unemployment status" ($Treatment^{I}$: -0.1389; $Treatment^{II}$: -0.1745), "job acquisition status" ($Treatment^{I}$: -0.1389; $Treatment^{II}$: -0.1746) and the rest show a very similar pattern. This suggests potential bias in our ATT estimates due to these negative weights.

4.3 Extended Difference-in-Difference Estimators (DiD)

Recognising the limitations of the TWFE regression, there has been a notable rise in methodological studies proposing alternative heterogeneity-robust estimators for different settings.[25] We adopt the estimator proposed by de Chaisemartin and D'Haultfoeuille (2022) for it can handle non-binary, non-staggered treatments and allows for dynamic/inter-temporal treatment effects estimation.[26]

Instead of calculating the ATT for all individuals in the panel jointly, as done in the TWFE regression, this estimator groups individuals carefully and performs calculations within these groups to avoid 'forbidden comparisons,' i.e., comparisons between individuals who start receiving treatment at different times or with different baseline treatment levels. It estimates the actual-versus-status-quo (AVSQ) effect for each treated individual, a variant of ATT. Additionally, we corroborate the consistency of our findings using the estimator by Callaway and Sant'Anna (2021).[27] For the most

[22] See for example, Borusyak and Jaravel (2018); de Chaisemartin and D'Haultfœuille (2020); Goodman-Bacon (2021); Imai and Kim (2021); Sun and Abraham (2021); de Chaisemartin and D'Haultfœuille (2022), among others.

[23] A convex combination of treatment effects means that weights assigned to each treatment effect are non-negative and sum up to one.

[24] Implemented with the Stata command "twowayfeweights". We use type(feTR) and estimated both with and without the covariates. Results remain largely similar. We report the results with the covariates included. For details, see de Chaisemartin et al. (2019).

[25] See, for example de Chaisemartin and D'Haultfœuille (2020); Borusyak et al. (2021); Callaway and Sant'Anna (2021); Callaway et al. (2021); Sun and Abraham (2021); Imai and Kim (2021); Wooldridge (2021); de Chaisemartin and D'Haultfoeuille (2022); de Chaisemartin et al. (2023b); Roth and Sant'Anna (2023), among others.

[26] Implemented with the Stata command "did_multiplegt_dyn". We clustered standard errors at the individual level, though if estimated without, the se are almost identical. For details, see de Chaisemartin et al. (2023a).

[27] Implemented with the Stata command "csdid". For details, see Rios-Avila et al. (2021).

part of our design, both estimators yield numerically analogous results.

The notation used aligns with that of de Chaisemartin and D'Haultfoeuille (2022), with slight modifications for compatibility with the TWFE section of our paper. We observe labour market outcomes of an individual ('local'), denoted as i, in district d within region r, across multiple quarters t, as reported by the LFSS data set. Since the LFSS is a rotating panel, we can only use data from the 1st quarter of 2021 to the 4th quarter of 2022 to estimate the AVSQ effect of the 2022 higher-than-usual levels of Ukrainian official employment on the labour market outcomes of Czech locals.[28] Treatment is assigned to locals at the district level d in region r, meaning that all individuals within a district receive identical treatment doses at time t. To simplify notation, we exclude d, r and denote treatment as $D_{i,t}$ for individual i at time t.

The individual AVSQ effect for ℓ periods, for every $\ell \in \{1, \ldots, \max(\ell)\}$ is estimated by:[29]

$$\mathrm{DID}_{i,\ell} = Y_{i,F_i-1+\ell} - Y_{i,F_i-1} - \frac{1}{N^i_{F_i-1+\ell}} \sum_{i':D_{i',1}=D_{i,1},F_{i'}>F_i-1+\ell} \left(Y_{i',F_i-1+\ell} - Y_{i',F_i-1}\right), \tag{7}$$

where i and t index individuals and time, respectively. The dependent variable, $Y_{i,t}$, is the labour market outcome of interest: employment, job separation, job acquisition, unemployment, inactivity, labour force participation statuses, and hours usually worked. F_i denotes the period in which the treatment changes for individual i for the first time. N^i_t is the number of individuals i' whose treatment either never change or has not yet changed by $F_i - 1 + \ell$ and who share the same baseline treatment as i from the beginning of our panel to $F_i - 1$. These individuals form the control group for treated individual i at time $F_i - 1 + \ell$.

The pre-treatment period (or baseline treatment) for an individual i begins sometime before 2022, depending on when i is observed for the first time in the rotating panel. This period continues until i experiences the first detectable change in treatment, accommodating non-zero baseline treatment levels. For instance, an individual might have been experiencing a treatment corresponding to 1% of Ukrainians employed in their respective district for multiple quarters. Only when this treatment level changes for the first time does the individual begin to receive the "treatment" whose effect we aim to estimate. The timing of this change can vary among individuals. The DiD estimator then compares the $F_i - 1$-to-$F_i - 1 + \ell$ outcome evolution of individual i, for whom the treatment changes, to the average outcome evolutions of individuals i' with the same baseline treatment level

[28]LFSS is a rotating data set, tracking an individual for up to five consecutive periods. To ascertain the AVSQ effect, one must observe the same individual at least once pre-treatment and once during the treatment period. At the earliest, individuals initiate treatment in the 1st quarter of 2022; hence, data on individuals recorded prior to the 1st quarter of 2021 are disregarded as their observations would not coincide with the treatment period. Consequently, we exclusively employ the 2021 and 2022 data, resulting in a sample of 333,346 observations across 77 districts. See Section 5 for details.

[29]This is conditionally unbiased under the assumptions of (i) no anticipation, (ii) parallel trends for the status-quo outcome conditional on the period-one treatment, (iii) the no-crossing condition, and (iv) confirming the design conforms with the constraints posited by de Chaisemartin and D'Haultfoeuille (2022). For a comprehensive overview of these assumptions, one can refer to Assumptions 1, 3, 4, and 5 in de Chaisemartin and D'Haultfoeuille (2022).

as i, who are either never treated or whose treatment has not changed yet by $F_i - 1 + \ell$.[30] We are able to estimate the instantaneous, dynamic and inter-temporale ffects of the treatment for all feasible $\ell \in \{1, \dots, \max(\ell)\}$ periods. In our setting, $\max(\ell)$ is 4 periods, i.e., from the 1st to the 4th quarter of 2022. But for those individuals who start receiving the treatment later than the 1st quarter of 2022, it is less.

Using the individual AVSQ effects estimated by $\text{DID}_{i,\ell}$, we calculate the average effects for all treated individuals who are exposed to either a weakly higher or a weakly lower treatment dose. The estimated values of $\text{DID}_{i,\ell}$ are summed up and weighted by the total number of individuals from whom they were estimated, for every $\ell \in \{1, \dots, \max(\ell)\}$:

$$\text{DID}_\ell = \frac{1}{N_\ell} \sum_{\substack{i: F_i - 1 + \ell \\ \leq 4^{\text{th}} \text{ quarter of 2022}}} \text{sgn}(\cdot)\text{DID}_{i,\ell}, \tag{8}$$

where N_ℓ represents the number of individuals for whom $\text{DID}_{i,\ell}$ can be estimated. The function $\text{sgn}(\cdot)$ determines the sign assigned to the estimated effect, conditional on the direction of the treatment dose. It is "+" (respectively, "-") for individuals whose treatment level, relative to the baseline treatment, increases (respectively, decreases) at F_i, resulting in a positive (respectively, negative) treatment dose. The sign is determined at F_i period. We estimate these effects separately.

Under such specification, the estimator does not distinguish between individuals treated more or less intensely. Also, given how the treatment variable was defined, setting for all individuals the baseline treatment level to zero, the estimator by de Chaisemartin and D'Haultfoeuille (2022) is numerically equivalent to that proposed by Callaway and Sant'Anna (2021). We therefore use both and compare their results to validate our findings' consistency.

Lastly, to be able to compare the estimated average AVSQ effects for every $\ell \in \{1, \dots, \max(\ell)\}$ with the results obtained from the TWFE regression, we adopt the approach suggested by de Chaisemartin and D'Haultfoeuille (2022) and divide the estimated effects obtained with $\text{DID}_{i,\ell}$ by the difference between the total treatment dose received by individual i from F_i to $F_i - 1 + \ell$, and the total treatment dose he/she would have received in the status-quo counterfactual. For example, if $\max(\ell)$ is 4 for an individual i and with the baseline treatment of zero, the difference between the total treatment dose received by individual i from F_i to $F_i - 1 + 4$, and the total treatment dose he/she would have received in the status-quo counterfactual would be $(D_{i,F_i} - 0 + D_{i,F_i+1} - 0 + D_{i,F_i+2} - 0 + D_{i,F_i+3} - 0)$. As a result, we obtain the estimator for the normalised actual-versus-status-quo (nAVSQ) effect, as coined by de Chaisemartin and D'Haultfoeuille (2022), a parameter that we interpret as an average total effect per unit of treatment.

[30] Most of the Y_{i,F_i-1} fall in the 4th quarter of 2021 or the 1st quarter of 2022. To check that the realisations of the dependent variable(s) are not systematically different for different quarters, we estimate the correlation coefficient between the quarters and the dependent variables. The correlations are: Employed - 0.003; Unemployed - -0.000; In the Labour Force - 0.003; Inactive - -0.003; Hours Usually Worked - 0.003. All correlation coefficients are very close to 0, suggesting a very weak linear relationship between the two variables.

4.3.1 No Anticipation Assumption

The 'no anticipation" assumption ensures that an individual's current outcome is not influenced by future treatments. Identification problems arise when individuals adjust their behaviour in anticipation of upcoming treatments (Abbring and Van Den Berg, 2003; Malani and Reif, 2015). Given that the influx of Ukrainian refugees was unexpected, concerns about this assumption are minimal for those subjected to a non-zero dose of the treatment from the outset. While some individuals might have anticipated the conflict, it is improbable that locals in the Czech Republic would have changed their labour market behaviours in response. A caveat exists, however: individuals treated after the 1$^{\text{st}}$ quarter of 2022 might have adjusted their behaviour upon observing the cohorts treated earlier.

To address this concern, we assign a binary treatment of $D_{i,t} = 1$ to districts that received a non-zero treatment for all t prior to their treatment changing for the first time in 2022. Conversely, $D_{i,t} = 0$ is assigned to districts that received a non-zero treatment for all t prior to 2022 and to those that were never treated. We limit our sample to observations and time periods where $D_{i,t}$ equals 1 or 0 and re-estimate the DID_ℓ. We then test if a significant effect can be identified for districts yet to be treated, which might suggest a breach of the 'no anticipation" assumption.

Results... *To be added.*

4.3.2 Parallel Trends Assumption

Another key assumption ensuring our estimator's unbiasedness is the parallel trends for the status-quo outcome, conditional on the baseline treatment. Put simply, when two individuals have identical baseline treatments, their expected outcomes should evolve similarly over time.

We test this assumption using placebo estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). These mimic the actual estimators and compare the outcome evolutions of individuals i before their treatment changes for the first time with the outcome evolution of their respective "control" individuals i' from the period $F_i - 1 - \ell$ to $F_i - 1$ for every $\ell \in \{1, \ldots, \max(\ell)\}$. This test provides an alternative to visually inspecting the pre-treatment outcomes.

However, the rotating nature of the panel limits us to go beyond $F_i - 3$ (see Section 5 for details). Therefore, we do not rely solely on the placebo test, but also draw insights from the descriptive statistics. Owing to the specification of our $Treatment^I$ and $Treatment^{II}$ variables, all individuals have a baseline treatment of zero. Hence, when we estimate the $\text{DID}_{i,\ell}$ separately for each $\ell \in \{1, \ldots, L\}$, the individuals making up the control group, i', are identical for each individual i with the same F_i. Since they all inherently share the same baseline treatment, the parallel trends for the status-quo outcome assumption, conditional on the baseline treatment, becomes equivalent to a much stronger unconditional parallel trends assumption for the status-quo outcome.

Table 16 reports descriptive statistics for the pre-treatment years 2019-2021 by different doses of $Treatment^I$.[31] As the treatment dose increases, the percentage of employed individuals and those

[31] The descriptive statistics for $Treatment^{II}$ are reported in Section A.2.

in the labour force in our panel appears to rise, while the percentage of inactive and unemployed individuals seems to decline. The number of hours typically worked remains relatively consistent. Furthermore, the levels of educational attainment of the locals also display disparities based on treatment doses. Thus, for $Treatment^I$, we regard individuals residing in smaller and potentially less economically developed districts (assuming district-level covariates serve as indicators for economic health) as controls. In contrast, we consider individuals in more densely populated districts with potentially greater employment opportunities (based on the number of active companies, large active companies, and vacancies) as treated. Although the outcome levels can differ between the control and treated groups, for our estimator to remain unbiased, their expected outcome evolutions should be the same; otherwise, the estimator will be biased.

Hypothetically, should individuals from control districts exhibit a declining trend in outcomes due to factors like lesser population density, economic health, or labour market demand conditions, we would still achieve a positive AVSQ estimator even if the treatment had no effect. Conversely, if the treatment had a negative effect, the true magnitude of this impact would be underestimated.

To minimise the chance of this bias, we extend our baseline model by: (i) allowing for diverse trends across individuals through exact matching on selected individual characteristics, (ii) allowing for diverse trends across districts through exact matching on a proxy for districts' labour market condition, and (iii) conditioning the estimator on pre-2022 employment levels of the Ukrainian diaspora.

(i) Allowing for Distinct Trends Across Individuals and Districts via Matching Based on Individual Characteristics. In estimating the AVSQ, we compare the evolution of outcomes between treated and untreated individuals who share selected individual characteristics, such as being of the same sex, age group, having the same pension or disability status, and education level. This approach is akin to exact matching. Consequently, we need the parallel trends assumption to hold separately within each subset of matched individuals, rather than universally.

(ii) Allowing for Distinct Trends Across Individuals and Districts via Matching Based on Individual Characteristics and Regional Labour Market Indicators. Up to this point, our Difference-in-Differences (DiD) model has only accounted for individual- and time-fixed effects. While we have mitigated the parallel trends assumption by matching based on selected individual characteristics, a key concern remains: adequately controlling for the economic and labour market dynamics unique to each district.

To address this, we introduce a variable as a proxy for regional labour market conditions. We calculate the average unemployment rate for each district during 2021-2022 and categorise this data into four quantiles. This variable is subsequently used for matching. By doing so, we ensure that matches and subsequent estimations are carried out only within districts of the same bracket, thereby controlling for the distinct labour market conditions of each district.

(iii) Conditioning the Estimator on Pre-2022 Employment Levels of the Ukrainian Diaspora. The specification of our Treatment^I and Treatment^{II} variables ensures that each individual starts with a baseline treatment of zero. This enables the estimation of the $\text{DID}_{i,\ell}$ for all individuals across all feasible F_i and every $\ell \in \{1, \ldots, \max(\ell)\}$ as controls are consistently available. However, the variables do not account in any way for the significant presence of the Ukrainian diaspora employed in Czechia before 2022 — around 195 thousand individuals across districts as of 2021.

	Treatment of <0%	Control of 0%	Treatment of 1%	Treatment of 2%	Treatment of 3%	Treatment of >3%
Labour Market Outcomes for locals						
Employed Status	0.56	0.51	0.52	0.53	0.53	0.55
Inactive Status	0.43	0.48	0.47	0.46	0.45	0.43
Unemployed Status	0.01	0.02	0.01	0.01	0.01	0.01
In Labour Force Status	0.57	0.52	0.53	0.54	0.55	0.57
Hours usually worked	40.19	39.54	39.71	39.42	38.86	39.29
Individual-level covariates						
Male	0.47	0.47	0.47	0.47	0.46	0.47
Age	52.78	52.55	52.83	53.08	53.55	52.14
Marital status	0.56	0.53	0.54	0.52	0.50	0.52
Pension or disability status	0.35	0.40	0.40	0.40	0.40	0.39
Foreigner	0.01	0.01	0.01	0.02	0.03	0.03
Education level						
No education	0.00	0.00	0.00	0.00	0.00	0.00
Basic education	0.10	0.15	0.14	0.12	0.09	0.14
Secondary without matriculation	0.32	0.38	0.37	0.34	0.22	0.35
Secondary with matriculation	0.36	0.32	0.33	0.35	0.37	0.34
University	0.22	0.14	0.15	0.19	0.31	0.16
Population density						
Dense population	0.38	0.19	0.12	0.36	0.80	0.25
Medium settlement	0.26	0.43	0.41	0.28	0.09	0.32
Sparsely populated	0.36	0.37	0.47	0.36	0.10	0.43
District-level covariates						
# active companies	25,116	16,772	17,529	55,963	222,218	17,053
# active large companies	38	25	24	100	442	33
# vacancies per population	0.06	0.02	0.03	0.07	0.22	0.06
Average wage rate (1,000)	34,476	32,610	34,075	35,433	41,233	35,729
Unemployment rate	0.02	0.04	0.03	0.03	0.03	0.02
Labour Market Dynamics						
# of Ukrainians of working age	2,728	764	1,033	6,198	29,097	3,189
# of employed Ukrainians	6,419	1,062	1,288	7,036	31,712	4,657
# of locals of working age	101,220	89,259	82,066	160,016	534,649	76,636
# of employed local	2,728	764	1,033	6,198	29,097	3,189
# of observations	9,898	82,476	255,253	93,018	48,781	16,511

Table 7: Descriptive statistics for 2019-2021 grouped by $Treatment^I$ doses

Note: Based on LFSS data for 2019-2021, the table reports mean values for local labour market outcomes ($y_{i,d,r,t}$), individual-level ($\mathbf{X}$), district-level variables ($\mathbf{Z}$) by the $Treatment^I$ doses. Data is restricted to locals aged 15+ and excludes individuals of Ukrainian descent and/or nationality. The immigration patterns data are sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

Consistent with the common pattern of migrants self-selecting into regions with favourable demand conditions, the distribution of the Ukrainian diaspora's employment before 2022 across districts closely aligns with each district's local labour demands and overall economic health, as shown by the correlation coefficients in Table 1. Furthermore, the majority of Ukrainians who arrived in 2022 and secured official work did so in districts where Ukrainians had predominantly been employed in prior years, evidenced by a strong correlation of 0.88. This underscores the importance of accounting for the pre-2022 employment data, as it helps control for both district-specific economic and labour market conditions, and also captures a district's historical labour demand for foreign employees.

By slightly amending both Treatment^{I} and Treatment^{II}, we can condition the AVSQ effects based on the pre-2022 employment patterns of the Ukrainian diaspora, while keeping the estimation procedure unchanged.

The amended conditional treatment variables are defined as:

$$\text{Conditional Treatment}^{I}_{(d,t)} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{(d,t)}}{\text{Employed Locals}_{(d,\text{average in 2021})}} & \text{if } t \geq 2022 \\[2ex] \dfrac{\text{Employed Ukrainians}_{(d,\text{average in 2021})}}{\text{Employed Locals}_{(d,\text{average in 2021})}} & \text{if } t < 2022 \end{cases} \tag{9}$$

or

$$\text{Conditional Treatment}^{II}_{(d,t)} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{(d,t)}}{\text{Employed Locals}_{(d,\text{average in 2021})}} & \text{if } t \geq 2022 \\[2ex] \dfrac{\text{Employed Ukrainians}_{(d,4^{\text{th}} \text{ quarter of 2021})}}{\text{Employed Locals}_{(d,\text{average in 2021})}} & \text{if } t < 2022 \end{cases} \tag{10}$$

where Conditional Treatment$^{I}_{(d,t)}$ and Conditional Treatment$^{II}_{(d,t)}$ are discrete variables, indexed by districts (d) and time (t).

The changes to the treatment variables become clear upon examining Figure **??**, where the variable Conditional Treatment^{I} is visualised for several districts. Notably, from 1st quarter of 2022 onwards, each district exhibits varying treatment trajectories with identical changes in the doses of treatment to that captured by Treatment^{I} and Treatment^{II}. However, before 2022, the "Treatment" value is not universally set to zero, but varies by district.

For example, both Bruntal and Ceska Lipa districts had a baseline Ukrainian employment level of 1% before 2022, normalised by their respective labour market sizes. In the 2nd quarter of 2022, while Ceska Lipa saw its treatment increasing by a dose of 1% to the level of 2%, Bruntal's treatment level remained unchanged. Therefore, when the $\text{DID}_{i,\ell}$ is estimated for individuals from Ceska Lipa for each $\ell \in \{1, \ldots, \max(\ell)\}$, the control group consists of those individuals residing in Bruntal and other districts with the baseline treatment level of 1%, provided their treatment level hadn't changed (yet) by the 2nd quarter of 2022. Subsequently, both the average effect (AVSQ) and the normalised accrual-versus-status-quo effect (nAVSQ) are calculated as before.

A key advantage of this conditional approach is that it inherently controls for the economic and labour conditions, as well as the historical demand for foreign labour within each district. Thus, any abnormal increase in the employment levels of Ukrainians in 2022 is unlikely to be solely due to these factors, suggesting an element of randomness. In Table 17, we report the 2022 descriptive statistics by various baseline levels of Conditional Treatment^{I}. It is evident that districts with higher percentages of Ukrainian employment before 2022 typically displayed higher employment rates, greater education attainment rates among the locals, and lower unemployment rates. These districts also tend to have, on average, a higher number of active and large companies registered, a higher average wage rate, and a denser population.

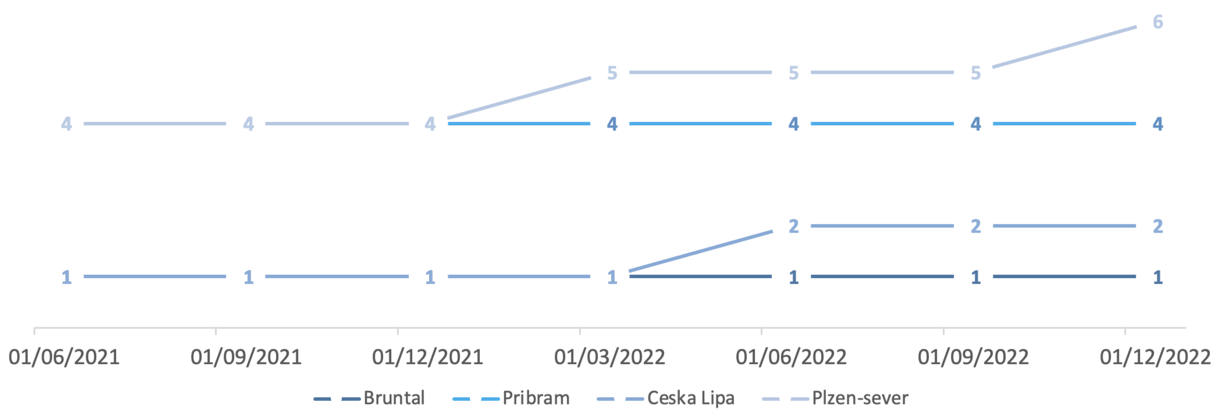

Table 8: Conditional Treatment I visualised: treatment trajectories for selected districts

Nevertheless, this approach has its limitations. Occasionally, the absence of control groups limits our ability to estimate the $\text{DID}_{i,\ell}$ for all individuals i across all feasible F_i and every $\ell \in \{1, \ldots, \max(\ell)\}$. Details on the extent of these limitations are provided alongside the results in Section §5.

5 Results and Discussion

Note: The Labour Force Survey data for the last quarter of 2022 is preliminary. Therefore, the results are preliminary too.

5.1 Summary of Selective Results

This section offers a concise overview of selected results. The primary focus is on comparing the estimations for the ATT and the normalised AVSQ effects. We pinpoint common patterns and inconsistencies. Further, we selectively report the non-normalised AVSQ effects, discussing the estimated dynamic/inter-temporal treatment effects and comparing them with the effects derived from Callaway and Sant'Anna (2021) estimator. Auxiliary statistics, such as sample sizes, statistical errors, and confidence bounds, if not reported here, are available in Sections A.3 and A.4. They support our discussion, but only a subset is detailed here due to the extensive volume of results.

	Employed Diaspora of					
	0%	1%	2%	3%	4%	> 4%
Labour Market Outcomes for locals						
Employed Status	0.50	0.51	0.51	0.51	0.53	0.53
Inactive Status	0.47	0.48	0.48	0.48	0.46	0.46
Unemployed Status	0.02	0.02	0.01	0.01	0.01	0.01
In Labour Force Status	0.53	0.52	0.52	0.52	0.54	0.54
Hours usually worked	38.35	39.41	39.53	39.38	38.37	39.25
Individual-level covariates						
Male	0.48	0.46	0.47	0.47	0.47	0.46
Age	53.26	53.49	54.09	54.02	53.74	54.02
Marital status	0.50	0.52	0.53	0.53	0.53	0.52
Pension or disability status	0.41	0.42	0.43	0.43	0.43	0.41
Foreigner	0.01	0.01	0.01	0.01	0.01	0.02
Education level						
No education	0.00	0.00	0.00	0.00	0.00	0.00
Basic education	0.14	0.15	0.14	0.12	0.11	0.11
Secondary without matriculation	0.37	0.37	0.39	0.37	0.34	0.31
Secondary with matriculation	0.34	0.32	0.34	0.34	0.35	0.35
University	0.14	0.16	0.14	0.17	0.21	0.24
Population density						
Dense population	0.20	0.16	0.05	0.22	0.36	0.43
Medium settlement	0.51	0.41	0.48	0.33	0.27	0.25
Sparsely populated	0.29	0.42	0.46	0.44	0.38	0.33
District-level covariates						
# active companies	19,098	18,314	15,216	17,311	32,318	119,245
# active large companies	26.27	27.91	20.66	22.28	50.83	221.27
# vacancies per population	0.01	0.02	0.02	0.03	0.06	0.12
Average wage rate (1,000)	36,535	37,097	37,459	37,592	38,258	41,668
Unemployment rate	0.05	0.04	0.03	0.03	0.04	0.03
Immigration patterns						
# of Ukrainians of working age	2,188	2,446	2,869	3,995	8,674	35,639
# of employed Ukrainians	576	1,244	1,741	2,442	5,520	22,860
# of locals of working age	111,158	88,441	69,363	74,164	107,900	280,435
# of employed local	83,684	69,188	55,083	60,251	88,572	232,114
Average Treatment Dose	0.44%	0.77%	1.16%	1.22%	1.83%	2.33%
# of observations	10,140	45,844	23,157	23,278	17,574	45,848

Table 9: Descriptive statistics for 2022 by baseline treatment levels ($Conditional\ Treatment^I$)

Note: Based on LFSS data for 2022, the table reports mean values for local labour market outcomes ($y_{i,d,r,t}$), individual-level ($\mathbf{X}$), district-level variables ($\mathbf{Z}$) by baseline treatment levels, that represent the percentage of employed Ukrainians in 2021 relative to the employed locals, according to $Conditional\ Treatment^I$. Data is restricted to locals aged 15+ and excludes individuals of Ukrainian descent and/or nationality. The immigration patterns data are sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

We report seven tables, each for the labour market outcome of interest: employment, job separation, job acquisition, unemployment, inactivity, labour force participation statuses, and hours usually worked. Refer to Tables 5-10. Each table contains the estimated ATT for Treatment^I and

Treatment^{II} and the normalised AVSQ effects for Treatment^{I}, Treatment^{II}, Conditional Treatment^{I} and Conditional Treatment^{II}. The results are further broken down by:

We report seven tables, each for the labour market outcome of interest: employment, job separation, job acquisition, unemployment, inactivity, labour force participation statuses, and hours usually worked. Refer to Tables 5-10. Each table contains the estimated ATT of Treatment^{I} and Treatment^{II} and the normalised AVSQ effects for Treatment^{I}, Treatment^{II}, Conditional Treatment^{I} and Conditional Treatment^{II}. The results are further broken down by:

- All districts.
- Districts without negative treatment doses.
- Districts with positive & never decreasing treatment doses, thus excluding negative and switching out treatments.
- Districts that received negative treatment doses.

Beyond the "baseline" estimations, each table reports the results of the extended versions of the models, as detailed in the paper's identification strategy section:

(i) ATT estimated effects with TWFE for Treatment^{I}, controlling for individual and time-fixed effects, and the interaction term between region-fixed effects and time-fixed effects.

(ii) ATT estimated effects with TWFE for Treatment^{I}, controlling for individual and time-fixed effects, the interaction term between region-fixed effects and time-fixed effects, and individual-level covariates such as age, sex, education level, and so on.

(iii) ATT estimated effects with TWFE for Treatment^{I}, controlling for individual and time-fixed effects, the interaction term between region-fixed effects and time-fixed effects, individual-level covariates, and district-level covariates like the number of operating companies in a district, average wage, number of vacancies per working age population, and so on.

(iii) ATT estimated effects with TWFE for Treatment^{I}, controlling for individual and time-fixed effects, the interaction term between region-fixed effects and time-fixed effects, individual-level covariates, and district-level covariates like the number of operating companies in a district, average wage, number of vacancies per working age population, etc.

(iv) Normalised AVSQ estimated effects with DiD for Treatment^{I}, controlling for individual and time-fixed effects.

(v) Normalised AVSQ estimated effects with DiD for Treatment^{I}, controlling for individual and time-fixed effects and incorporating exact matching on selected individual characteristics such as age, sex, foreign status, education levels, and so on.

(vi) Normalised AVSQ estimated effects with DiD for Treatment^{I}, controlling for individual and time-fixed effects and incorporating matching on selected individual characteristics as well as the districts' labour market conditions.

(vii)-(xii) Identical in setting to the previously listed settings, but for Treatment^{II}.

(xiii) Normalised AVSQ estimated effects with DiD for Conditional Treatment^{I}, controlling for individual and time-fixed effects and conditioning on the pre-2022 levels of employed Ukrainian diaspora.

(xiv) Normalised AVSQ estimated effects with DiD for Conditional Treatment^{I}, controlling for individual and time-fixed effects and incorporating exact matching on selected individual characteristics such as age, sex, foreign status, education levels, etc and conditioning on the pre-2022 levels of employed Ukrainian diaspora.

(xv) Normalised AVSQ estimated effects with DiD for Conditional Treatment^{I}, controlling for individual and time-fixed effects and incorporating matching on selected individual characteristics as well as the districts' labour market conditions and conditioning on the pre-2022 levels of employed Ukrainian diaspora.

(xvi)-(xviii) Identical in setting to the previously listed settings, but for Conditional Treatment^{II}.

Employment Status. The estimated coefficients vary across different model specifications and/or treatment variables. Refer to Table 4. The sign of the estimated ATT often contrasts with the estimated AVSQ effects. For Treatment^{II}, the ATT (vii) yields marginally significant results for all locals, both across all districts and when limited to districts without any negative treatment doses. The corresponding normalised AVSQ (x) closely mirrors the ATT coefficients. However, the placebo test for AVSQ (x), which assesses the parallel trends assumption, fails, raising concerns about the estimation's reliability.

A pattern emerges when focusing on districts with positive and never-decreasing treatment doses: the magnitude of the coefficients increases compared to more inclusive district sub-samples. For females, these coefficients become negative for both Treatment^{I} and Treatment^{II} and are statistically significant for Treatment^{I}. Both Conditional Treatment^{I} and Conditional Treatment^{II} estimate the inter-temporal 'Effect_1' as negative. Notably, for Treatment^{I}, this effect is significant, and not just under the baseline specification (xiii), but also when we perform exact matching on selected variables (xiv-xv). Refer to Figure 10. The first-period significant negative effects for females are also identified in larger samples of districts, i.e., all districts and those without negative treatment doses. However, the coefficients are marginally smaller than those observed for districts with no negative and never-decreasing treatment doses.

A pattern emerges when focusing on districts with positive and never-decreasing treatment doses: the magnitude of the coefficients increases compared to that for all districts and districts with no negative treatment doses. For females, these coefficients become negative for both Treatment^{I} and Treatment^{II}, and are statistically significant for Treatment^{I}. Both Conditional Treatment^{I} and Conditional Treatment^{II} estimate the inter-temporal 'Effect_1' as negative. Notably, for Treatment^{I}, this effect is significant not only under the baseline specification (xiii) but also when we perform exact matching on selected variables (xiv-xv). Refer to Figure 10. The first-period significant negative effects for females are also identified in larger samples of districts, such as all districts and those without negative treatment doses. However, these coefficients are marginally smaller than those observed for districts with consistently positive treatment doses.

The evidence suggests that upon their first treatment change — when more Ukrainians secured employment in those districts — local females from districts with consistently positive treatment doses might have experienced a temporary decline in employment likelihood. After the inter-temporal 'Effect_1', coefficients for 'Effects_2, 3, and 4' predominantly become positive, although they generally lack statistical significance, potentially indicating that the labour market adjusted to the inflow of refugees. This trend is not observed for males, reinforcing the hypothesis that local females might have faced a short-term adverse effect. Given that a significant number of employed Ukrainian refugees were female, they were likely in competition with local women in similar roles with matching demographics.

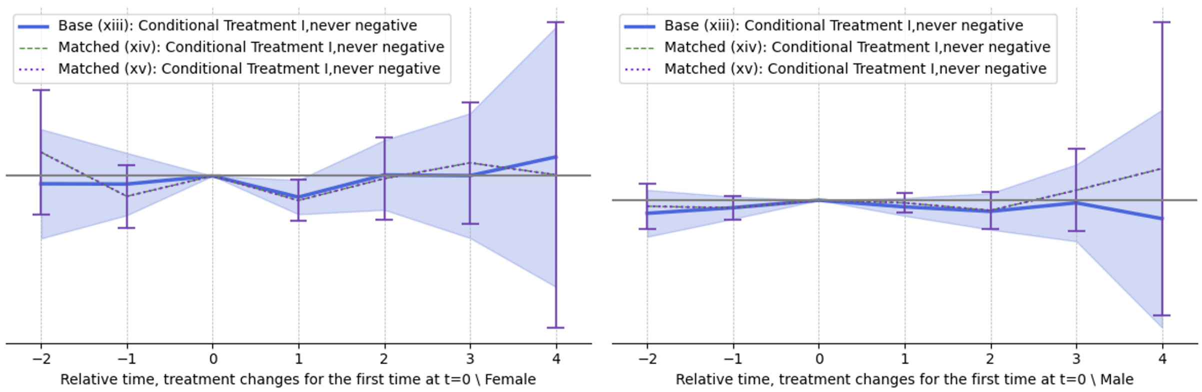

Table 10: Employment status: DID$_\ell$ from the last period before treatment changes (i.e., $t = 0$) to time t.

Note: Both estimate effects for individuals residing in districts that never experience negative treatment doses. The panel to the left reports estimations for females under specifications (xiii-xv). The panel to the right reports estimations for males under specifications (xiii-xv). Based on LFSS data for 2021-2022, statistics estimated with the Stata command "did_multiplegt_dyn". Plotted in Python. The full set of results is available in Section A.4.

In districts where the number of employed Ukrainians declined compared to the previous year, the likelihood of male employment might have decreased, at least in the short term. However, this pattern is challenging to interpret, as the employment declines were predominantly due to Ukrainian men leaving their jobs, possibly returning to Ukraine. Intuitively, this should have increased local employment chances due to emerging vacancies in specific sectors.

Hours Usually Worked. Throughout (i-xviii), the coefficients largely maintain consistency in both their sign and magnitude. Refer to Table 5. "Hours usually worked" is the dependent variable for which we find the most consistent estimated effects among all the dependent variables we have investigated. The coefficients for every district, for districts without negative treatment doses, and for those with neither negative nor switching treatment doses are predominantly positive. In most cases, female subjects exhibit a larger coefficient magnitude than males. Notably, as we refine the sample from the first to the third group, the magnitude of the coefficients increases for all (i-xii). This bolsters the hypothesis that the effects identified are not random but can be attributed to the treatment; the estimated effects appear to increase as the intercity consistency and magnitude of treatment dose increase.

When introducing more covariates to the TWFE regression for estimating the ATT and extending the DiD with additional exact matching steps for estimating the AVSQ effects, the magnitudes of the coefficients slightly decrease. The DiD estimators often yield coefficients with a larger magnitude, and these are typically statistically significant, except for (vi) and (xii). See Figure 11 for visualised estimated inter-temporal, non-normalised AVSQ effects for (iv-vi) and (x-xii). However, we note that the sub-sample for which the effect on "hours usually worked" can be estimated is already restrictive since those individuals should be employed. Furthermore, incorporating the exact matching step, not just based on individual characteristics and NACE job types but also on a proxy for labour market conditions, further restricts the sample size — perhaps too much to identify significant effects. Refer to Table 12 for auxiliary statistics on the sample sizes.

Upon narrowing the sample to districts that experienced neither negative nor switching treatment doses, an interesting pattern emerges. The estimated (i-iii) and (iv-vi) ATTs seem to almost match the size of the estimated (iv-vi) and (x-xii) AVSQ effects. They also show similar significance levels for females under the Treatment^{I} specification in (i-iii). This consistency between both TWFE and DiD estimators indicates positive effects of the treatment on hours typically worked, at least for local females.

Significant and positive effects persist under the (xiii-xviii) Conditional Treatment^{I} and Conditional Treatment^{II} specifications. However, for Conditional Treatment^{I} and Conditional Treatment^{II}, we consistently fail the placebo tests for females, suggesting the parallel trends assumption may be compromised. We do not observe this pattern for (iv-vi) and (x-xii) Treatment^{I} and Treatment^{II}. Such inconsistency might result from conditioning on the pre-2022 Ukrainian employed diaspora. The exclusion of certain observations, owing to a lack of controls, has significantly decreased the sub-sample of individuals for whom the AVSQ effects could be estimated.

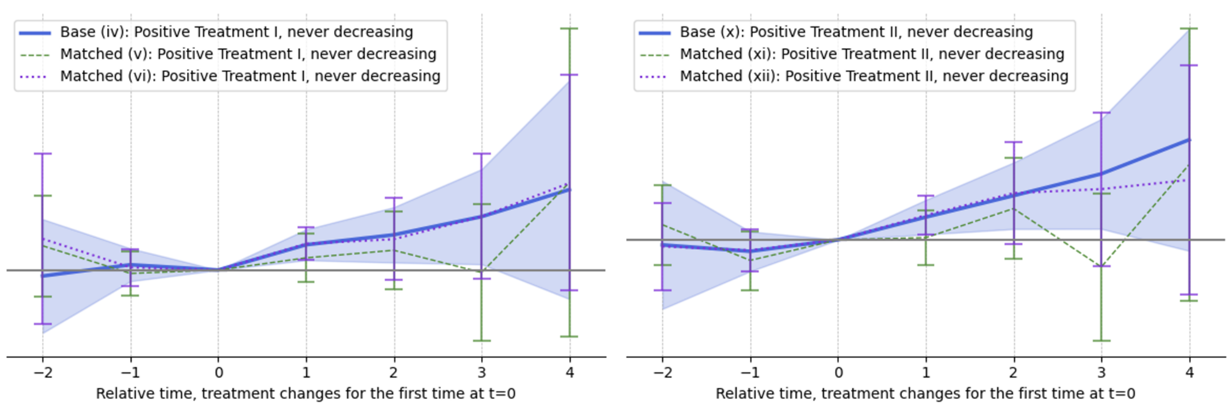

Table 11: Hours usually worked for all locals: DID$_{\ell}$ from the last period before treatment changes (i.e., $t = 0$) to time t.

Note: Both estimate effects for individuals residing in districts that never experience decreasing treatment doses. The panel to the left reports estimations for females under specifications (xiii-xv). The panel to the right reports estimations for males under specifications (xiii-xv). Based on LFSS data for 2021-2022, statistics estimated with the Stata command "did_multiplegt_dyn". Plotted in Python. The full set of results is available in Section A.4.

Regarding the estimated inter-temporal, non-normalised AVSQ effects for (iv-vi) and (x-xii) for districts not receiving negative treatment doses, the effects are consistently positive and substantially increase in magnitude as we transition from 'Effect_1' to 'Effects_2, 3, and 4'. Refer to Table 12. Many of these effects remain significant beyond 'Effect_1'. Similarly, the effects consistently escalate in magnitude when moving from 'Effect_1' to 'Effects_2, 3, and 4' across all districts, especially those without negative or switching treatment doses—with the latter displaying a more pronounced uptick in the effect's magnitude.

Districts with no negative treatment	**Treatment I**			**Treatment II**			**Conditional Treatment I**			**Conditional Treatment II**		
Hours usually worked	**(iv)**	**(v)**	**(vi)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
Effect 1	**0.1703**	**0.1775**	**0.1506**	**0.1391**	**0.1703**	**0.1775**	**0.0895**	**0.1639**	**0.0073**	**0.1134**	**0.1266**	**0.0251**
SE	0.0530	0.0563	0.0595	0.0540	0.0530	0.0563	0.0657	0.0708	0.0922	0.0640	0.0797	0.1157
# of individuals	40,239	30,782	30,208	38,968	40,239	30,782	32,750	17,684	7,941	28,237	15,572	6,635
# of treated	20,524	16,504	16,474	20,094	20,524	16,504	15,117	8,476	4,259	13,046	7,736	3,616
Effect 2	**0.2376**	**0.2079**	**0.2864**	**0.2706**	**0.2376**	**0.2079**	**0.1547**	**0.2155**	**0.3834**	**0.1116**	**0.1403**	**0.3951**
SE	0.0953	0.1416	0.1594	0.1040	0.0953	0.1416	0.0925	0.1112	0.1651	0.1276	0.1504	0.2154
# of individuals	19,277	11,654	12,416	19,762	19,277	11,654	14,986	6,555	2,809	12,559	5,560	2,204
# of treated	13,463	8,096	8,569	13,822	13,463	8,096	8,508	3,709	1,560	7,120	3,267	1,225
Effect 3	**0.3603**	**0.3611**	**0.3110**	**0.4044**	**0.3603**	**0.3611**	**0.1841**	**0.3252**	**-0.0693**	**0.2711**	**0.1837**	**-0.3432**
SE	0.1639	0.2160	0.2404	0.1718	0.1639	0.2160	0.1234	0.1720	0.2494	0.2149	0.2729	0.3396
# of individuals	8,949	3,675	4,748	9,556	8,949	3,675	5,877	2,363	1,053	4,849	1,864	667
# of treated	7,743	2,907	3,759	8,161	7,743	2,907	4,270	1,455	608	3,653	1,183	373
Effect 4	**0.5432**	**0.5872**	**0.3670**	**0.6133**	**0.5432**	**0.5872**	**-0.0594**	**0.2343**	**1.1004**	**1.0411**	**-0.0326**	**1.0278**
SE	0.3770	0.3715	0.3595	0.3471	0.3770	0.3715	0.2194	0.3919	1.1361	0.6715	0.5839	1.3903
# of individuals	2,382	706	916	2,700	2,382	706	1,055	294	66	751	208	30
# of treated	2,278	612	795	2,564	2,278	612	842	186	39	613	138	18
Average total effect per treatment unit	**0.1545**	**0.1400**	**0.1434**	**0.1662**	**0.1545**	**0.1400**	**0.0958**	**0.1693**	**0.0881**	**0.1317**	**0.1164**	**0.0857**
SE	0.0459	0.0482	0.0563	0.0510	0.0459	0.0482	0.0501	0.0599	0.0794	0.0736	0.0788	0.1100
# of individuals	63,748	43,330	44,545	63,598	63,748	43,330	48,466	24,929	11,331	41,680	21,841	9,250
# of treated	44,008	28,119	29,597	44,641	44,008	28,119	28,737	13,826	6,466	24,432	12,324	5,232
Placebo test	0.8046	0.7237	0.5678	0.5079	0.8046	0.7237	0.1091	0.3814	0.2669	0.0152	0.1235	0.0181

Table 12: Hours usually worked for all locals: DID_ℓ reported separately for every $\ell \in \{1, \ldots, \max(\ell)\}$.

Note: For all locals. Blue-shaded cells signify statistical significance. 'Effect_1' means $\ell = 1$, act. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results is available in Section A.4.

The body of evidence suggests that the treatment — i.e., the increase in the number of officially employed Ukrainians relative to the baseline period, normalised by the size of each district's labour market — had a positive effect on the hours usually worked by local females, and this effect increased over time. The evidence for males is less consistent; hence, we refrain from drawing any conclusions for them.

Unemployment Status. No consistent patterns in effects could be identified. Refer to Table 9. There are some significant results appearing for the (i-iii) and (vii-ix) ATT under Treatment^{I} and Treatment^{II} specifications. Especially for females, the effect coefficients are positive and significant for all districts and for districts with no negative treatment doses. This signals that local females potentially experienced an increased likelihood of unemployment. However, as we restrict the sample to districts with no negative and no switching treatment doses, the coefficients lose their significance though increases in magnitude for Treatment^{I} and even switched the sign from positive to negative for Treatment^{II}; not supportive of the hypothesis. These results are not mirrored in the (iv-vi) and (x-xviii) normalised AVSQ effects for either Treatment^{I} or Treatment^{II} and neither Conditional Treatment^{I} nor Conditional Treatment^{II}.

Shifting focus to districts with negative results, most coefficients consistently show negative values, which are occasionally statistically significant (i-iii) for females. The significance for (vii-ix) could not be estimated because there were more covariates than individuals; due to the interaction term between time-fixed effects and region-fixed effects and a small sample size. However, when re-estimating the (vii-ix) without the interaction term, they turn out to be significant for females as well.

Job Separation Indicator. Refer to Table 7.*Discussion to be added after the final q4 2022 data is available.*

Job Finding Indicator. Refer to Table 6. *Discussion to be added after the final q4 2022 data is available.*

Inactive Status. Refer to Table 8. *Discussion to be added after the final q4 2022 data is available.*

Labour Force Participation Status. *Discussion to be added after the final q4 2022 data is available.*

5.2 The Limitations Introduced by the Rotating Panel and the Treatment Patterns.

We do not consistently observe individuals over the entire time frame because of the survey design. Individuals are frequently and systematically replaced, presumably to prevent attrition, making the LFSS a rotating panel with a maximum of five periods in which an individual can be consecutively observed. This has implications for the estimators and our subsequent results.

For the AVSQ effects estimated with DiD, the rotating nature of the panel reduces the number of individuals for whom effects higher than order 1 can be estimated. The first-order effect, Effect 1, represents the impact of experiencing a change in treatment for the first time over the entire timeframe during which this treatment change occurs. Effect 2 captures the dynamic effects of the treatment change from period 1 and also the impact of the ongoing or again altered treatment in period 2.

The maximum effect we can estimate for some individuals is 4. To do this, we would need an individual who was observed in the rotating panel for the first time in Q4 2021 and then experienced a change in treatment for the first time in Q1 2022. They would then need to continue being observed up to their final fifth wave in the panel (Q4 2022) without attrition. Any other scenario would not

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Employment status	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(1: yes, 0: no)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	0.0002	0.0001	0.0000	0.0009	-0.0007	0.0021	0.0004*	0.0002	0.0002	0.0004```	-0.0004	0.0015	-0.0023	-0.0018	-0.0017	0.0008	0.0011	0.0001
Female	0.0002	-0.0000	-0.0000	0.0029	0.0007	0.0038	0.0003	0.0001	0.0001	0.0005```	0.0001	0.0011	-0.0021	-0.0025	-0.0022	0.0012	0.0020	0.0025
Male	0.0002	0.0002	0.0002	-0.0015	-0.0022	0.0001	0.0004	0.0003	0.0003	0.0003	-0.0010	0.0019	-0.0025	-0.0009	-0.0012	0.0007	-0.0000	-0.0027
Districts with no negative treatment																		
All locals	0.0001	-0.0000	-0.0000	0.0007	-0.0009	0.0020	0.0004*	0.0002	0.0002	0.0004```	-0.0004	0.0015	-0.0022	-0.0018	-0.0017	0.0008	0.0011	0.0001
Female	0.0001	-0.0001	-0.0001	0.0026	0.0002	0.0035	0.0003	0.0001	0.0001	0.006```	0.0001	0.0011	-0.0020	-0.0026	-0.0026	0.0012	0.0020	0.0020
Male	0.0002	0.0001	0.0001	-0.0014	-0.0022	0.0002	0.0005	0.0004	0.0004	0.0003	-0.0010	0.0019	-0.0024	-0.0008	-0.0008	0.0007	0.0000	0.0000
Districts with positive & not decreasing																		
All locals	-0.0001	-0.0006	-0.0011	0.0008	-0.0010	0.0021	0.0008	-0.0002	-0.0006	0.0004```	-0.0004	0.0014	0.0021	-0.0017	-0.0018	0.0013	0.0013	0.0000
Female	-0.0020*	-0.0026*	-0.0031*	0.0028	0.0000	0.0036	0.0028	-0.0012	-0.0015	0.0005```	0.0001	0.0012	-0.0021	-0.0028	-0.0028	0.0013	0.0021	0.0021
Male	0.0023**	0.0016	0.0012	-0.0014	-0.0022	0.0002	0.0018*	0.0008	0.0003	0.0004	-0.0010	0.0017	-0.0019	-0.0005	-0.0005	0.0014	0.0003	0.0003
Districts with negative treatment																		
All locals	-0.0179***	-0.0121***	-0.0113***	0.0016	0.0128```	0.0036	-0.0179	-0.0131	-0.0044	-0.0004	0.0008	0.0038	-0.0129	-0.0045	-0.0005	-0.0143	-0.0082	0.0007
Female	-0.0092***	-0.0072	-0.0112***	0.0051	0.0284	0.0117	-0.0092	-0.0113	-0.0075	0.0055	0.0012	-0.0097	-0.0003	0.0061	0.0061	-0.0038	-0.0045	-0.0045
Male	-0.0279***	-0.0190***	-0.0117***	-0.0023	-0.0036	-0.0054	-0.0279	-0.0167	-0.0062	-0.0064	0.0003	0.0167	-0.0248	-0.0144	-0.0144	-0.0237	-0.0117	-0.0117

Figure 4: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on Employment Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: ‘***‘ $p < 0.01$, ‘**‘ $p < 0.05$, ‘*‘ $p < 0.1$. (‘‘‘) indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Hours usually worked	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(if hrs. > 0)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	0.0053	0.0042	0.0041	0.1520	0.1370	0.0561	0.0053	0.0049	0.0049	0.1710	0.1490	0.0242	0.0964‘‘‘	0.1690	0.0881	0.1317‘‘‘	0.1160	0 .0857‘‘‘
Female	0.0099	0.0068	0.0070	0.1590	0.1200	0.0292	0.0107	0.0096	0.0098	0.1740	0.1240	0.0099	0.0317‘‘‘	0.1007‘‘‘	0.1007‘‘‘	0.2014‘‘‘	0.1530	0.1532
Male	0.0014	0.0015	0.0014	0.1430	0.1510	0.0779	0.0008	0.0013	0.0012	0.1670	0.1690	0.0361‘‘‘	0.1410	0.2240	0.2237	0.0680	0.0870	0.0871
Districts with no negative treatment																		
All locals	0.0078	0.0069	0.0068	0.1550	0.1400	0.0601	0.0059	0.0055	0.0054	0.1660	0.1430	0.0248	0.0960	0.1690	0.0881	0.1317‘‘‘	0.1160	0.0857‘‘‘
Female	0.0096	0.0064	0.0066	0.1620	0.1200	0.0325	0.0100	0.0090	0.0091	0.1710	0.1230	0.0115	0.0330‘‘‘	0.1006‘‘‘	0.0706‘‘‘	0.2014‘‘‘	0.1530	0.1399‘‘‘
Male	0.0061	0.0063	0.0062	0.1460	0.1570	0.0823	0.0024	0.0029	0.0027	0.1600	0.1610	0.0358‘‘‘	0.1390	0.2250	0.1017	0.0680	0.0870	0.0433
Districts with positive & not decreasing																		
All locals	0.0376	0.0212	0.0218	0.1650	0.1440	0.0555	0.0116	0.0045	0.0074	0.1730	0.1520	0.0256	0.1038‘‘‘	0.1770	0.0962	0.1416‘‘‘	0.1230	0.0923‘‘‘
Female	0.1158**	0.0908*	0.1015*	0.1800	0.1320	0.0377	0.0375	0.0286	0.0372	0.1700	0.1250	0.0087	0.0419‘‘‘	0.1105‘‘‘	0.0807‘‘‘	0.2197‘‘‘	0.1660	0.1457‘‘‘
Male	-0.0319	-0.0414	-0.0484	0.1510	0.1540	0.0699	-0.0100	-0.0142	-0.0160	0.1720	0.1750	0.0397‘‘‘	0.1460	0.2300	0.1081	0.0720	0.0880	0.0507
Districts with negative treatment																		
All locals	-1.7154***	-1.7769**	-0.3732*	-0.2300	-0.3460	0.0937	-1.7154	-1.8723	-1.3291	0.0710	-0.3640	-0.2369	-0.2100	-0.3290	-0.3981	-0.2170	-0.3020	-0.2264
Female	-0.7110***	-0.8032**	-0.3444**	-0.4020	-0.7130	-0.4688	-0.7110	-0.8654	-0.5173	0.3970	0.0440	0.2356	-0.3980	-0.5630	-0.5500	-0.4340	-0.7360	-0.1354
Male	-2.5688***	-2.6341**	-0.3884*	-0.0720	-0.0260	0.5543	-2.5688	-2.7973	-2.0547	-0.2130	-0.6840	-0.6092	-0.0710	-0.1580	-0.2848	-0.0610	0.0070	-0.2936

Figure 5: Estimated effects of Treatment^I, Treatment^{II}, Conditional Treatment^I, and Conditional Treatment^{II} on Hours Usually Worked.

Note: Blue-shaded cells signify statistical significance. Significance levels: ‘***‘ $p < 0.01$, ‘**‘ $p < 0.05$, ‘*‘ $p < 0.1$. (“‘) indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Job finding status	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(1: yes, 0: no)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	0.0004***	0.0004***	0.0004***	0.0003	0.0009	0.0011	0.0005***	0.0005***	0.0005***	0.0006	0.0012	0.0017```	-0.0020	-0.0023	-0.0008	-0.0011	-0.0006	0.0005```
Female	0.0004**	0.0004**	0.0003**	0.0015	0.0024	0.0018	0.0005**	0.0005**	0.0004**	0.0009	0.0018	0.0017	-0.0018	-0.0027	-0.0001	-0.0020	-0.0015	0.0022
Male	0.0005***	0.0005***	0.0005***	-0.0011	-0.0008	0.0003```	0.0005***	0.0005***	0.0005***	0.0001	0.0006	0.0017```	-0.0022	-0.0019	-0.0015```	-0.0001	0.0003	-0.0014```
Districts with no negative treatment																		
All locals	0.0004***	0.0004***	0.0004***	0.0003	0.0008	0.0011	0.0005***	0.0005***	0.0005***	0.0006	0.0012	0.0017```	-0.0020	-0.0023	-0.0008	-0.0011	0.0006	0.0005```
Female	0.0004***	0.0003**	0.0003***	0.0015	0.0022	0.0017	0.0005**	0.0005**	0.0005**	0.0010	0.0018	0.0017	-0.0018	-0.0027	-0.0027	-0.0020	-0.0015	-0.0015
Male	0.0004***	0.0004***	0.0004***	-0.0011	-0.0008	0.0004```	0.0006***	0.0006***	0.0006***	0.0001	0.0006	0.0017```	-0.0022	-0.0019	-0.0019	-0.0001	0.0003	0.0003
Districts with positive & not decreasing																		
All locals	0.0011*	0.0008	0.0005	0.0002	0.0008	0.0011	0.0011**	0.0010**	0.0008	0.0005	0.0012	0.0017```	-0.0019	-0.0023	-0.0008	-0.0009	-0.0007	0.0005```
Female	0.0012*	0.0010	0.0004	0.0014	0.0021	0.0017	0.0014*	0.0013*	0.0009	0.0009	0.0017	0.0018	-0.0018	-0.0028	-0.0028	-0.0020	-0.0016	-0.0016
Male	0.0009	0.0005	0.0004	-0.0011	-0.0008	0.0004```	0.0007	0.0006	0.0006	0.0002	0.0006	0.0016```	-0.0019	-0.0018	-0.0018	0.0003	0.0004	0.0004
Districts with negative treatment																		
All locals	0.0041***	0.0017*	-0.0003	0.0022	0.0063	0.0013	0.0041	0.0011	0.0027	0.0019	0.0024	-0.0014	-0.0076	-0.0015	0.0014	-0.0066	0.0007	0.0038
Female	0.0030***	-0.0007	0.0015	0.0068	0.0149	0.0060	0.0030	-0.0003	-0.0028	0.0052	0.0029	-0.0091	-0.0015	0.0033	0.0033	-0.0001	0.0057	0.0057
Male	0.0053***	0.0043	-0.0022	-0.0028	-0.0027	-0.0039	0.0053	0.0020	0.0015	-0.0017	0.0019	0.0059	-0.0135	-0.0059	-0.0059	-0.0129	-0.0039	-0.0039

Figure 6: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on Job Finding Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: '***' $p < 0.01$, '**' $p < 0.05$, '*' $p < 0.1$. ('''') indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Job separation status	ATT/ TWFE			Normalised AVSQ			ATT/ TWFE			Normalised AVSQ			Normalised AVSQ			Normalised AVSQ		
(1: yes, 0: no)	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)	(xvi)	(xvii)	(xviii)
All district																		
All locals	-0.0001	-0.0001	-0.0001	-0.0005```	-0.0008```	-0.0011	-0.0002	-0.0001	-0.0001	-0.0005```	-0.0006	-0.0005	0.0007	0.0006```	0.0001	-0.0010	-0.0005	-0.0005
Female	0.0000	0.0001	0.0001	-0.0015```	-0.0017	-0.0011	0.0000	0.0001	0.0001	-0.0009	-0.0010	-0.0002	0.0010	0.0007	0.0001	-0.0020	-0.0012	-0.0017
Male	-0.0003**	-0.0003**	-0.0003**	0.0006	0.0003	-0.0012	-0.0003***	-0.0003**	-0.0003**	-0.0001	-0.0001	-0.0007	0.0004	0.0004	0.0001	0.0001```	0.0003```	0.0007
Districts with no negative treatment																		
All locals	-0.0002	-0.0002	-0.0002	-0.0005```	-0.0007	-0.0010	-0.0002	-0.0001	-0.0001	-0.0005```	-0.0005	-0.0005	0.0007	0.0006```	0.0001	-0.0010	-0.0005	-0.0005
Female	-0.0000	0.0000	0.0000	-0.0014```	-0.0016	-0.0009	-0.0000	0.0001	0.0001	-0.0009	-0.0009	-0.0002	0.0009	0.0007	0.0007	-0.0020	-0.0012	-0.0012
Male	-0.0003***	-0.0003***	-0.0003***	0.0006	0.0003	-0.0012	-0.0004***	-0.0004***	-0.0004***	-0.0000	-0.0001	-0.0007	0.0004	0.0004	0.0004	0.0001```	0.0003```	0.0003```
Districts with positive & not decreasing																		
All locals	0.0013	0.0012	0.0014	-0.0006```	-0.0008```	-0.0011	0.0008	0.0010	0.0012	-0.0006```	-0.0006	-0.0005	0.0008	0.0006```	0.0001	-0.0010	-0.0006	-0.0006
Female	0.0026**	0.0024*	0.0026*	-0.0018```	-0.0018	-0.0010	0.0012	0.0014	0.0015	-0.0010	-0.0006	-0.0003	0.0010	0.0008	0.0008	-0.0022	-0.0015	-0.0015
Male	-0.0001	-0.0001	0.0000	0.0007	0.0003	-0.0012	0.0002	0.0006	0.0008	-0.0001	-0.0006	-0.0007	0.0005	0.0005	0.0005	0.0001```	0.0003```	0.0003```
Districts with negative treatment																		
All locals	0.0160***	0.0108*	0.0058*	0.0035```	-0.0001```	-0.0040```	0.0160	0.0096	0.0032	0.0044```	-0.0006```	-0.0001	-0.0012	-0.0012	-0.0002	0.0015	0.0048	0.0009
Female	0.0125***	0.0079**	0.0052**	0.0088```	0.0013```	-0.0057	0.0125	0.0078	0.0023	0.0079```	-0.0006	0.0029	0.0005	-0.0004	-0.0004	0.0046	0.0048	0.0097
Male	0.0198***	0.0138	0.0062	-0.0023	-0.0016	-0.0021	0.0198	0.0110	0.0040	0.0001```	-0.0006	-0.0030	-0.0034	-0.0019	-0.0019	-0.0024	0.0048	0.0001

Figure 7: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on Job Separation Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: '***' $p < 0.01$, '**' $p < 0.05$, '*' $p < 0.1$. (''') indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Inactive status	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(1: yes, 0: no)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	-0.0003**	-0.0002	-0.0002	0.0000	0.0015	-0.0017	-0.0005***	-0.0003**	-0.0003**	0.0011‘‘‘	0.0019	0.0005‘‘‘	-0.0020	-0.0023	0.0017	-0.0011	-0.0006	0.0015
Female	-0.0005**	-0.0003	-0.0003	-0.0011	0.0014	-0.0030	-0.0006**	-0.0004	-0.0004	0.0012‘‘‘	0.0021	0.0009‘‘‘	-0.0018	-0.0027	0.0034	-0.0020	-0.0015	0.0025
Male	-0.0002	-0.0001	-0.0001	0.0012	0.0016	-0.0003	-0.0004	-0.0003	-0.0003	0.0009	0.0016	0.0001	-0.0022	-0.0019	-0.0003	-0.0001	0.0003	0.0004
Districts with no negative treatment																		
All locals	-0.0003**	-0.0001	-0.0002	0.0002	0.0020	-0.0015	-0.0005***	-0.0003**	-0.0003**	0.0010‘‘‘	0.0019	0.0005‘‘‘	-0.0020	-0.0023	0.0017	-0.0011	-0.0006	0.0015
Female	-0.0004	-0.0002	-0.0002	-0.0007	0.0035	-0.0026	-0.0005**	-0.0003	-0.0003	0.0011‘‘‘	0.0020	0.0009‘‘‘	-0.0018	-0.0027	0.0017	-0.0020	-0.0015	-0.0000
Male	-0.0002	-0.0001	-0.0001	0.0013	0.0015	-0.0002	-0.0004	-0.0003	-0.0003	0.0009	0.0017	0.0001	-0.0022	-0.0019	0.0008	-0.0001	0.0003	0.0000
Districts with positive & not decreasing																		
All locals	-0.0006	-0.0002	0.0002	0.0002	0.0019	-0.0016	-0.0006	-0.0001	0.0003	0.0011	0.0019	0.0005‘‘‘	-0.0019	-0.0023	0.0017	-0.0009	-0.0007	0.0016
Female	0.0014	0.0016	0.0019	-0.0009	0.0021	-0.0028	0.0013	0.0015	0.0017	0.0013	0.0022	0.0007‘‘‘	-0.0018	-0.0028	0.0020	-0.0020	-0.0016	0.0000
Male	-0.0029***	-0.0022	-0.0018	0.0014	0.0017	-0.0001	-0.0027**	-0.0018*	-0.0013	0.0008	0.0016	0.0002	-0.0019	-0.0018	0.0006	0.0003	0.0004	-0.0001
Districts with negative treatment																		
All locals	0.0286***	0.0218	0.0117*	-0.0049‘‘‘	-0.0148	-0.0087	0.0286	0.0279	0.0099	0.0018	0.0023	0.0049	-0.0076	-0.0015	-0.0013	-0.0066	0.0007	-0.0036
Female	0.0329***	0.0286*	0.0174**	-0.0057‘‘‘	-0.0249	-0.0099	0.0329	0.0324	0.0196	-0.0060	-0.0007	0.0131	-0.0015	0.0033	-0.0160	-0.0001	0.0057	-0.0027
Male	0.0240***	0.0155	0.0056	-0.0039	-0.0042	-0.0073	0.0240	0.0238	0.0084	0.0102	0.0054	-0.0030	-0.0135	-0.0059	0.0095	-0.0129	-0.0039	0.0061

Figure 8: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on Inactive Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: ‘***‘ $p < 0.01$, ‘**‘ $p < 0.05$, ‘*‘ $p < 0.1$. (‘‘‘) indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
Unemployment status	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(1: yes, 0: no)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	0.0001*	0.0001	0.0001*	-0.0009	-0.0008	-0.0004	0.0001	0.0001	0.0001	-0.0015	-0.0015	-0.0020	0.0012	0.0005	0.0001	-0.0004	-0.0011	-0.0016
Female	0.0003**	0.0003***	0.0003***	-0.0019	-0.0021	-0.0008	0.0003*	0.0003*	0.0003*	-0.0018	-0.0022	-0.0020	0.0005	0.0009	-0.0012	-0.0018	-0.0020	-0.0050
Male	-0.0000	-0.0001	-0.0000	0.0003	0.0006	0.0002	-0.0000	-0.0000	-0.0000	-0.0012	-0.0006	-0.0020	0.0019	-0.0000	0.0014	0.0011	-0.0001	0.0023
Districts with no negative treatment																		
All locals	0.0002**	0.0002**	0.0002**	-0.0009	-0.0009	-0.0004	0.0001	0.0001	0.0001	-0.0014	-0.0015	-0.0020	0.0012	0.0005	0.0001	-0.0004	-0.0011	-0.0016
Female	0.0003***	0.0003***	0.0003***	-0.0019	-0.0021	-0.0008	0.0002	0.0002	0.0002	-0.0017	-0.0021	-0.0020	0.0005	0.0009	0.0009	-0.0018	-0.0020	-0.0020
Male	-0.0000	-0.0000	-0.0000	0.0001	0.0005	0.0000	-0.0001	-0.0001	-0.0001	-0.0011	-0.0007	-0.0020	0.0019	-0.0000	-0.0000	0.0011	-0.0001	-0.0001
Districts with positive & not decreasing																		
All locals	0.0008	0.0008	0.0009	-0.0010	-0.0009	-0.0005	0.0002	0.0003	0.0004	-0.0015	-0.0015	-0.0019	0.0009	0.0003	0.0000	-0.0008	-0.0012	-0.0017
Female	0.0009	0.0009	0.0012	-0.0019	-0.0021	-0.0008	-0.0005	-0.0003	-0.0001	-0.0018	-0.0023	-0.0020	0.0002	0.0007	0.0007	-0.0022	-0.0022	-0.0022
Male	0.0006	0.0006	0.0006	0.0000	0.0004	-0.0001	0.0009	0.0010	0.0010	-0.0012	-0.0006	-0.0018	0.0017	-0.0001	-0.0001	0.0008	-0.0002	-0.0002
Districts with negative treatment																		
All locals	-0.0107***	-0.0097	-0.0003	0.0032	0.0020	0.0051	-0.0107	-0.0147	-0.0055	-0.0014	-0.0031	-0.0087	0.0132	0.0073	0.0018	0.0133	0.0064	0.0029
Female	-0.0237***	-0.0215***	-0.0062**	0.0006	-0.0035	-0.0018	-0.0237	-0.0210	-0.0122	0.0005	-0.0005	-0.0034	0.0141	0.0099	0.0099	0.0143	0.0072	0.0072
Male	0.0039***	0.0035	0.0061	0.0062	0.0078	0.0127	0.0039	-0.0070	-0.0022	-0.0038	-0.0057	-0.0137	0.0125	0.0049	0.0049	0.0126	0.0057	0.0057

Figure 9: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on Unemployment Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: ‘***‘ $p < 0.01$, ‘**‘ $p < 0.05$, ‘*‘ $p < 0.1$. (“‘) indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

	Treatment I						Treatment II						Conditional Treatment I			Conditional Treatment II		
In labour force status	**ATT/ TWFE**			**Normalised AVSQ**			**ATT/ TWFE**			**Normalised AVSQ**			**Normalised AVSQ**			**Normalised AVSQ**		
(1: yes, 0: no)	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**
All district																		
All locals	0.0003**	0.0002	0.0002	-0.0000	-0.0015	0.0017	0.0005***	0.0003**	0.0003	-0.0011‘‘‘	-0.0019	-0.0005‘‘‘	-0.0011	-0.0013	-0.0017	0.0004	0.0000	-0.0015
Female	0.0005**	0.0003	0.0003	0.0011	-0.0014	0.0030	0.0006**	0.0004	0.0004	-0.0012‘‘‘	-0.0021	-0.0009‘‘‘	-0.0016	-0.0016	-0.0034	-0.0007	0.0001	-0.0025
Male	0.0002	0.0001	0.0001	-0.0012	-0.0016	0.0003	0.0004	0.0003	0.0003	-0.0009	-0.0016	-0.0001	-0.0006	-0.0009	0.0003	0.0018	-0.0001	0.0004
Districts with no negative treatment																		
All locals	0.0003**	0.0001	0.0002	-0.0002	-0.0018	0.0015	0.0005***	0.0003**	0.0003**	-0.0010‘‘‘	-0.0019	-0.0005‘‘‘	-0.0011	-0.0013	-0.0017	0.0004	0.0000	-0.0015
Female	0.0004	0.0002	0.0002	0.0007	-0.0019	0.0026	0.0005**	0.0003	0.0003	-0.0011‘‘‘	-0.0020	-0.0009‘‘‘	-0.0015	-0.0017	-0.0017	-0.0007	0.0000	0.0000
Male	0.0002	0.0001	0.0001	-0.0013	-0.0017	0.0002	0.0004	0.0003	0.0003	-0.0009	-0.0017	-0.0001	-0.0005	-0.0008	-0.0008	0.0018	-0.0000	-0.0000
Districts with positive & not decreasing																		
All locals	0.0006	0.0002	-0.0002	-0.0002	-0.0019	0.0016	0.0006	0.0001	-0.0003	-0.0011‘‘‘	-0.0019	-0.0005‘‘‘	-0.0011	-0.0014	-0.0017	0.0005	0.0001	-0.0016
Female	-0.0014	-0.0016	-0.0019	0.0009	-0.0021	0.0028	-0.0013	-0.0015	-0.0017	-0.0013‘‘‘	-0.0022	-0.0007‘‘‘	-0.0019	-0.0020	-0.0020	-0.0010	-0.0000	-0.0000
Male	0.0029***	0.0022**	0.0018*	-0.0014	-0.0017	0.0001	0.0027**	0.0018*	0.0013	-0.0008	-0.0016	-0.0002	-0.0003	-0.0006	-0.0006	0.0022	0.0001	0.0001
Districts with negative treatment																		
All locals	-0.0286***	-0.0218	-0.0117*	0.0049‘‘‘	0.0148	0.0087	-0.0286	-0.0279	-0.0099	-0.0018	-0.0023	-0.0049	0.0003	0.0027	0.0013	-0.0010	-0.0018	0.0036
Female	-0.0329***	-0.0286*	-0.0174**	0.0057‘‘‘	0.0249	0.0099	-0.0329	-0.0324	-0.0196	0.0060	0.0007	-0.0131	0.0139	0.0160	0.0160	0.0105	0.0027	0.0027
Male	-0.0240***	-0.0155	-0.0056	0.0039	0.0042	0.0073	-0.0240	-0.0238	-0.0084	-0.0102	-0.0054	0.0030	-0.0123	-0.0095	-0.0095	-0.0111	-0.0061	-0.0061

Figure 10: Estimated effects of Treatment^{I}, Treatment^{II}, Conditional Treatment^{I}, and Conditional Treatment^{II} on In Labour Force Participation Status.

Note: Blue-shaded cells signify statistical significance. Significance levels: ‘***‘ $p < 0.01$, ‘**‘ $p < 0.05$, ‘*‘ $p < 0.1$. (‘‘‘) indicates a significant placebo test, suggesting the parallel trends assumption may not be met. (i),(vii) control for individual-, time-fixed effects, and the interaction between region-fixed effects and time-fixed effects. (ii),(viii) also incorporate individual-level characteristics. (iii),(ix) include district level characteristics. (iv),(x),(xiii), (xvi) control for individual- and time-fixed effects. (v),(xi),(xiv), (xvii) perform exact matching on individual characteristics. (vi),(xii),(xv), (xviii) match on districts' labour market conditions proxy. The full set of results are available in Section A.3.

allow us to estimate Effect 4 in our context. Additionally, there should still be individuals who would be suited to act as "controls".

In each quarter, approximately 8,300 individuals, limited to locals aged 15 and over and excluding those of Ukrainian descent or nationality, enter the panel for the first time. This means that when estimating Effect 4, we are restricted to a maximum of around 8,300 locals. Then, the AVSQi,l, averaged AVSQl, and subsequently the normalised AVSQ, are weighted by the correct average of treatment effects.

In principle, the decreasing number of individuals is not a concern, provided that (i) the subsample remains reflective of the broader Czech Republic population, (ii) attrition patterns do not introduce bias and (iii) the absence of controls does not . . . .

(i) LFSS sampling design.

The first requirement is more straightforward and is met by the sample design of the LFSS(Commission, 2019). The sampling strategy is a two-stage stratified sampling plan based on the Register of Census Areas from 2013. The primary sampling units are census areas, selected using probability proportional to size, which corresponds to the number of dwellings per census area. Dwellings are then chosen through simple random sampling. This systematic, randomised approach ensures that the sample is representative of the entire population. Moreover, the survey encompasses the entire country and includes everyone living in the selected dwellings, regardless of the type of stay, with some exceptions such as those residing abroad or in collective accommodations. Thus, while the sample is a subset, it's designed to mirror the broader population.

(ii) Sample attrition analysis.

Variables	All patterns	1111.	111..	11…	1….
The person did not attrite	236,000	296,527	304,135	313,012	322,364
The person attrited	97,346	36,819	29,211	20,334	10,982

Table 13: Attrition patterns statistics

Note:

Extend and implication of absence of controls for Conditional Treatment I and II. *To be added.*

5.3 Concerns about secondary effects

Population movement. The identified effects of the treatment on the labour market outcomes for the locals might have been distorted by secondary effects, primarily due to the potential movement of locals away from the most affected districts.

Table 14 reports a matrix of correlations, broken down by district, which relates the net migration of locals to varying treatment levels. The correlations suggest a weak relationship: Treatment^{I} and Treatment^{II} are negatively correlated with net migration, while for Treatment^{III} and Treatment^{IV}, the correlation is positive. However, these correlation coefficients hover near zero. Notably, many districts with negative net migration in 2022 also showed a similar pattern in the earlier years before the treatments.

	Treatment I	Treatment II	Treatment III	Treatment IV
Net migration (absolute data)				
Total	-0.05	-0.06	0.09	0.05
Female	-0.06	-0.07	0.07	0.03
Net migration (relative data per 1,000 inhabitants)				
Total	0.08	0.14	0.10	0.18

Table 14: Correlation Matrix: Net Migration of Locals vs. Treatment Levels

Note: Data sourced from the Office) (2023)

Initial Condition Problem. *To be added.*

6 Robustness check

Examining Sensitivity to Treatment Normalisation. *To be added.*
Examining Sensitivity to Treatment Discretisation. *To be added.*
Testing the 'No Anticipation' Assumption. *To be added.*

7 Conclusions

To be completed when the final data for the q4 2022 is available and all the analysis is done.

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A Appendix

A.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) (Czech Statistical Office, 2023a).

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 countryMVCR (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 15: 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, 15+
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

A.2 Appendix B: Auxiliary Figures and Tables

	Treatment of <0%	Control of 0%	Treatment of 1%	Treatment of 2%	Treatment of 3%	Treatment of >3%
Labour Market Outcomes for locals						
Employed Status	0.59	0.51	0.52	0.52	0.52	0.56
Inactive Status	0.40	0.47	0.47	0.46	0.47	0.43
Unemployed Status	0.01	0.02	0.01	0.01	0.01	0.01
In Labour Force Status	0.60	0.53	0.53	0.54	0.53	0.57
Hours usually worked	41.69	39.46	39.66	39.46	39.14	39.23
Individual-level covariates						
Male	0.48	0.46	0.47	0.47	0.46	0.47
Age	52.49	52.50	52.78	53.36	52.95	52.06
Marital status	0.63	0.52	0.54	0.53	0.52	0.52
Pension or disability status	0.34	0.40	0.40	0.41	0.41	0.38
Foreigner	0.01	0.01	0.01	0.02	0.02	0.03
Education level						
No education	-	0.00	0.00	0.00	0.00	0.00
Basic education	0.09	0.16	0.14	0.12	0.12	0.14
Secondary without matriculation	0.29	0.37	0.37	0.33	0.33	0.35
Secondary with matriculation	0.31	0.32	0.33	0.35	0.34	0.35
University	0.31	0.15	0.16	0.20	0.20	0.16
Population density						
Dense population	-	0.23	0.18	0.35	0.47	0.28
Medium settlement	0.63	0.46	0.38	0.29	0.22	0.29
Sparsely populated	0.37	0.31	0.44	0.37	0.31	0.43
District-level covariates						
# active companies	28,038	18,398	31,022	88,237	31,563	18,159
# active large companies	28	28	51	176	54	36
# vacancies per population	0.03	0.02	0.04	0.10	0.07	0.07
Average wage rate (1,000)	37,999	32,215	34,277	37,031	35,311	35,374
Unemployment rate	0.02	0.05	0.03	0.03	0.03	0.02
Labour Market Dynamics						
# of Ukrainians of working age	2,493	696	2,646	11,603	3,544	3,199
# of employed Ukrainians	3,891	856	3,101	12,901	4,134	5,263
# of locals of working age	89,219	99,926	112,198	237,777	115,065	82,147
# of employed local	81,391	75,851	90,315	196,097	95,403	66,318
# of observations	1,379	60,967	266,011	127,751	30,715	19,114

Table 16: Descriptive statistics for 2019-2021 grouped by $Treatment^{II}$ doses

Note: Based on LFSS data for 2019-2021, the table reports mean values for local labour market outcomes ($y_{i,d,r,t}$), individual-level ($\mathbf{X}$), district-level variables ($\mathbf{Z}$) by the $Treatment^{II}$ doses. Data is restricted to locals aged 15+ and excludes individuals of Ukrainian descent and/or nationality. The immigration patterns data are sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

	Employed Diaspora of					
	0%	1%	2%	3%	4%	> 4%
Labour Market Outcomes for locals						
Employed Status	0.51	0.50	0.51	0.51	0.53	0.53
Inactive Status	0.47	0.48	0.48	0.48	0.46	0.46
Unemployed Status	0.02	0.02	0.01	0.01	0.01	0.01
In Labour Force Status	0.53	0.52	0.52	0.52	0.54	0.54
Hours usually worked	38.37	39.47	39.44	39.44	38.52	39.23
Individual-level covariates						
Male	0.47	0.47	0.47	0.47	0.47	0.46
Age	53.37	53.52	53.86	54.33	53.56	54.02
Marital status	0.51	0.52	0.53	0.53	0.54	0.52
Pension or disability status	0.41	0.42	0.43	0.44	0.42	0.41
Foreigner	0.00	0.01	0.01	0.01	0.01	0.03
Education level						
No education	0.00	0.00	0.00	0.00	0.00	0.00
Basic education	0.14	0.14	0.14	0.12	0.12	0.10
Secondary without matriculation	0.37	0.37	0.39	0.37	0.33	0.30
Secondary with matriculation	0.34	0.32	0.34	0.34	0.34	0.35
University	0.14	0.16	0.14	0.17	0.21	0.24
Population density						
Dense population	0.14	0.18	0.04	0.23	0.35	0.47
Medium settlement	0.50	0.40	0.50	0.31	0.28	0.23
Sparsely populated	0.35	0.42	0.46	0.46	0.37	0.30
District-level covariates						
# active companies	18,584	18,162	15,238	17,244	35,070	128,720
# active large companies	25	28	20	22	53	242
# vacancies per population	0.01	0.02	0.02	0.03	0.07	0.13
Average wage rate (1,000)	36,548	37,236	37,142	38,042	38,266	41,954
Unemployment rate	0.05	0.04	0.03	0.03	0.04	0.03
Immigration patterns						
# of Ukrainians of working age	1,969	2,504	2,888	4,036	9,103	38,725
# of employed Ukrainians	606	1,289	1,748	2,485	6,158	24,669
# of locals of working age	104,814	87,492	69,506	72,883	120,749	297,595
# of employed local	79,682	68,391	55,192	59,367	98,739	246,649
Average Treatment Dose	0.48%	0.87%	1.23%	1.40%	1.84%	2.56%
# of observations	14,051	41,775	27,605	22,934	17,811	41,665

Table 17: Descriptive statistics for 2022 by baseline treatment levels ($Conditional\ Treatment^{II}$)

Note: Based on LFSS data for 2022, the table reports mean values for local labour market outcomes ($y_{i,d,r,t}$), individual-level ($\mathbf{X}$), district-level variables ($\mathbf{Z}$) by baseline treatment levels, that represent the percentage of employed Ukrainians in 2021 relative to the employed locals, according to $Conditional\ Treatment^{I}$. Data is restricted to locals aged 15+ and excludes individuals of Ukrainian descent and/or nationality. The immigration patterns data are sourced from Ministry of the Interior (2023), Ministry of Labour and Social Affairs (2023) and Czech Statistical Office (2023b).

Variable	All patterns				1111.				111..				11…				1.....			
Attrition pattern	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**	**(vii)**	**(viii)**	**(ix)**	**(x)**	**(xi)**	**(xii)**	**(xiii)**	**(xiv)**	**(xv)**	**(xvi)**	**(xvii)**	**(xviii)**	**(xix)**	**(xx)**
Status in Employment																				
Employed	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Unemployed	0.05	0.06	0.01	0.02	-0.05***	-0.05**	-0.04*	-0.04*	0.03	0.03	0.01	0.01	0.02	0.02	0.03	0.03	0.06**	0.06**	0.02	0.02
Inactive	-0.01	0.00	0.00	0.00	-0.05***	-0.04***	-0.03**	-0.03*	-0.02	-0.02	-0.01	-0.01	0.01	0.02	0.03*	0.03*	0.05***	0.05***	0.01	0.01
Hours usually worked	0.00	-0.00*	-0.00**	-0.00**	-0.00**	-0.00**	-0.00*	-0.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00**	-0.00**
Job separation status	-0.17***	-0.17***	-0.11***	-0.10***	-0.01	-0.01	-0.02	-0.02	-0.04**	-0.04**	-0.04**	-0.04**	-0.05***	-0.05***	-0.02*	-0.02*	-0.07***	-0.07***	-0.02*	-0.02*
Job fining status	-0.03***	-0.03***	-0.02	-0.02	0.01	0.01	0.0	0.00	0.00	0.00	-0.01***	-0.01***	-0.01***	-0.01***	0.00	0.00	-0.03***	-0.03***	-0.00***	-0.00***
Treatment I	6.5		4.23		2.15		2.32		1.98*		1.92		1.55		0.00		0.82		0.00	
Treatment II		8.88*		6.04*		2.98*		3.30*		2.72*		2.73*		2.09*		0.00		1.10*		0.00
Individual-level covariates																				
Male			-0.00***	-0.00***			0.00	0.00			-0.00***	-0.00***			-0.00***	-0.00***			-0.00*	-0.00*
Age			-0.01**	-0.01*			-0.01*	-0.01			0.00	0.00			-0.00**	-0.00**			-0.00***	-0.00***
Marital status			0.01	0.01			0.00	0.00			0.01	0.01			0.00***	0.00***			0.00**	0.00**
Pension or disability status			-0.03**	-0.03**			-0.03***	-0.03***			0.00	0.00			0.00	0.00			0	0
Foreigner			-0.00***	-0.00***			0.00	0.00			-0.00***	-0.00***			-0.00***	-0.00***			-0.00*	-0.00*
Parental status																				
No children			-	-			-	-			-	-			-	-			-	-
Child(ren) < 3y.o.			0.00	0.00			0.01	0.01			0.00	0.00			-0.00***	-0.00***			0.00	0.00
3y.o. ≤Child(ren) < 15y.o.			-0.01**	-0.01**			-0.01***	-0.01***			0.01	0.01			-0.00***	-0.00***			-0.00**	-0.00**
15y.o. ≤Child(ren) < 18y.o.			0.00	0.00			-0.01	-0.01			0.01**	0.01**			-0.00**	-0.00**			0.00	0.00
Education level																				
No education			-	-			-	-			-	-			-	-			-	-
Basic education			0.21***	0.21***			0.10***	0.10***			0.10***	0.10***			0.01***	0.01***			0.00***	0.00***
Secondary without matriculation			0.19***	0.19***			0.09***	0.09***			0.09***	0.09***			0.01***	0.01***			0.00***	0.00***
Secondary with matriculation			0.18***	0.19***			0.09***	0.09***			0.09***	0.09***			0.01***	0.01***			0.00***	0.00***
University			0.18***	0.19***			0.09***	0.09***			0.09***	0.09***			0.01***	0.01***			0.00***	0.00***
Population density																				
Dense population			-	-			-	-			-	-			-	-			-	-
Medium settlement			-0.05**	-0.05*			-0.02	-0.02			-0.03**	-0.02**			0.00	0.00			-0.00*	-0.00*
Sparsely populated			-0.06**	-0.06**			-0.03*	-0.02			-0.03**	-0.03**			-0.00**	-0.00**			-0.00***	-0.00***
District-level covariates																				
# active companies			0.00	0.00			0.00	0.00			0.00	0.00			0.00	0.00			0.00	0.00
# active large companies			0.00	0.00			0.00	0.00			0.00	0.00			0.00	0.00			0.00	0.00
# vacancies per population			-1.72***	-1.80***			-0.74**	-0.78**			-0.93***	-0.96***			-0.04***	-0.04***			-0.02***	-0.02***
Unemployment rate			-0.32	0.02			-0.30	-0.11			-0.04	0.11			0.04	0.04			-0.01	-0.01
Average wage rate (1,000)			0.00***	0.00***			0.00***	0.00***			0.00***	0.00***			-0.00***	-0.00***			-0.00**	-0.00*
Overall R^2	0.06	0.09	0.1	0.11	0.01	0.02	0.04	0.05	0.02	0.02	0.06	0.06	0.01	0.02	0.00	0.00	0.01	0.01	0.00	0.00
# of Obs.	172,328	172,328	156,528	156,528	172,328	172,328	156,528	156,528	172,328	172,328	156,528	156,528	172,328	172,328	156,528	156,528	172,328	172,328	156,528	156,528

Figure 11: Emp

A.3 Appendix C: Extended Results of TWFE regression

To be completed when the final data for the q4 2022 is available and all the analysis is done. Preliminary results can be provided on request.

A.4 Appendix D: Extended Results of DiD regression

To be completed when the final data for the q4 2022 is available and all the analysis is done. Preliminary results can be provided on request.