Postepska, Agnieszka; Voloshyna, Anastasiia

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

Agnieszka Postepska[1] · **Anastasiia Voloshyna**[1,2]

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Abstract

Following the Russian Federation's invasion of Ukraine on 24th February 2022, over a quarter of the Ukrainian population became displaced. Czechia emerged as a key destination, granting temporary protection to approximately 433,000 Ukrainians by the end of 2022, thus sheltering the highest per capita number of Ukrainian refugees worldwide. The swift enactment of the 'Lex Ukraine Act' granted the refugees unrestricted access to the labour market. This led to a notable increase in the number of legally employed Ukrainians and expanded Czechia's workforce. Using individual micro-level data from 16 waves of the Labour Force Sample Survey (LFSS), collected between the 1st quarter of 2019 and the 4th quarter of 2022, we examine the short-term impact of the influx of the Ukrainian refugees into the workforce on the labour market outcomes of locals in Czechia. Incorporating several empirical strategies, including a two-way fixed effects model (TWFE), extensions to the canonical difference-in-differences (DiD) estimator, and matching on selective characteristics of individuals/districts and pre-treatment trends, we find consistent evidence that the influx of refugees had no economically meaningful impact on employment, unemployment, or inactivity rates within the local population, regardless of gender, educational level, or industry. Most importantly, we find consistent evidence of an increase in weekly working hours among local females in treated districts. This increase is primarily driven by workers with secondary education employed in the most affected sectors.

Keywords Ukrainian refugees · Immigrants · Local labour market · Labour supply

JEL Classification F22 · J15 · J21

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✉ Agnieszka Postepska
a.postepska@rug.nl

Anastasiia Voloshyna
a.o.voloshyna@rug.nl

1 Faculty of Economics and Business, Department of Economics, Econometrics & Finance, University of Groningen, 9700 AV Groningen, The Netherlands

2 Max Planck Institute for Demographic Research, Rostock, Germany

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1 Introduction

Following the invasion of Ukraine by the Russian Federation on 24^{th} February 2022, over a quarter of the Ukrainian population became displaced (IOM 2023b; UNHCR 2023b). 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 programmes. This refugee crisis is the largest in Europe since World War II, exceeding the displacement caused by the Yugoslav Wars of the 1990 s and the Syrian Civil War.[1]

Due to their geographical and cultural proximity, the Visegrad Group (V4) countries became primary destinations for Ukrainians fleeing the conflict (GLOBSEC 2023). Czechia, in particular, emerged as a key refuge. By the end of 2022, this mid-sized European country with 10.5 million inhabitants had granted temporary protection to approximately 433,000 individuals.[2] Consequently, Czechia hosts the highest per capita number of Ukrainian refugees worldwide.

In response to the sudden influx of refugees, the Czech government swiftly enacted the 'Lex Ukraine Act' in March 2022 (European Commission 2022b). Aligned with the European Union Temporary Protection Directive (TPD), this legislation temporarily extended benefits reserved for permanent residents to Ukrainian citizens, their family members, and other specified individuals. Refugees were granted unrestricted access to the labour market, retraining programmes, opportunities for self-employment, unemployment benefits, healthcare, education, and living allowances. This approach contrasts sharply with the usual lengthy procedures in the EU, where refugees often wait months or even years to gain such rights.[3]

Typically, refugees face prolonged procedures to access employment opportunities, resulting in a gradual and less exogenous influx of workers into host countries' labour markets. However, the immediate and unrestricted access granted to Ukrainian refugees meant that the demographic shock quickly translated into a significant labour supply shock. By the end of 2022, Ukrainian refugees legally employed represented approximately 1.4% of all employed individuals in Czechia.[4] This influx was unevenly distributed across districts and industries. Certain regions—such as Cheb, Plzeň-South, Plzeň-City, Praha-East, Mladá Boleslav, and Tachov—experienced particularly high inflows, with Ukrainian refugees at times constituting between 3 and 32% of their total employment. Moreover, the refugees arrived during favourable conditions in the

[1] The Yugoslav Wars in the 1990 s resulted in approximately 2 million people fleeing Bosnia, 500,000 from Croatia, 100,000 from Serbia, and 30,000 from Slovenia (USCRI 1998). The Syrian Civil War displaced around 6.6 million Syrians, with European countries hosting just over 1 million (UNHCR 2023a).

[2] This count includes only those who secured temporary protection status; the actual number of refugees in Czechia may be higher or lower.

[3] In the EU, the time refugees wait to obtain the right to work varies (ECRE 2024); since March 2020, for example Germany generally prohibits asylum seekers in initial reception centres from taking up employment, with most adults facing a wait of 18 months and up to 24 months in some federal states (ECRE 2023).

[4] By 'legal employment', we refer to positions officially registered with the Czech Ministry of Labour and Social Affairs, including all types of contracts such as DPP for short-term work, but excluding self-employed individuals.

Czech labour market, characterised by the lowest in the EU unemployment rate of just 2.22% and a persistent surplus of job vacancies over job seekers (Ministry of Labour and Social Affairs 2023b; Eurostat, 2023).

In our paper, we exploit this natural experiment of the sudden and forced influx of Ukrainian refugees, which significantly expanded Czechia's workforce. We assess the short-term impact—over 1 year—of legally employed Ukrainian refugees on the labour market outcomes of local workers in Czechia. Previous research has often utilised such large-scale migration waves triggered by wars or political upheavals to examine their effects on host countries' labour markets. A prominent example is the 1980 Mariel Boatlift, during which approximately 125,000 Cuban refugees increased Miami's labour force by about 7%. While Card (1990) initially found minimal effects on local wages and employment, later studies by Card (2001) and Borjas (2003, 2017) contested these findings, revealing significant wage reductions among low-skilled natives. Similarly, after Algeria's independence in 1962, France experienced an influx of about 900,000 repatriates—amounting to 1.6% of the total French labour force—with estimates indicating minimal impacts on unemployment but somewhat larger negative impacts on wages (Hunt 1992). In Israel, the arrival of immigrants from the former Soviet Union between 1990 and 1994 increased the population by 12%, with studies identifying no or only short-lasting adverse effects on native employment and wages (Friedberg 2001; Cohen-Goldner and Paserman 2011). More recently, between 2012 and 2016, the influx of Syrian refugees increased Germany's population by ~0.7% and Sweden's by ~1.5%, although the effects on local labour markets remain largely unexamined.

In summary, empirical research often finds little to no impact of immigration on the population-wide employment or wages of local workers.[5] However, when analyses focus on specific demographic groups—particularly those who share characteristics with the immigrants—more pronounced and varied effects emerge; for instance, adverse effects of immigration have been identified for local low-skilled males and minorities when immigrants compete directly with local workers,[6] whereas the influx of female immigrant labour providing affordable household services has been linked to increased labour force participation among high-potential female earners, indicating that immigrants can also complement the local workforce.[7] Moreover, several studies—such as those by Angrist and Kugler (2003); Lemos and Portes (2008); Glitz (2012); Aydemir and Kırdar (2017)—have emphasised the crucial role of local labour market conditions, including market flexibility, wage rigidity, and pre-existing employment rates, in determining how effectively host economies can absorb immigrants and the consequent effects on native workers.

Building on empirical strategies commonly employed in this literature, we adopt a regional approach. First, we construct a set of three treatment variables, each designed

[5] See, for example Card (1990); Friedberg and Hunt (1995); Borjas et al. (1996); Pischke and Velling (1997); Friedberg (2001); Angrist and Kugler (2003); Card (2009).

[6] See, for example Hunt (1992); Borjas (1994); Carrington and de Lima (1996); Card (2001); Borjas (2003); Nickell and Saleheen (2008); Dustmann et al. (2005); Borjas and Katz (2007); Lemos and Portes (2008); Mansour (2010); Cohen-Goldner and Paserman (2011); Ottaviano and Peri (2011); Glitz (2012); Maystadt and Verwimp (2014); Aydemir and Kırdar (2017); Borjas (2017); Ceritoğlu et al. (2017).

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

to capture the exposure of local labour markets in Czechia to the labour supply shock resulting from Ukrainian refugees entering the workforce. Using aggregated district-level data on the number of legally employed Ukrainians provided by the Ministry of Labour and Social Affairs (2023a), we estimate the number of employed refugees in each quarter of 2022 and normalise this by the size of the local labour force in each corresponding district. The resulting treatment variables vary in intensity (referred to as 'treatment doses', ranging from 0% to 32%) across districts and over time, with each 'dose' representing a 1% increase in the district's workforce attributable to Ukrainian refugees who became legal employees.

With the treatment variables defined, we exploit variation in treatment doses across time and districts to relate them to changes in the labour market outcomes of locals—primarily Czech nationals and a small subsample of non-Ukrainian migrants. We utilise individual quarterly panel microdata from 16 waves of the Labour Force Sample Survey (LFSS) conducted in Czechia, spanning from the 1st quarter of 2019 to the 4th quarter of 2022. These data allow us to examine changes over time in both the extensive margin (employment, unemployment, and inactivity statuses) and the intensive margin (weekly hours worked). To account for potential heterogeneity in treatment effects across different demographic groups, we disaggregate the estimated impacts by gender, educational attainment, industry of employment, type of employment contract, and country of origin (foreign-born versus native-born).

Our identification strategy unfolds in several steps. We begin by implementing a static two-way fixed effects (TWFE) regression. Recognising the limitations of the TWFE approach in our complex setting—specifically, its potential failure to capture treatment effect heterogeneity across individuals and over time—we subsequently adopt the heterogeneity-robust estimator proposed by de Chaisemartin and D'Haultfœuille (2024) as our primary method. This extended difference-in-differences (DiD) method enables unbiased estimation of treatment effects using (non-)binary, (non-)staggered treatments and allows for dynamic/inter-temporal treatment effect analysis, making it highly suitable for our context.

Given the absence of a randomised experiment, we pay careful attention to the possibility of self-selection among the refugees. We normalise our treatment variables by district labour market size to provide a meaningful measure of treatment intensity and to mitigate biases from self-selection. This approach reveals heterogeneity in pre-treatment trends in analysed labour market outcomes as well as in pre-treatment economic characteristics across both treatment and control districts. To ensure the robustness of our estimates and leveraging the heterogeneity in pre-treatment trends across both treated and control districts, we match treated and control districts on their pre-2022 trends, calculated separately for subgroups defined by gender and education level, as well as gender and industry of employment. Additionally, we introduce matching on individual characteristics to ensure that treated and control individuals are always compared with similar counterparts.

Finally, for our main estimator—the extended DiD—we rigorously test the parallel trends assumption using placebo estimators. Reassuringly, for the majority of our analyses across all model specifications and sub-populations, these placebo tests are not significant. Additionally, beyond addressing any potential issues with the 'no anticipation' and 'no self-selection among locals' assumptions, we demonstrate that there are no systematic associations between pre-2022 economic conditions and 2022 treatment intensities across districts, further enhancing the credibility of our findings.

Our results are in line with the existing literature. We find consistent evidence that the influx of refugees had no economically meaningful impact on employment, unemployment, or inactivity rates of Czech nationals in the short run, regardless of gender, educational level, or industry of employment. Examining the most affected industries, we identify minor negative effects on employment within sectors that saw the largest influx of workers. Additionally, there is some evidence to suggest that foreign-born individuals in Czechia may have experienced a slight decrease in employment probability alongside a corresponding increase in unemployment probability. However, due to the small sample sizes, we treat these results with caution. We suggest that the combination of a tight labour market and existing shortages in key industries likely mitigated potential disruptions from the influx of refugees, enabling the Czech economy to absorb the new workforce relatively smoothly, at least in the short term. Most importantly, we find consistent evidence of an increase in weekly working hours among local women in treated districts. This increase is primarily driven by workers with secondary education employed in the most affected sectors. The concentration of positive effects among women with secondary education likely reflects both the nature of the jobs Ukrainian refugees are taking and the specific demands of the Czech labour market. Individuals with secondary education can occupy roles that complement those filled by the incoming workforce, leading to longer hours due to increased demand or collaborative opportunities.

We acknowledge that the scope of our study is limited to estimating the effect of Ukrainian refugees who are legally employed in Czechia. While incorporating data on the informal sector would be of significant interest, little is known about the number and location of undocumented refugee workers. Although some attempts have been made to estimate these figures at different points in time—for example a survey conducted in Czechia by Kavanová et al. (2022a) found that 7% of refugees reported using informal labour brokers, and another survey across several EU countries by European Union Agency for Fundamental Rights (2023) indicated that 8% of surveyed refugees had worked without a contract or with a contract that did not cover all working hours—the accuracy of these percentages and their variation by district and over time remain unknown. If we accept these estimates, it indicates that most refugees are not employed informally, stressing the relevance of our analysis.

Similarly, to infer the effects on local Czech workers, we rely on the highly reliable LFSS data, which effectively captures formal employment sectors. However, due to its sampling design, it may not fully reflect the experiences of those in informal employment or certain migrant groups. Consequently, we can only discuss the partial effect of the refugee inflow. We interpret the impact on other migrant groups in the country with caution.

Within the scope of the analysis, we contribute to several strands of the literature. To our knowledge, we are the first to provide a thorough analysis of the impact of the most recent refugee crisis in Europe on the labour market. Since the Ukrainians were granted access to the labour market almost immediately after entry, we contribute to the broader literature on the effects of immigration on the host country's labour market. We also document refugee settlement patterns consistent with the literature

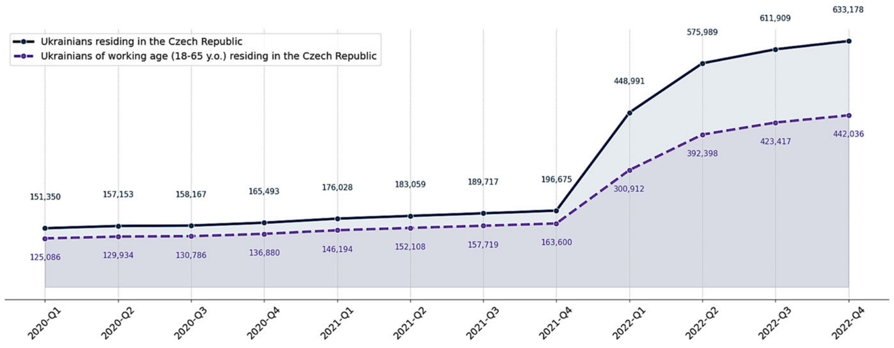


Fig. 1 Evolution of Ukrainian immigrant and refugee registrations in Czechia. Note: This figure details the count of Ukrainian immigrants residing in Czechia, distinguishing between the total population and those of working age (18–65 years). The noticeable uptick corresponds to the arrival of refugees. The plot was created by the authors from data reported by the Ministry of the Interior (2023a, b) of Czechia

on network effects and self-selection of immigrants (Hatton and Williamson 1998; Woodruff and Zenteno 2007; Patel and Vella 2013; Stuart and Taylor 2021).

Lastly, the results of this paper are particularly important for policymakers. First, our findings clearly point to groups of workers that are vulnerable to the influx of foreign workers. Second, given the increasingly polarised public attitudes towards past and future policies on refugee integration and accommodation (including financial assistance to Ukrainian refugees) and future EU accession, there is a pressing need for objective, data-driven insights into the effects of refugees' active participation in labour markets.[8] The unique circumstances of the unrestricted access to employment of Ukrainian refugees allow us to understand these effects already in the short term. This is important for expanding the body of academic knowledge and informing effective policymaking.

The remainder of this paper is organised as follows. The next section provides background information on the Ukrainian refugee influx in 2022, detailing the demographic characteristics of Ukrainian refugees, settlement patterns, and workforce integration. Section 3 discusses the data and descriptive statistics, while Section 4 outlines the identification strategy. Baseline results, along with all extensions to the estimators and discussion, are presented in Section 5, followed by auxiliary robustness checks in Section 6 and conclusions in Section 7.

[8] In Poland, a Pollster Research Institute survey shows increasing opposition to aiding Ukrainians, with 36% opposed and 26% in support (Forsal 2023). Another survey indicates a divided stance, with 49.1% in favour of aid but 39.4% viewing Ukrainians negatively, some citing perceptions of a 'demanding attitude' by refugees, and 14.5% believe Ukrainians have more rights than Poles (DGP 2023). EU-wide, Eurobarometer reveals a slight decline in support for Ukraine: 86% (down from 88%) back humanitarian aid and 77% (down from 86%) support accepting war refugees (European Commission 2023a, b). Regarding Ukraine's EU accession, 67% of Europeans endorse it, but support varies: high in Denmark (79%) and Portugal (88%), lower in Germany (60%) and France (60%), and very low in Greece (43%), Hungary (50%), and Slovakia (50%) (European Commission 2023a). Another survey confirms 63% overall support for Ukraine's EU membership, with less enthusiasm in France (52%) and Germany (49%) (GMF 2023).

2 Contextual details and economic theory: analysing potential labour market responses

To understand the economic implications of the observed data patterns, we examine the influx of Ukrainian refugees into Czechia, focusing on their settlement patterns, demographic profiles, and integration into the labour market. We identify industries that experienced a notable increase in refugee workers and summarise the local labour market conditions in Czechia. With relevant economic theory in mind, we also discuss the potential effects of the refugee influx on the labour market outcomes of local workers.

Demographic characteristics of the Ukrainian refugees By 31 December 2022, Czechia had welcomed approximately 433,000 Ukrainian refugees (Fig. 1)—predominantly working-age women and children—a demographic profile distinct from the country's typical migration patterns.[9] As shown in Table 1, the age distribution of Ukrainians who sought refuge in Czechia largely mirrors that of the local population, with a notable divergence only in the group over 65 years old (just 4% of refugees versus 20% of locals). Approximately 64% of refugees were of working age (18–65 years old), 69% of whom were women. This gender imbalance is mostly attributable to Ukraine's wartime regulations, which restricted many males of combat age from leaving the country.

The refugees generally had higher educational attainment levels than the local Czech population (Table 2). Depending on the source, the percentage of those with tertiary education was estimated to be between 35 and 49%, noticeably exceeding the 18% average rate among Czech locals. While this gap was somewhat narrower in urban areas such as Capital City Prague and Brno-City, with local tertiary rates at 34% and 32%, respectively, it became more pronounced in smaller, more peripheral districts like Tachov and Cheb.

Settlement patterns and workforce integration The influx of Ukrainian refugees led to a significant expansion of Czechia's population and workforce. By the end of 2022, refugees constituted around 4% of the country's residents—the highest per capita number of Ukrainian refugees globally. Due to the immediate and unrestricted access to the local labour market granted to Ukrainian refugees by the 'Lex Ukraine Act', the demographic shock rapidly translated into a significant labour supply shock, with approximately 75,000 securing legal employment by the end of 2022, 79% of whom were women (Ministry of Labour and Social Affairs 2023a).[10] According to surveys conducted by Kavanová et al. (2022b), this accounted for roughly half of the economically active Ukrainian refugees.

[9] From 2016 to 2021, approximately 57% of immigrants in Czechia were male, primarily from Ukraine, Slovakia, and Russia (Ministry of the Interior 2023a). Most of these immigrants were labour migrants employed in manufacturing, as well as in semi-skilled administrative and support service roles (Ministry of Labour and Social Affairs 2023a). Until 2022, Czechia had received fewer refugees than most EU countries, with only 1046 by 2021 (Ministry of the Interior 2022). This group comprised largely younger males from the former Soviet Bloc and countries such as China and Syria who were escaping conflicts and crises.

[10] We approximated this number. For the details, see Section 4.1.

Table 1 Age and gender of Ukrainian refugees compared to the Czech population

	Refugees					Locals				
	Overall	Prague	Brno-mésto	Tachov	Cheb	Overall	Prague	Brno-mésto	Tachov	Cheb
Gender										
Female	63%	64%	63%	69%	66%	51%	51%	51%	50%	51%
Male	37%	36%	37%	31%	34%	49%	49%	49%	50%	49%
Age										
0–5 y.o	8%	8%	7%	4%	7%	5%	5%	6%	5%	5%
6–14 y.o	18%	17%	16%	11%	16%	11%	10%	10%	11%	11%
15–17 y.o	6%	6%	6%	4%	5%	5%	4%	4%	5%	5%
18–64 y.o	64%	65%	67%	79%	67%	59%	62%	61%	61%	58%
65+ y.o	4%	4%	3%	2%	5%	20%	18%	20%	19%	21%

Note: This table compares the age and gender distribution between Ukrainian refugees in Czechia as of 31 December 2022 and the Czech native population based on the 2021 Census. The table was created by the authors using data sourced from the Ministry of the Interior (2023b) and the 2021 Census (Czech Statistical Office, 2024b). Age categories have been harmonised to ensure comparability. Capital City Prague and Brno-City were selected as economically stronger districts, while Tachov and Cheb were chosen to represent more peripheral regions, with both selected randomly to highlight the heterogeneity of indicators across different areas

By 'legal employment', we refer to positions officially recorded by the Ministry of Labour and Social Affairs (2023a), including all types of contracts such as DPP for short-term work, but excluding self-employed individuals. While another 5000 Ukrainians obtained valid trade licences, enabling entrepreneurial activities (Ministry of Industry and Trade 2023), the locations of these individuals by district and their variation over time are not reported. Therefore, this paper focuses solely on employees. Additionally, refugees working unlawfully without registration are naturally also not included among the legally employed.

Table 2 Educational attainment of Ukrainian refugees compared to the Czech population

	Refugees			Locals				
	MoLSA	IOM	UNHCR	Overall	Prague	Brno-mésto	Tachov	Cheb
Education attainment								
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%

Note: The table was created by the authors using 2021 Census data for Czechs (Czech Statistical Office, 2021) and Ukrainian refugee education data from surveys conducted by the Czech Ministry of Labour and Social Affairs (2022) (MoLSA), IOM (2023a), and UNHCR (2022). The latter two surveys, being non-representative, provide only indicative insights. Educational categories were harmonised for comparability. For detailed information on these changes, including survey timings and sample sizes, refer to the extended Table B.1

By the end of the year, Ukrainian refugees legally employed represented around 1.4% of all employed individuals in Czechia, but this influx was unevenly distributed across districts and industries. Certain regions—such as Cheb, Plzeň-South, Plzeň-City, Praha-East, Mladá Boleslav, and Tachov—experienced significantly higher inflows, with Ukrainian refugees constituting at times between 3% and as high as 32% of their employed populations. In other words, in these districts, around one in every 25 to as many as one in every three employed individuals was a Ukrainian refugee (see Fig. 2b). Conversely, districts like Bruntál, Domažlice, Frýdek-Místek, Karviná, Pelhřimov, and Praha-East saw minimal changes. We exploit this regional variation for our identification strategy.

The employment patterns among refugees also varied notably by gender and industry (Czech Statistical Office 2022c, b, 2023c, b). Female refugees, based on approximate statistics, primarily secured legal employment in administrative and support service activities (~33%) and manufacturing (~29%), with smaller proportions employed in accommodation and food service activities (~8%), transportation and storage (~7%), and wholesale and retail trade and repair of motor vehicles and motorcycles (~7%). Male refugees, in turn, predominantly joined the manufacturing and construction sectors (both ~31%), with around 19% employed in administrative and support service activities.

Free to move within the country, the refugees exhibited distinct patterns of self-selection in their choices of settlement and employment locations (see Table 3). They gravitated towards economically prosperous areas with higher GDP, wages, and education levels, on the lookout for the so-called 'sorting gains'. We discuss the implications of this for our empirical analysis in detail in Section 4.4.1.

Districts with more large companies and tighter local labour markets—characterised by lower unemployment rates and higher ratios of job openings to job seekers—were particularly attractive to refugees. Established Ukrainian diasporas also played a significant role in attracting newcomers, acting as magnets. This is evidenced by the high correlation coefficients (0.99 and 0.81) between the locations of Ukrainians residing and working in 2021 and those of refugees in 2022 and is further supported by a 2022 UNHCR survey, where the largest group of refugees (23%) reported choosing Czechia primarily because they had family or friends already there (UNHCR 2022). This high correlation across districts suggests that areas with an established Ukrainian presence were more attractive for refugee settlement and employment, aligning with prevailing migration and network theories (Hatton and Williamson 1998; Woodruff and Zenteno 2007; Patel and Vella 2013; Stuart and Taylor 2021). Additionally, refugees may have found employment more readily in these districts, even without personal diaspora connections, due to historical demand for foreign labour.

Constraints and demand conditions in the local labour market The rapid integration of Ukrainian refugees into the Czech labour market is not surprising, given that most were well-educated and of working age, fitting the profile of employable candidates. Moreover, their integration was much quicker in Czechia compared with other EU countries (Kosyakova et al. 2024), probably due to favourable conditions in the Czech labour market—characterised by an unemployment rate of just 2.22% in 2022 (the lowest in the EU) and a continuous surplus of job vacancies over job seekers (for details, see Appendix C). Additionally, most of the industries where the majority of

Table 3 Matrix of correlations demonstrating self-selection among Ukrainian refugees

Variables	(1)	(2)	(3)	(4)
(1) Ukrainians residing in Czechia in 2021 (diaspora)	1.00			
(2) Ukrainian refugees residing in Czechia in 2022	0.98	1.00		
(3) Ukrainians employed in Czechia in 2021 (diaspora)	0.98	0.97	1.00	
(4) Ukrainian refugees employed in Czechia in 2022	0.86	0.86	0.80	1.00
(5) No. active companies in 2021	0.98	0.97	0.96	0.86
(6) No. active large companies in 2021	0.98	0.97	0.95	0.87
(7) Labour market tightness in 2021	0.08	0.07	0.18	0.10
(8) Unemployment rate in 2021	−0.05	−0.05	−0.10	−0.02

Note: Table created using data from the Ministry of the Interior (2023a, b), the Ministry of Labour and Social Affairs (2023a), and the Czech Statistical Office (2024a). The figures for 2021 and 2022 represent the monthly percentage of the district total for the diaspora and employed diaspora in 2021, as well as refugees, calculated as a percentage of the district's total the refugees found employment had already experienced persistent labour shortages (McGrath 2021; European Commission 2022a).

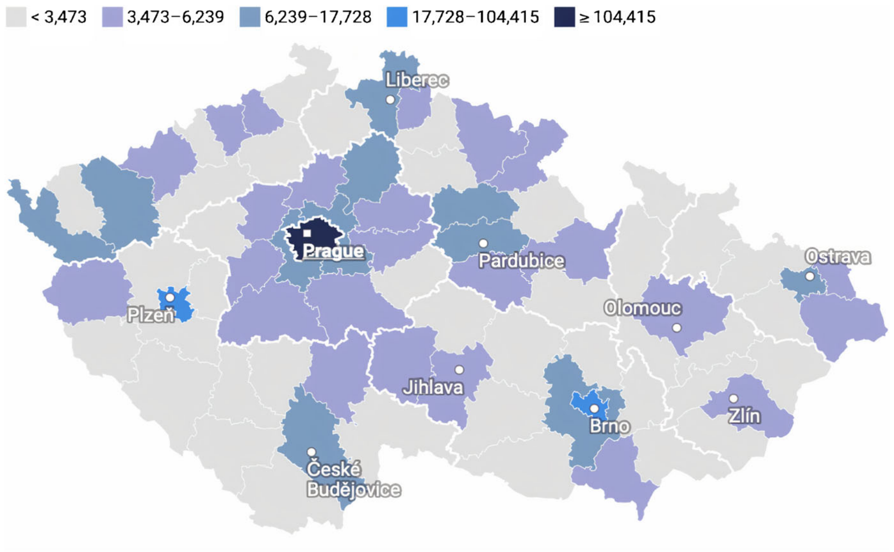
However, despite their qualifications, a significant proportion of Ukrainian refugees accepted employment in positions that underutilised their existing skills and at lower wages than they previously earned in Ukraine (Kavanová et al. 2022b). By August 2022, 44% of the refugees were employed in jobs below their previous occupations, often transitioning from specialised professions to low-skilled manual labour. The most common jobs among refugees were as product and equipment assemblers, helpers in construction, production, and transport, or as stationary machine operators (EURES 2023).

These patterns can be attributed to the imperfect transferability of refugees' human capital to the new labour market, particularly in the short term—a challenge that often results in underemployment and is well-documented in the literature.[11] For Ukrainian refugees, transferring their higher educational qualifications into skilled roles in Czechia was challenging due to strict certification barriers. Healthcare professionals, for instance, had to undergo nostrification (qualification recognition), prove Czech language proficiency, and pass an approbation exam, often leading to delays or forcing them into roles below their skill level (Ministry of Health 2022). Similarly, Ukrainian teachers faced barriers, as they were allowed to teach only Ukrainian pupils or take non-teaching roles unless they could demonstrate fluency in Czech (Ministry of Education, Youth and Sports 2022).

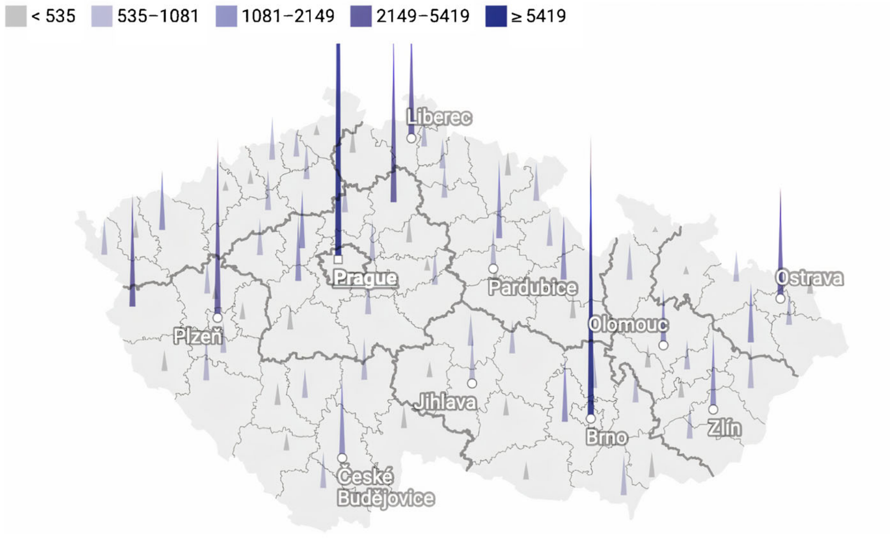
Additionally, although approximately 7% of the Czech population reportedly speaks Russian (Parys 2012), and despite Russian and Ukrainian both being Slavic languages—albeit from different branches—the language barrier initially posed a significant obstacle for Ukrainians. According to several surveys, between 60 and 87% reported being unable to speak English, and 69% to 91% had no knowledge of Czech (Ministry of Labour and Social Affairs 2022; UNHCR 2022). Over time, however, follow-up studies indicated improvements in Czech language skills among adult refugees (Ministry of Labour and Social Affairs et al. 2023).

Economic theory offers various predictions concerning the impact of a large-scale immigration event like the Ukrainian refugee influx. 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 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 substitutes for or complements to native workers. Given that the majority of incoming refugees were educated, working-age women—and using educational attainment as a proxy for skills (Belot and Hatton 2012)—one

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



(a) District-Wise Distribution of Ukrainian Refugee Registrations (Settlement Pattern)



(b) District-Wise Growth in Ukrainian Refugee Employment (Employment Pattern)

Fig. 2 Geographical distribution of Ukrainian refugee settlements and employment in Czechia. Note: **a** maps the distribution of refugee settlements in Czech districts as of December 2022; **b** illustrates the increases in Ukrainian nationals' employment (y-o-y change) by district as of December 2022. The plot was created by the authors using the data reported by the Ministry of the Interior (2023b) and the Ministry of Labour and Social Affairs (2023a) of Czechia might expect a notable increase in medium– to highly skilled labour in the Czech labour market. However, the challenges previously discussed suggest that Ukrainian refugees often found themselves competing for roles mainly filled by locals with lower educational backgrounds. In particular, local women with low to medium education might have faced competition from Ukrainian women, especially in sectors already dominated by them.

Nevertheless, the exceptionally low unemployment rate and surplus of job vacancies in the Czech labour market likely mitigated these potential negative effects. Additionally, the arrival of refugees could have stimulated demand in certain sectors due to their consumption of essential goods and services, such as accommodation and food services, administrative and support services, retail trade, healthcare, education, and transportation. This increased demand might have offset adverse supply-side effects, reflecting the broader socio-economic impact of the refugee influx on the Czech labour market.

3 Data and descriptive statistics

We utilise four datasets for the empirical analysis, which we subsequently merge across time and districts in Czechia: (i) aggregated district-level data on Ukrainians residing in Czechia, including both refugees and members of the Ukrainian diaspora who arrived before 2022, provided by the Ministry of the Interior (2023a, b); (ii) aggregated district-level data on both Ukrainian refugees and diaspora legally working in Czechia, sourced from the Ministry of Labour and Social Affairs (2023a), with both ministries maintaining detailed records updated monthly; (iii) the LFSS, which provides individual-level microdata on Czechs' labour market outcomes; and (iv) aggregated district-level data on local demographic, economic, and labour market indicators—such as unemployment rates, the number of employed locals, locals of working age, and job vacancies—sourced from the public statistics database of the Czech Statistical Office (2024a). Descriptive statistics for key variables are reported in Table 4, and detailed descriptions of the variables are provided in Appendix A.

While we use the three aggregated district-level datasets (i, ii, and iv) to construct our treatment variables and introduce demographic and economic indicators into the analysis, it is the LFSS that forms the core of this study's empirical analysis. The LFSS allows us to follow employment outcomes of local Czechs as well as a small sample of migrants (around 4% of the sample) over time. Administered quarterly across all 77 Czech districts by the Czech Statistical Office (2023f)—which collects and provides access to the data for scientific research—the LFSS is a rotating panel dataset where the same individuals are surveyed for up to five consecutive time periods.

We rely on data from 16 consecutive waves of the LFSS, spanning from the 1st quarter of 2019 to the 4th quarter of 2022, and limit our analysis to Czechs and other non-Ukrainian migrants aged 15 years and older. All individuals of Ukrainian nationality, both diaspora and refugees, were excluded, accounting for approximately 0.76%

Table 4 Descriptive statistics

	2019	2020	2021	Q4 2021	2022	Q4 2022
Labour market outcomes for locals						
Employed	0.53	0.51	0.51	0.51	0.51	0.51
Inactive	0.46	0.47	0.47	0.47	0.48	0.48
Unemployed	0.01	0.01	0.01	0.01	0.01	0.01
Hours usually worked	39.78	39.69	39.20	39.15	39.22	39.17
Individual-level covariates						
Male	0.47	0.47	0.47	0.47	0.47	0.47
Age	52.02	52.47	52.76	52.96	53.38	53.73
Married	0.53	0.53	0.52	0.52	0.52	0.52
On pension or disabled	0.40	0.41	0.38	0.40	0.42	0.42
Born abroad	0.03	0.03	0.04	0.04	0.04	0.04
Part-time employed	0.04	0.04	0.04	0.04	0.04	0.04
Child(ren) $<$ 15y.o	0.20	0.20	0.20	0.20	0.20	0.19
Education level						
No education	0.00	0.00	0.00	0.00	0.00	0.00
Basic education	0.15	0.14	0.14	0.14	0.14	0.13
Secondary without matriculation	0.35	0.35	0.34	0.34	0.35	0.35
Secondary with matriculation	0.33	0.34	0.33	0.34	0.33	0.33
University	0.17	0.17	0.18	0.18	0.18	0.18
Employment and demographic patterns						
No. of employed Ukrainians	151,956	158,821	196,791	195,116	254,676	269,911
No. of Ukrainians residing in CZ	139,503	158,041	186,370	196,675	567,517	633,178
No. of employed locals	–	–	5,290,071	5,290,071	–	–
No. of locals of working age (18–65 y.o.)	6,421,748	6,437,187	6,403,993	6,320,428	6,327,572	6,331,273
No. of districts	77	77	77	77	77	77
No. of individuals	71,892	70,199	70,368	42,657	68,778	41,156
No. of observations	175,355	168,775	170,642	42,657	167,985	41,156

Note: The table reports mean values for labour market outcomes among locals ($y_{i,d,t}$) and individual-level covariates ($X_{i,d,t}$), based on Labour Force Survey Statistics (LFSS) data. The data are restricted to locals aged 15 years and older. Additionally, the employment and demographic patterns among both the locals, Ukrainian refugees, and diaspora data are sourced from the Ministry of the Interior (2023a,b), the Ministry of Labour and Social Affairs (2023a), and the Czech Statistical Office (2024a). Data on local employment levels in the Czech Republic are available only for the year 2021, as they are derived from the recent 2021 population census of the total dataset. This results in a sample of 682,757 observations, corresponding to 179,525 individuals.[12]

The LFS survey employs a stratified two-stage cluster sampling design and generates a nationally representative dataset with a large sample size, providing detailed longitudinal information on individuals' socio-demographic characteristics (e.g. age, education, marital status) and labour market outcomes (e.g. employment status, employment history, industry and occupation, hours worked, and unemployment duration). Given our focus on the impact of legally employed Ukrainian refugees on the employment outcomes of Czechs, this dataset is highly reliable as it accurately captures the dynamics of the local formal employment sector. However, due to the nature of its sampling design (detailed in Appendix A), the survey may not fully capture the experiences of Czech workers in informal employment or certain migrant groups. Consequently, our findings are restricted mainly to the formal employment sector, and we interpret any effects on other migrant groups affected by Ukrainian refugees with caution.

4 Identification strategy

In our analysis, we exploit the natural experiment of the sudden and forced influx of Ukrainian refugees, which significantly expanded Czechia's workforce. Adopting a regional approach, we assess the short-term impact—over 1 year from the 1st quarter up to and including the 4th quarter of 2022—of legally employed Ukrainian refugees on the labour market outcomes of 'local' workers in Czechia. Local workers include primarily Czech nationals and a small subsample of non-Ukrainian migrants. We examine both the extensive margin—analysing statuses of employment, unemployment, or inactivity among the locals—and the intensive margin, focusing on weekly hours worked. Furthermore, we differentiate the estimated effects based on gender, educational attainment, industry of employment, type of employment contract (fixed term versus permanent), and the country of origin of the Czech residents (foreign-born versus Czech-born). Figure 3 illustrates the central focus of the paper.

The identification strategy unfolds in several steps, beginning with the construction of the 'treatment' variables in Section 4.1. Subsequently, we implement a static two-way fixed effects (TWFE) regression, detailed in Section 4.2. Recognising the

[12] Due to a regulatory change implemented by the Czech Statistical Office (CZSO), unique identifiers (IDs) for individuals were no longer disclosed in the third and fourth quarters of 2022. However, the methodology remained consistent, ensuring that the subset of individuals observed in Q3 and Q4 was the same as in Q2 and earlier. We recovered the panel structure of the data by first using deterministic matching to identify unique pairs among individuals based solely on available time-invariant variables such as the sequence number of the observation period, gender, year of birth, country of birth, and employment status from all previously observed periods. This approach successfully matched around 67% of the observations in the third and fourth quarters of 2022 to their corresponding observations from the previous quarter. For the remaining 33% of observations, where duplicates existed due to individuals sharing the same time-invariant characteristics, we employed probabilistic matching. A random forest model, highly suitable for this classification task, was used to calculate the likelihood of two individuals being a match, allowing the incorporation of time-variant variables such as education level, marital status, and others. As a result, we reliably matched the remaining observations, with only 0.8% of the observations unmatched in Q3 and 2.2% in Q4 2022. The matching process is detailed in Appendix D.

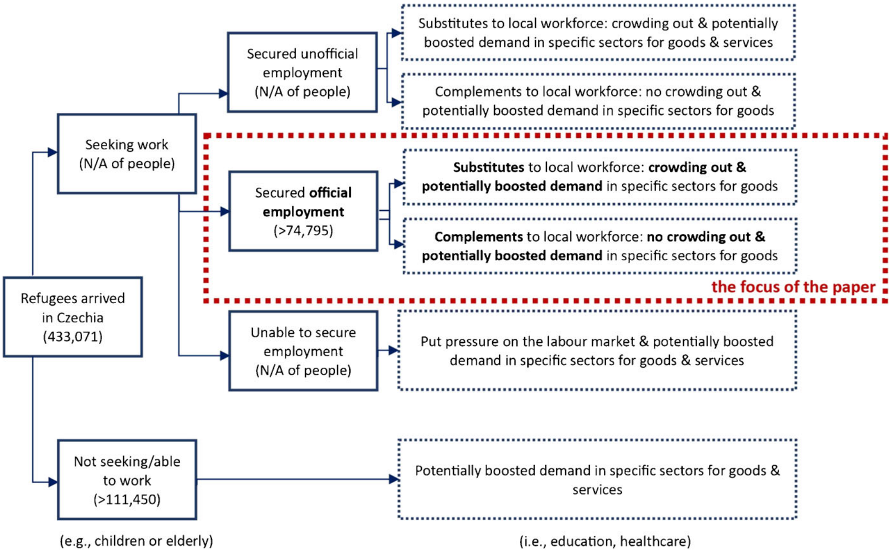


Fig. 3 Pathways of refugee employment and their potential effects on Czechia's labour market. Note: The plot was created by the authors using the data reported by the Ministry of the Interior (2023b) and the Ministry of Labour and Social Affairs (2023a) of Czechia. It illustrates the central focus of the paper: the impact of Ukrainian refugees securing legal employment on the labour market outcomes for the local population (highlighted by the red dotted line). The number of individuals categorised as 'not seeking employment' is indicative and includes people under 18 or over 65

limitations of the TWFE regression in our complex setting—specifically, its potential failure to identify a convex combination of individual treatment effects and its difficulty in capturing treatment effect heterogeneity across individuals and time—we adopt a heterogeneity-robust estimator in Section 4.3. Accordingly, we select as our primary estimator the method proposed by de Chaisemartin and D'Haultfœuille (2024), a variant of the extended DiD, which enables the unbiased estimation of treatment effects using (non-)binary, (non-)staggered treatments and allows for dynamic/inter-temporal treatment effect analysis, making it highly suitable to our setting. Finally, in Section 4.4, we discuss the assumptions and limitations of both estimators, addressing issues such as self-selection among refugees, testing for the parallel trends, extending the DiD estimator by matching on pre-trends, testing for systematic associations between pre-2022 economic conditions and 2022 treatment intensities across districts, and examining the 'no anticipation' and 'no self-selection among locals' assumptions.

4.1 Defining the treatment variables

To evaluate the impact of the refugee influx, we first identify Czech districts that experienced significant increases in Ukrainian employment in 2022 due to the integration of refugees into the labour market. The year 2021 is chosen as the baseline, representing the 'normal' employment levels among the Ukrainian diaspora before the arrival of refugees. This baseline provides a stable point of comparison, as by 2021, employment levels for foreign nationals in Czechia had returned to pre-COVID-19 conditions (Czech Statistical Office 2023e). Employment levels in 2022 are then compared to those in 2021. Treatment status is assigned at the district level to local residents. Districts with minimal to no increase in refugee employment are considered control (or 'not yet treated'), while those with significant growth in Ukrainian employment are classified as treated. All districts are regarded as 'untreated' before 2022 due to the absence of Ukrainian refugees. The treatment variable is defined at the district level, as it is the most granular geographic unit available in the LFSS for identifying individuals' places of residence.

We focus on the employment surge in 2022 to isolate the effects specifically attributable to the employment of Ukrainian refugees, distinct from prior inflows of Ukrainian migrants into Czechia. This distinction is essential as the demographic profile of the refugees—predominantly higher-educated and female—differs significantly from that of the typical, less-educated, male Ukrainian migrants who arrived before 2022 (Czech Statistical Office 2021). Combining these groups would obscure these demographic differences and complicate the identification strategy. Additionally, we chose to analyse the realised employment of Ukrainian refugees rather than the overall demographic shock to the Czech labour market, which would include all Ukrainians of working age regardless of employment status. This approach is justified as data on refugees' residence might be affected by individuals returning to Ukraine, relocating to other countries without deregistering, or unreported stays. However, the legally mandated official employment figures offer a higher degree of accuracy.[13]

For the number of employed Ukrainians in Czechia, we rely on aggregated district-level data sourced from the Ministry of Labour and Social Affairs (2023a). Since foreign employment data in Czechia is reported by citizenship without distinguishing between visa or residence permit types, we infer, as a best approximation, that the substantial employment surges from the first quarter of 2022 onwards primarily reflect the influx of newly arrived Ukrainian refugees. This estimate may slightly overstate refugee employment if some diaspora members (re-)entered the workforce. However, given the high employment rate (99%) among the Ukrainian diaspora with residence permits as of 31 December 2021 (Czech Statistical Office 2024b), it is likely that the majority of the increase reflects refugee employment. Conversely, the estimate may understate refugee employment if some previously employed Ukrainians relocated within Czechia, left the country, or exited the workforce. However, we observe no significant internal or external migration within Czechia (see Section 6), suggesting that our results are robust to this potential bias.

To account for the routine dip in foreign employment observed in the 4$^{\text{th}}$ quarter of each year—likely due to seasonal workers leaving employment at the end of the harvest season—we rely on two separate benchmarks for 'usual' Ukrainian employment levels: the average 2021 employment level of Ukrainians in Czechia by district (d), as in Eq. 1; and the actual number of the employment of Ukrainians in Czechia in the

[13] Any employer in Czechia is free to hire Ukrainian refugees, but he/she is obligated to report it to the local labour authorities.

4^{th} quarter of 2021 by district (d), as in Eq. 2.

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

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

Since the impact of an influx of, say, 10,000 foreign employees may vary across districts depending on the size of the local labour market, we normalise the treatment variable relative to each district's labour market size, using two measures: the number of locals employed in 2021 by district (d), as in Eq. 3; and the number of working-age locals (18–65 years old) by district (d), as in Eq. 4,[14]

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

$$\text{Locals of Working Age}_{d,t} \tag{4}$$

The employment variable in Eq. 3, sourced from the 2021 census (Czech Statistical Office 2021), is anchored to the year 2021, thus remaining static over time while varying by district. Fixing this value to 1 year prior to the labour shock prevents contamination of the treatment variable by subsequent realisations of outcome variables in 2022, such as local employment status, which could otherwise create a feedback loop. Employment levels in Czechia for 2021 were consistent with historical norms. Despite a dip in employment numbers to 5.235 million in 2020, attributed to the COVID-19 pandemic, the 2021 figure of 5.29 million aligns with pre-pandemic data from 2019 and 2018, which recorded 5.303 million and 5.293 million, respectively, indicating a recovery in the labour market (Czech Statistical Office 2022a, 2021). For more details on local labour market conditions, see Appendix C.

Since census data was collected in the first half of the year—typically reporting slightly lower employment levels due to seasonal patterns—we include working-age locals (Czech Statistical Office 2024b) as a second proxy for the local labour market size, as shown in Eq. 4, to ensure robustness. Unlike Eq. 3, this proxy varies both by time and across districts, remaining responsive to demographic and labour market shifts without being affected by outcome variables in 2022, unless significant migration of locals to or from refugee-impacted districts occurred. This possibility was tested in Section 6, where no supporting evidence was found.

Accordingly, we employ three variants of the treatment variable, detailed in Eqs. 5, 6, and 7:

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

[14] To prevent double-counting, the number of officially employed Ukrainians was subtracted from the total number of employed locals for Eq. 3 and the number of working-age Ukrainians was subtracted from the total number of working-age locals for Eq. 4.

and

$$\text{Treatment}^{II}_{d,t} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,\ 4^{\text{th}}\text{quarter of 2021}}}{\text{Employed Locals}_{d,\ \text{census 2021}}} & \text{if } t \geq 2022 \\ 0 & \text{if } t < 2022 \end{cases} \tag{6}$$

and

$$\text{Treatment}^{III}_{d,t} = \begin{cases} \dfrac{\text{Employed Ukrainians}_{d,t} - \text{Employed Ukrainians}_{d,\ \text{average in 2021}}}{\text{Locals of working age 18-65}_{d,t}} & \text{if } t \geq 2022 \\ 0 & \text{if } t < 2022 \end{cases} \tag{7}$$

where d and t index districts and time (year: quarter), respectively. Each variant is designed to capture the same phenomenon: significant shifts in Ukrainian employment levels due to the refugee influx during any quarter of 2022, relative to the 'usual' employment levels of the Ukrainian diaspora in 2021, normalised by the labour market size of each district. We round up the resulting values to the nearest integer, making them discrete, which results in the treatment 'doses'. Each 'dose' reflects a 1% change in Ukrainian employment in district d at time t, such that $t \geq 2022$, relative to the 'usual' level in the baseline period t, where $t \in \{\text{average in 2021}, 4^{\text{th}} \text{ quarter of 2021}\}$, adjusted for each district's labour market size.

The treatment doses derived from all three treatment specifications range from –2% to as high as 32% and are comparable in terms of sign, magnitude, and timing of onset. A substantial proportion of locals resided in districts that received a positive treatment dose, predominantly between 1 and 4% as documented in Fig. 4. Additionally, a subset of locals lived in districts that were virtually unaffected by the treatment, with a treatment dose of 0%. Additionally, instances of negative treatment doses were observed in one to three districts, depending on the treatment variable specification. These negative doses are primarily attributable to seasonality in employment (as evidenced by treatment II showing only one such district compared to two or three for treatments I and III) and possibly to the departure of male Ukrainian immigrants.

Dynamic treatment trajectories The specification of the 'treatment' variables results in a complex design where treatment can turn on or off, fluctuate across time periods, and commence at different times in various districts. Before 2022, all districts are set to a baseline 'treatment' dose of zero. From 2022 onwards, districts exhibit varying treatment trajectories. Districts may experience treatment doses that are either still zero, negative, positive, or both. For example, as depicted in Fig. 5 for Treatment^{I}, Bruntál remains at zero treatment levels, serving as our control district for all four quarters of 2022. In contrast, Blansko consistently receives a 1% positive treatment dose starting from the 1st quarter of 2022. Treatment varies not only in intensity but also in timing; for instance, Prerov's treatment begins in the 2nd quarter of 2022, making it a control (not yet treated) district for the 1st quarter. Treatment doses can also change over time, possibly reverting back to zero after an initial change. Praha's

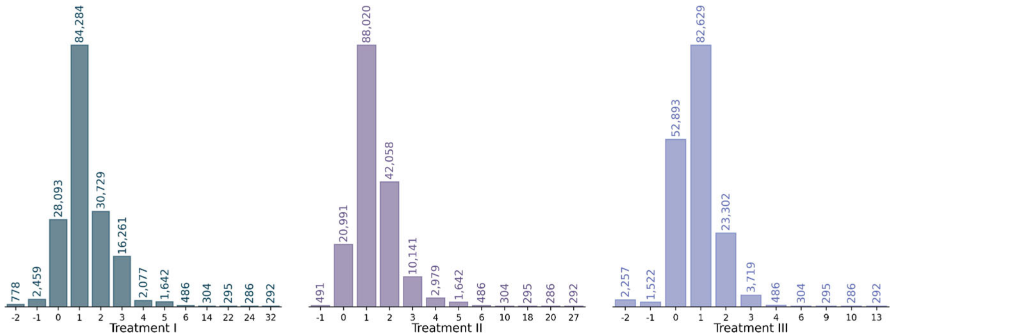


Fig. 4 Distribution of treatment doses I, II, and III in 2022. Note: This histogram, created by the authors using LFSS data, displays the counts of individuals receiving treatment doses I, II, and III in 2022, covering the 1st to 4th quarters, respectively

treatment doses increase over time, reaching 3% by the 2nd quarter of 2022, while Pelhřimov received a positive treatment dose of 2% in the 1st quarter of 2022 before reverting back to the baseline level of zero. There are also districts like Pardubice that, after an initial positive dose, experience negative treatment doses.

To introduce structure and facilitate identification for the empirical analysis, we categorise districts d for each quarter t as either 'control', 'switchers in', or 'switchers out'. We always estimate the effects for 'switchers in' and 'switchers out' groups separately for each of the treatment variables. Table B.2 provides an overview of the treatment doses of Treatment^{I}, Treatment^{II}, and Treatment^{III} disaggregated by district and time.

Districts with positive treatment doses—control The 'control' group refers to districts d that, at quarter t, still have a level of treatment equal to the baseline (consistently zero in our case).

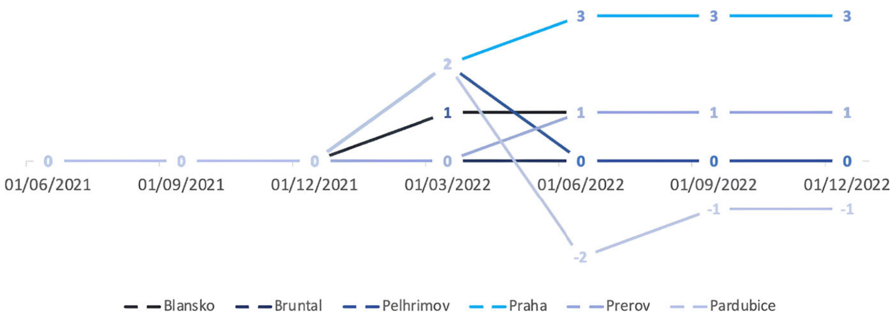


Fig. 5 Visualisation of treatment I: treatment trajectories for selected districts. Note: Variables Treatment^{II} and Treatment^{III} are identical to Treatment^{I} by design; hence, we provide an example for Treatment^{I} only

Districts with positive treatment doses—switchers in 'Switchers in' refers to districts d where, at time F, the treatment level either increases for the first time from zero to some positive value, or for the same district d in any subsequent periods t, $t \geq F$, given that the treatment level remained greater than or equal to the baseline. For special cases of districts like Pardubice, which initially experienced a treatment dose higher than the baseline (positive) and then subsequently lower (negative), we only include (d, t) before the treatment changes from positive to negative. For Pardubice, this means that when estimating effects for the 'switchers in', we incorporate observations from the 1st quarter of 2022, categorising them as 'switchers in', and then exclude all observations from the following quarters. The rationale behind these exclusions is that the interpretation of the weighted average of the treatment effects, resulting from both positive and negative treatment doses, becomes ambiguous.

Districts with negative treatment—switchers out 'Switchers out' are the districts that have ever experienced a negative treatment dose. Under this specification, all observations for districts like Pardubice would be considered as 'switchers out'.

4.2 Static two-way fixed effects (TWFE)

We start the analysis by employing the following static two-way fixed effects model:

$$y_{i,d,t} = \alpha + \beta(\text{Treatment}^{I \text{ or } II \text{ or } III})_{d,t} + \theta' X_{i,d,t} + f_i + f_t + \epsilon_{i,d,t}, \tag{8}$$

where i, d, and t index individuals, districts, and time (year: quarter), respectively. The dependent variable, $y_{i,d,t}$, represents the labour market outcome of interest (employment, unemployment, inactivity,and weekly hours worked). The coefficients β on the $Treatment^{I}$, $Treatment^{II}$, or $Treatment^{III}$ variables are of primary interest. 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 factors, under the assumption of linear additive effects (Allison 2009; Wooldridge 2010).

Leveraging the detailed individual-level data in the LFSS, our analysis incorporates a comprehensive range of individual-level characteristics (X) such as age category (15–19, 20–25, …, 60–65); a dummy variable for being married; a dummy variable for having children younger than 15 years; a categorical variable indicating education level (ISCED); a dummy variable for pension or disability status; and a dummy variable for part-time employment. Additionally, a categorical variable for NACE-1 industries is included, but only for the weekly hours worked as a dependent variable. We further estimate the model separately by gender, education level, type of employment contract (fixed term versus permanent), and the country of birth (foreign-born versus Czech-born). Appendix A provides detailed descriptions of the control variables and how they were constructed.

4.3 Estimating heterogeneous treatment effects with extended difference-in-differences (DiD) estimator

We start with the TWFE regression because it is widely used in microeconomics empirical research—largely due to its perceived equivalence to the DiD estimator. The canonical DiD model, featuring only two time periods, a binary treatment variable, and distinct treatment and control groups, allows for the unbiased identification of the average treatment effect on the treated (ATT). In such a simple setting, the ATT can indeed be estimated using a static TWFE regression. However, the design of our treatment variable complicates the setting beyond this canonical model, as our treatment can turn on or off, vary across time periods, and commence at different times in different districts.

To ensure unbiased ATT estimates in our TWFE regression, one solution is to impose a stringent assumption of constant treatment effects across individuals and over time. This assumption effectively precludes heterogeneous treatment effects, an exclusion which, as indicated by recent literature, is seldom realistic in applied research.[15] Applying the test developed by de Chaisemartin and d'Haultfoeuille (2017), we examine the potential bias introduced by negative weights—a signal of treatment effect heterogeneity—in our ATT estimates. Our findings indicate that negative weights indeed likely bias the ATT estimates, particularly regarding the variable weekly hours worked. Full results and a detailed description of the testing procedure are provided in Appendix F.

Therefore, as we cannot assume constant treatment effects across individuals and over time in our context, we adopt the heterogeneity-robust estimator proposed by de Chaisemartin and D'Haultfœuille (2024) as our primary estimator. This estimator can be seen as an extension of the canonical DiD approach, but it allows for (non-)binary, (non-)staggered treatments and facilitates dynamic/inter-temporal treatment effect estimation, making it particularly suitable for our setting. Unlike the TWFE regression, it groups individuals in a way that avoids 'forbidden comparisons'—that is comparisons between individuals who are both treated but commence treatment at different times. It estimates the actual-versus-status-quo (AVSQ) effect for each treated individual, a variant of the ATT.

Firstly, we estimate individual effects for each treated individual across all possible periods, comparing the evolution of labour market outcomes between treated individuals and a control (or not yet treated) group, pre– and post-treatment. Following the approach suggested by de Chaisemartin and D'Haultfœuille (2024), we normalise the effects to help with their interpretation and make comparison with the TWFE regression results easier.[16] Normalisation is done through dividing the estimated individual effects by the difference between the actual treatment dose received and the baseline treatment level (zero in our context) for each period. The result is a normalised AVSQ (nAVSQ) effect, which is interpreted as the average total effect per unit of treatment.

[15] See, for example de Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021); Imai and Kim (2021); Sun and Abraham (2021); de Chaisemartin and d'Haultfoeuille (2022); Borusyak et al. (2024), among others.

[16] This is implemented using the Stata command 'did_multiplegt_dyn'. For details, see de Chaisemartin et al. (2023).

We then aggregate these individual effects to derive average effects for all treated individuals, weighted by the number of individuals contributing to each period-specific estimate. See Appendix F for details of the estimation procedure.

4.4 Assumptions and limitations of the TWFE and extended did estimators

4.4.1 Refugees' self-selection patterns

In the absence of a randomised experiment, migration research frequently faces the problem of self-selection (Borjas 1987; Abowd and Freeman 1991; Jaeger 2007). In this context, self-selection implies that immigrants with a higher inherent probability of employment—due to specific skill sets or a strong motivation to work—may choose to settle in districts with robust economies and high labour demand. Ukrainian refugees, who have the freedom to settle in any district within Czechia, might similarly seek economically thriving areas. The presence of established Ukrainian diasporas and refugee reception centres in central districts may further intensify this non-random settlement pattern, making direct comparisons of labour market outcomes for locals across districts with more versus less employed Ukrainian refugees potentially biased.

Without normalising our treatment variables by district labour market size, our data indeed indicates clear evidence of self-selection, with a significant concentration of refugees in economically thriving regions characterised by higher GDP per capita, wages, and levels of educational attainment (Czech Statistical Office 2023a). Furthermore, refugee distribution across districts is positively correlated with the presence of active companies, large firms, labour market tightness, and substantial Ukrainian diasporas, while negatively correlated with unemployment rates (see Table 3).

However, normalising the treatment variables not only provided a more meaningful measure of treatment intensity but, more importantly, allowed us to mitigate biases introduced by self-selection. After normalisation, the highest treatment intensities ('doses') shifted towards smaller, less economically dominant districts—such as Cheb, Mladá Boleslav, and Tachov—where Ukrainian refugees at times comprised between 3 and 32% of the employed populations. Additionally, pairs of adjacent districts with similar treatment intensities emerged, typically involving a central district and its surrounding areas. Examples include Plzeň-South and Plzeň-City, as well as Praha-East and Capital City Prague. Table B.2 provides an overview of the treatment doses of Treatment^{I}, Treatment^{II}, and Treatment^{III} disaggregated by district and time.

Thus, although larger districts like Capital City Prague and Plzeň-City still met the criteria to be considered treated in some quarters of 2022, normalising treatment by labour market size uncovered meaningful heterogeneity across districts, revealing substantial variation in both treated and control districts in (i) pre-treatment trends in analysed labour market outcomes, such as changes in employment and unemployment rates and (ii) pre-treatment economic characteristics. In Section 4.4.2, we leverage point (i) by matching control and treated districts based on pre-trends across key variables, while in Section 4.4.3, we apply point (ii) to examine whether a systematic, statistically significant association exists between the pre-2022 economic and labour market conditions of all 77 Czech districts and their treatment intensities in 2022.

4.4.2 Parallel trends assumption

A crucial assumption for both our estimators is that the trends in the status-quo outcome, conditional on baseline treatment, are parallel. For our main estimator—the extended DiD—and all its specifications, we extensively test this assumption using placebo estimators as proposed by de Chaisemartin and D'Haultfœuille (2024). These placebo estimators replicate the actual estimators used in our empirical analysis by comparing the outcome evolution of individuals i who later become treated with the outcome evolution of their respective 'control' individuals across pre-treatment periods. The rationale is that if trends are parallel, there should be no statistically significant effects observed, as treatment has not yet started.

Reassuringly, for the vast majority of our extensive set of estimations—across all model specifications and sub-populations—the placebo tests were not significant. We summarise the results of this test in Section 5 and report detailed results for each variable and model specification in Tables B.3–B.5.

Extension I: allowing for distinct trends across treated and control districts Recognising the limitations of placebo estimators in testing the parallel trends assumption (Roth 2022), as well as the constraints imposed by the rotating structure of our panel, which limits the number of pre-treatment quarters available for testing, we introduce an additional step in our empirical analysis. Normalising the treatment variables has yielded a heterogeneous set of both treated and control districts in terms of their pre-treatment trends across key variables of interest—employment, unemployment, inactivity rates, and weekly hours worked. Leveraging this heterogeneity, we extend our primary DiD estimator by matching treated and control districts on their pre-2022 trends for each variable separately.

To capture subgroup-specific dynamics that aggregated to the district level trends might obscure, we calculate pre-2022 trends separately for the subgroups within districts defined by (i) gender and education level and (ii) gender and industry of employment according to NACE level 1. Thus, by accounting for socio-economic factors that may impact specific groups differently and allowing for distinct trends across treated and control districts, we mitigate potential bias.

Using the LFSS data from the pre-treatment period (2019–2021), we estimate seasonally adjusted trends for each subgroup within all of the 77 Czech districts by regressing each variable of interest on the intercept, time, and seasonal dummies. The estimated slope serves as a proxy for the trend in each district. A detailed account of the trend calculation and categorisation process is provided in Appendix G. Given the continuous nature of the resulting trend variable, we convert it into a categorical variable through a 'scaled discretisation' process. By multiplying the continuous trend by a selected factor and rounding to the nearest integer, this approach preserves the data's inherent variability and improves compatibility with matching algorithms by avoiding arbitrary cutoffs and maintaining finer distinctions within the data. Finally, using these categorical proxies for the pre-trends, we match control and treated districts that exhibit similar pre-treatment trends for the variables of interest.

Extension II: allowing for distinct trends across treated and control individuals Furthermore, similarly to how we control for the individuals characteristics in the TWFE (8) regression, we match individuals on the same set of individual-level characteristics (X) in our DiD estimator. Given the large sample size of our data, we employ exact matching, pairing individuals with identical observed characteristics. This approach enables a like-for-like comparison between treated and control individuals, thereby relaxing the parallel trends assumption. Rather than requiring it to hold universally across all populations, we assume it only within each subset of matched individuals.

Extension III: allowing for distinct trends across treated and control districts and individuals Lastly, in the most complex DiD model specification, we incorporate both extensions by matching on individual characteristics (X) as well as on the generated pre-2022 trends for each variable of interest. This approach allows for distinct trends across both individuals and districts, further enhancing the credibility of our results.

4.4.3 No systematic associations between pre-2022 economic conditions and 2022 treatment intensities across districts

For a robust analysis, it is preferable that no systematic, statistically significant association exists between the pre-2022 economic and labour market conditions of all 77 districts in Czechia and their respective treatment intensities in 2022. We test for this by leveraging the observed variation in pre-treatment economic characteristics across treated and control districts introduced by the normalised treatment variables. We start by calculating Average Treatment$^{I,II,\text{ or }III}d$ for each district during the post-refugee influx period (2022).[17] We then limit our data sample to the pre-refugee influx years (2019–2021) and regress $Average\ Treatment_d^{I,II,\text{ or }III}$ on the same individual-level characteristics (X) used in the TWFE regression Eq. 8, alongside additional covariates (Z)—number of employed locals, number of employed Ukrainians, number of active companies, number of active large companies, labour market tightness, and unemployment rate—chosen to proxy both the size of the local and foreign labour markets and the prevailing labour market conditions.

The resulting regression specification is

$$\text{Average Treatment}_d^{I,II,\text{ or }III} = \alpha + \theta' X_{i,d,t} + \kappa' Z_d + \epsilon_{i,d,t}, \tag{9}$$

where i, d, and t index individuals, districts, and time (year: quarter), respectively.

As shown in Table 5, the results reveal no statistically significant association between the district-level covariates (Z) and our treatment variables across all three specifications, whether these variables are the sole controls (columns 4–6) or combined with individual characteristics (X) (columns 7–9). This indicates that local economic

[17] See Appendix E for details on the Average Treatment doses calculations.

Table 5 Associations between treatment intensity and local socioeconomic and labour market factors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Individual-level covariates (coefficients and standard errors are multiplied by 1000 for readability):									
Female	−25.22*	−17.86	−10.11				−13.44*	−8.86	−4.62
	(13.39)	(11.00)	(6.96)				(7.37)	(5.94)	(4.49)
Age	−2.42	−2.89	−0.92				−2.28	−1.43	−1.11
	(4.98)	(3.47)	(3.50)				(3.26)	(2.71)	(2.22)
Married	−84.79***	−36.67*	−65.47***				−57.46***	−51.27***	−41.38***
	(32.03)	(18.43)	(22.78)				(17.14)	(13.56)	(12.59)
On pension or disabled	52.25**	25.05	47.87*				52.29*	40.28	38.86*
	(26.16)	(19.66)	(26.16)				(28.33)	(25.26)	(21.33)
Born abroad	601.4**	437.12**	353.84***				343.48**	291.59***	228.02**
	(239.39)	(210.11)	(113.08)				(130.54)	(104.03)	(79.91)
Part-time employed	228.36***	139.64***	172.59***				137.01**	112.03**	110.8***
	(52.11)	(48.49)	(44.22)				(52.54)	(48.21)	(41.19)
Child(ren) < 15 y.o	15.14	15.57	6.1				20.21	8.4	17.66
	(45.37)	(34.43)	(24.76)				(19.34)	(14.82)	(13.80)
Education level									
No education	−170.72	−96.01	−177.51				36.31	−34.72	−29.22
	(158.81)	(95.17)	(129.77)				(93.05)	(73.47)	(77.91)
Basic education	−178.55	−73.16	−208.11				−28.36	−67.32	−76.57
	(215.78)	(144.22)	(143.18)				(75.91)	(68.77)	(67.16)
Second without matriculation	−198.41	−71.14	−202.02				−57.44	−74.51	−78.28
	(181.02)	(108.82)	(130.57)				(60.71)	(55.37)	(59.46)
Second with matriculation	−94.07	−19.83	−109.96				−21.37	−36.23	−38.86
	(111.41)	(71.70)	(81.24)				(42.99)	(38.20)	(43.49)

Table 5 continued

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
District-level covariates (Coefficients and standard errors are multiplied by 1000 for readability):									
No. of employed Ukrainians				−0.10	−0.05	−0.08	−0.10	−0.05	−0.08
				(0.14)	(0.1)	(0.11)	(0.14)	(0.1)	(0.11)
No. of employed locals				−0.02	−0.01	−0.01	−0.02	−0.01	−0.01
				(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
No. of active companies				−0.00	−0.02	−0.00	−0.00	−0.02	0.01
				(0.05)	(0.04)	(0.03)	(0.05)	(0.04)	(0.03)
No. of active large companies				30.04	21.49	12.18	30.01	21.5	12.19
				(20.71)	(17.23)	(10.8)	(20.63)	(17.16)	(10.74)
Labour market tightness				815.29	664.47	295.44	816.25	665.21	295.71
				(578.82)	(485.89)	(286.33)	(579.04)	(485.97)	(286.17)
Unemployment rate				29,200.3	16,340.2	9295.29	29,088.7	16,287.3	9251.59
				(31,138.1)	(24,921.4)	(15,802.8)	(31,109)	(24,894.8)	(15,780.8)
No. of observations	504,421	504,421	504,421	514,772	514,772	514,772	504,421	504,421	504,421
No. of districts	77	77	77	77	77	77	77	77	77

Note: The table presents coefficient estimates of model 9 where the dependent variable is $Average\ Treatment^{I}$ reported in columns (1, 4, 7), $Average\ Treatment^{II}$ in columns (2, 5, 8), and $Average\ Treatment^{III}$ in columns (3, 6, 9) that is constant across time t but varies across districts d. Furthermore, columns (1–3) report the estimates of the regression with covariates added for the individual-level characteristics X; columns (4–6) report the estimates of the regression with covariates added for the district-level characteristics Z; and columns (7–9) report the estimates of the regression when both X and Z are controlled for. Robust standard errors clustered at the district level are in parentheses. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

and labour conditions in 2019–2021 do not predict the average treatment intensity experienced by each district in 2022. Moreover, a joint test of the prevailing labour market condition variables—including the number of active businesses, the number of large businesses, labour market tightness, and the unemployment rate—confirms their lack of significance across all treatments, with F-statistics of $F(4, 76) = 1.05$ ($p = 0.39$), $F(4, 76) = 1.53$ ($p = 0.20$), and $F(4, 76) = 0.61$ ($p = 0.66$) for average treatment I, II, and III, respectively.

In contrast, individual characteristics (X) such as marital status, foreign origin, and part-time work show statistically significant associations with treatment intensity. However, this is less concerning since all our estimators explicitly control for these characteristics.

4.4.4 No anticipation assumption

The 'no anticipation' assumption is another crucial requirement of our estimators. This assumption posits that an individual's current outcomes are unaffected by future treatments. Identification issues arise if individuals adjust their behaviour in anticipation of upcoming treatments (Abbring and van den Berg 2003; Malani and Reif 2015). For example, in our case, if local Czechs had joined the labour force in advance of the refugee crisis to preempt foreign competition, it would constitute a violation of this assumption. However, since the influx of Ukrainian refugees was unexpected, concerns regarding this assumption are minimal. Although some individuals might have foreseen the conflict, it is unlikely that locals in Czechia would have significantly altered their labour market behaviour in response.

4.4.5 No self-selection among the locals

A final concern is the potential for self-selection, where locals may move to treated or control districts to gain anticipated benefits. Such strategic migration would constitute a secondary treatment effect, introducing bias into our estimates. To address this, in Section 6, we analyse 2022 migration patterns among locals and compare them with typical internal and external migration trends in Czechia from previous years. We find no evidence of strategic relocation, suggesting minimal risk of such self-selection bias.

5 Results

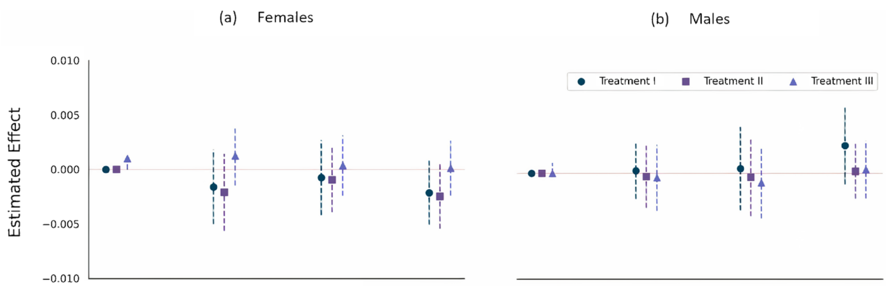
Throughout the 'Results' section, we report results from a subset of the model specifications outlined in Section 4. The complete set of results, including all models (1–10), is available in Tables B.3–B.5 and Figures B.1–B.13. TWFE(2) is our preferred specification for the two-way fixed effects specifications as it accounts for individual and time-fixed effects and controls for individual characteristics. DiD(4) is our preferred specification for the difference-in-differences model, as it mirrors TWFE(2) by controlling for individual and time-fixed effects, with the added benefit of matching identical individual characteristics. We further validate our results using the DiD(7, 8, 10) models, which extend the matching criteria to include both the individual characteristics and district-specific (DiD(7)), or district-, gender-, and education-specific (DiD(8)), or district- and industry-specific (DiD(10) pre-treatment trends of the dependent variable, while being mindful of the reduction in our sample size resulting from the extensive matching criteria.

Each figure reports for Treatment^{I}, Treatment^{II}, and Treatment^{III} the average treatment effects on the treated (ATTs), as estimated by the TWFE model outlined in Section 4.2, alongside normalised actual-versus-status-quo (nAVSQ) effects, calculated by the extended DiD model introduced in Section 4.3. Since the number of districts experiencing negative treatment doses is very small, we focus on districts experiencing positive treatment doses only in our discussion.

5.1 Probability of unemployment and inactivity

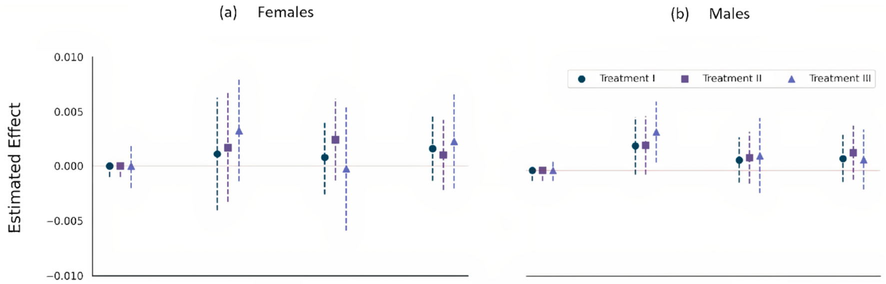
We start our analysis by looking at how the sudden and large influx of workers affected unemployment and inactivity among local workers. Results are presented in Figs. 6 and 7 and show no significant correlation between treatment doses and unemployment or inactivity probabilities for male and female workers.

To assess the robustness of our results for the DiD estimates, we test the parallel trends assumption with placebo estimators. These placebo tests are designed to assess whether the treatment and control groups were following a similar trend before the intervention, which is critical for the DiD method's validity. The p-value from these



	TWFE(2)	DiD(4)	DiD(7)	DiD(8)	TWFE(2)	DiD(4)	DiD(7)	DiD(8)
TR I	0.000	-0.002	-0.001	-0.002	-0.000	0.000	0.000	0.003
SE	(0.000)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.002)
No. obs.	340,550	61,412	44,129	48,945	299,812	53,554	38,260	40,635
TR II	0.000	-0.002	-0.001	-0.002	-0.000	-0.000	-0.000	0.000
SE	(0.000)	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)
No. obs.	341,511	62,953	48,164	50,940	300,635	54,681	41,033	40,547
TR III	0.000	0.001	0.000	0.000	0.000	-0.000	-0.001	0.000
SE	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)
No. obs.	339,899	63,271	55,237	54,360	299,209	55,098	47,707	47,713

Fig. 6 Positive treatment doses—probability of unemployment by gender. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–8) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7) and DiD(8) match on both the (X) individual characteristics and district-specific DiD(7), or district-, gender-, and education-specific DiD(8) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–8), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

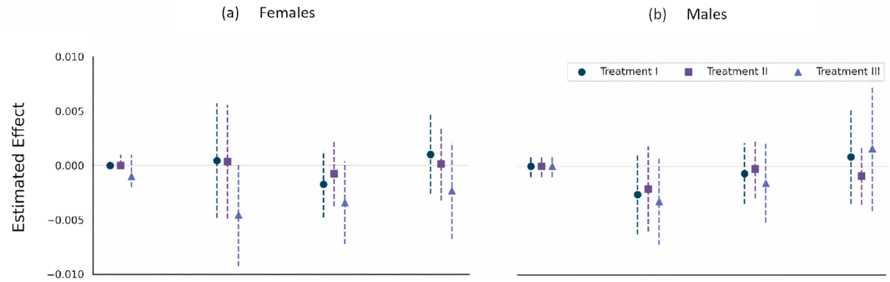


	TWFE(2)	DiD(4)	DiD(7)	DiD(8)	TWFE(2)	DiD(4)	DiD(7)	DiD(8)
TR I	-0.000	0.001	0.001	0.002	-0.000	0.002*	0.001	0.001
SE	(0.000)	(0.003)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
No. obs.	340,550	61,412	41,137	28,990	299,812	53,554	35,588	24,331
TR II	-0.000	0.002	0.002	0.001	-0.000	0.002*	0.001	0.002
SE	(0.000)	(0.003)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
No. obs.	341,511	62,953	40,418	29,502	300,635	54,681	34,860	23,459
TR III	0.000	0.003	-0.000	0.002	0.000	0.004**	0.001	0.001
SE	(0.001)	(0.002)	(0.003)	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)
No. obs.	339,899	63,271	47,189	34,563	299,209	55,098	40,659	28,800

Fig. 7 Positive treatment doses—probability of inactivity by gender. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–8) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7) and DiD(8) match on both the (X) individual characteristics and district-specific DiD(7), or district-, gender-, and education-specific DiD(8) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–8), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

tests measures the likelihood that any observed pre-treatment differences between the groups occurred by chance. Parallel trend tests with placebo estimators yield average p-values of 0.7 (unemployment) and 0.5 (inactivity) for women and 0.8 and 0.4, respectively, for men, detailed in Tables B.4 and B.5. Notably, none of the estimates reached statistical significance, with all p-values exceeding 0.1. Average p-values greater than 0.1 among placebo estimators suggest a significant probability that any observed differences during placebo periods are due to random variation. This supports the core DiD assumptions of parallel trends and the absence of anticipation effects, thus validating our empirical approach.

Moreover, by including all three variations of the treatment variable, we significantly enhance the robustness of our findings. Treatments I and II typically show minimal differences in estimated effects, instilling confidence in the method employed to quantify Ukrainian employment within Czechia. Treatment III often produces larger coefficients, either more positive or more negative, depending on the variable of interest, but generally aligns in sign with the other two treatments. This difference arises because it uses the number of working-age individuals as a proxy for the size of the labour market in each district, contrasting with the other treatments that utilise the number of currently employed locals. Consequently, the treatment variable is normalised against this larger base to calculate treatment doses, leading to inherently more modest doses than those derived from the other two treatments. Thus, when translating



	TWFE(2)	DiD(4)	DiD(7)	DiD(8)	TWFE(2)	DiD(4)	DiD(7)	DiD(8)
TR I	-0.000	0.000	-0.002	0.001	0.000	-0.003	-0.001	0.001
SE	(0.000)	(0.003)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.002)
No. obs.	340,550	61,412	39,194	28,328	299,812	53,554	33,899	24,396
TR II	0.000	0.000	-0.001	0.000	0.000	-0.002	-0.000	-0.001
SE	(0.000)	(0.003)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)
No. obs.	341,511	62,953	41,073	27,473	300,635	54,681	35,260	24,038
TR III	-0.001	-0.005*	-0.003*	-0.002	-0.000	-0.003	-0.002	0.002
SE	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
No. obs.	339,899	63,271	45,632	33,785	299,209	55,098	39,395	28,828

Fig. 8 Positive treatment doses—probability of employment by gender. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–8) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7) and DiD(8) match on both the (X) individual characteristics and district-specific DiD(7) or district-, gender-, and education-specific DiD(8) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–8), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

the estimated actual-versus-status-quo (AVSQ) effects for the DiD into normalised actual-versus-status-quo (nAVSQ) effects reported herein—by dividing the average estimated effects by the treatment dose in each treated period—the nAVSQ values turn out to be larger.

Further examination by education level (shown in Figures B.5 and B.6) found no significant effects, indicating that a 1% rise in officially employed Ukrainians does not affect the unemployment or inactivity rates of Czech men and women.

5.2 Probability of employment

Next, we consider employment among local workers. Similarly to unemployment, we find no consistently significant effects of the influx of Ukraininan refugees and employment probabilities for local workers (Fig. 8). Treatment III showed a weak (but positive) statistically significant effect for females in the DiD(3-7) models. However, without corroboration from other specifications, we refrain from drawing significant conclusions from this result. Testing the parallel trends assumption with placebo estimators yielded average p-values of 0.3 for both genders, detailed in Tables B.4 and B.5. This supports our DiD assumptions and validates our methodology. Further analysis by education level (reported in Figure B.7) did not reveal any significant hidden impacts, suggesting that a 1% increase in officially employed Ukrainians has no noticeable short-term effect on the average employment probability of Czech locals.

When examining sectors most impacted by the refugee influx, the trend among females remains consistent with previous results (Figure B.9).[18] For local male workers, the DiD(4) estimator indicated a potential decrease in employment probability.

A sector-specific analysis indicates that this effect is mainly driven by a small (−0.003), but statistically significant (for treatment I only) reduction in employment probability within the manufacturing sector (Figure B.10). Moreover, for females, there is a reduction in employment probability in accommodation and food service activities (−0.001 to −0.0005) and administrative and support service activities (−0.0005 to −0.0001). However, the results are somewhat inconsistent in significance across treatments and estimators. When we examine the data industry by industry, the number of observations who are employed and have reported weekly hours worked within industries becomes relatively small: ~6.5 thousand in the manufacturing industry, ~2.7 thousand in accommodation and food service activities, and ~1.9 thousand in administrative and support service activities. Given the smaller sample sizes and variation in treatments, this inconsistency is not surprising.

Notably, around one-third of male and one-third of female refugees have found employment in the manufacturing sector. Additionally, one-third of female refugees have entered administrative and support service activities. This pattern suggests that, at least in the short run, workers in the most affected sectors may have faced direct competition from Ukrainian refugees. However, caution is warranted when drawing conclusions due to the small sample sizes.

To analyse the most vulnerable part of the local population, we focused on males and females with no-to-basic and secondary education levels who were employed on temporary contracts, as these positions are typically less secure. Figure 9 reports that females with no-to-basic education experienced small but significant increases in employment probability according to our DiD estimators. In contrast, males with no-to-basic education faced a slight decrease in employment probability under treatment II. For those with secondary education, both genders showed minimal changes, with no consistent significant effects observed.

5.3 Weekly hours worked

Our results along the extensive margin do not show an economically significant effect of Ukrainian refugees on local workers. Next, we turn to the intensive margin and consider weekly working hours. Figure 10 summarises the results and shows a small but statistically significant positive correlation between the treatment doses and the weekly hours worked by both Czech women and men, implying that a 1% increase in officially employed Ukrainians relative to the local labour market size of each district has a short-term positive effect on the weekly hours worked by locals.

[18] The sectors with the highest refugee employment are N-administrative and support service activities (~30%), C-manufacturing (~29%), H-transportation and storage (~7%), I-accommodation and food service activities (~7%), G-wholesale and retail trade (~6%), and F-construction (~6%).

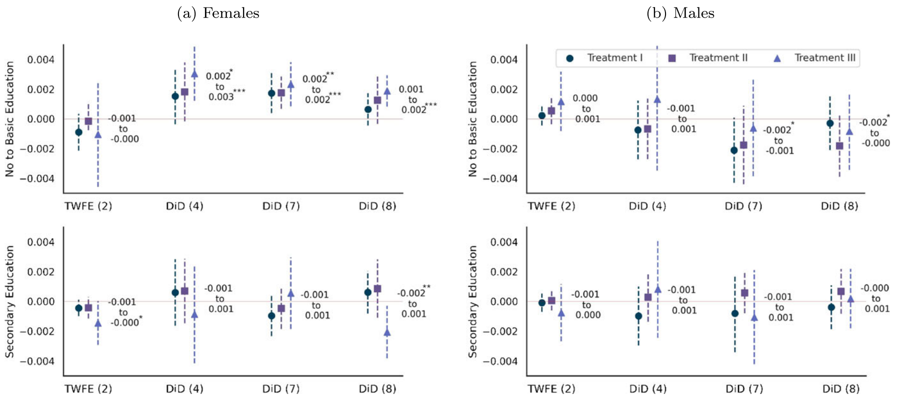
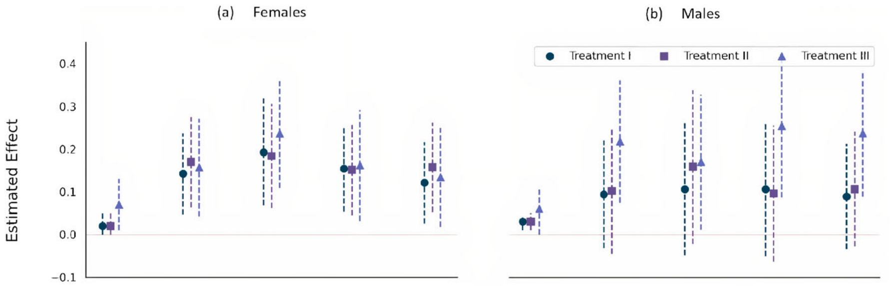


Fig. 9 Positive treatment doses—probability of employment with temporary contract by gender and education level. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–8) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7) and DiD(8) match on both the (X) individual characteristics and district-specific DiD(7) or district-, gender-, and education-specific DiD(8) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–8), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

While for females, the coefficients are significant across all models, reinforcing the reliability of the observed treatment effects, for male workers, the significance in DiD models diminishes after controlling for individual characteristics, district-specific factors, and pre-treatment trends specific to district, gender, education, or industry. This suggests that the initial treatment effects for males may be confounded by pre-existing trends, casting doubt on the treatment's actual impact on them. Even though the extensions to the baseline DiD(3) model come at the cost of a loss in observations—ranging from 0.7 to 65.4% for females and 0.4 to 62.5% for males, especially notable in the extensions where matching on individual characteristics and on pre-treatment trends are applied—they substantially bolster the robustness of our findings. Parallel trend tests with placebo estimators yield an average p-value of 0.6 for females and 0.5 for males for all DiD estimates, as detailed in Table B.3.

The economic significance of the identified effects can be better understood by examining the relative increases against the backdrop of the average working hours in 2021. For males, the analysis based on the TWFE(2) model suggests a slight increase in weekly hours worked, ranging from 0.07 to 0.14%, compared to the average of 40.5 h worked the previous year. This is equivalent to an additional 0.03 to 0.06 h (or approximately 1.8 to 3.6 min) per week. For females, the estimated increase is marginally higher, ranging from 0.05 to 0.18% relative to their average workweek of 38.0 h in 2021, which translates to an additional 0.02 to 0.07 h (or roughly 1.2 to 4.2 min) weekly.



	TWFE(2)	DiD(4)	DiD(7)	DiD(8)	DiD(10)	TWFE(2)	DiD(4)	DiD(7)	DiD(8)	DiD(10)
TR I	0.02*	0.14***	0.19***	0.15***	0.12**	0.03***	0.09	0.11	0.11	0.09
SE	(0.01)	(0.05)	(0.06)	(0.05)	(0.05)	(0.01)	(0.06)	(0.08)	(0.08)	(0.06)
No. obs.	157,128	16,012	10,150	10,322	14,797	179,956	19,427	12,485	12,847	17,973
TR II	0.02*	0.17***	0.18***	0.15***	0.16***	0.03***	0.10	0.16*	0.10	0.11
SE	(0.01)	(0.05)	(0.06)	(0.05)	(0.05)	(0.01)	(0.07)	(0.09)	(0.08)	(0.07)
No. obs.	157,601	16,370	10,488	10,376	15,172	180,459	19,883	12,740	13,087	18,504
TR III	0.07**	0.16***	0.24***	0.16**	0.13**	0.06**	0.22***	0.17**	0.25***	0.23***
SE	(0.03)	(0.06)	(0.07)	(0.07)	(0.06)	(0.03)	(0.07)	(0.08)	(0.08)	(0.08)
No. obs.	156,777	18,286	12,462	12,376	16,800	179,590	22,472	15,490	15,782	20,891

Fig. 10 Positive treatment doses—weekly hours worked by gender. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–10) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7), DiD(8), and DiD(10) match on both the (X) individual characteristics and district-specific DiD(7), or district-, gender-, and education-specific DiD(8), or district- and industry-specific DiD(10) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–10), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

The preferred DiD(4) model specification estimates reveal a more sizable effect for men and women. Men experience an increase in weekly work hours by 0.22 to 0.54%, corresponding to an increase of 0.09 to 0.22 h (or 5.4 to 13.2 min). For females, the impact is a 0.37 to 0.45% rise relative to their usual work hours in 2021, leading to 0.14 to 0.17 additional hours (or 8.4 to 10.2 min) per week. Interestingly, introducing the extended DiD(7, 8, 10) models further magnifies the effect estimated for females, indicating a 0.32% up to a 0.62% increase in weekly hours worked.[19]

Individually, these increases amount to a relatively modest change in weekly working hours. The larger effects observed in the DiD model, compared to the TWFE, can be attributed to the DiD model's ability to capture dynamic treatment effects over time. In aggregate terms, though, even small percentage increases in average weekly hours worked can accumulate to a substantial impact across the workforce. These

[19] It is interesting to note that TWFE consistently reports larger coefficients than DiD. This difference arises because TWFE incorporates all the data available before the treatment from 2019 to 2021. This period includes the year 2020 and sometimes also the first quarter of 2021, when there was a slight decrease in hours worked, employment rate, and participation rate. By including this data, the resulting coefficients for treatment effects are lower than those derived using DiD, which only considers the single period before the treatment begins. It might also result from the potential bias in our ATT estimates due to the influence of negative weights on the treatment effects (non-convex combination of the effects) that we tested for in Appendix F. Our tests revealed that, in our case, the TWFE model indeed appears to be affected by this issue.

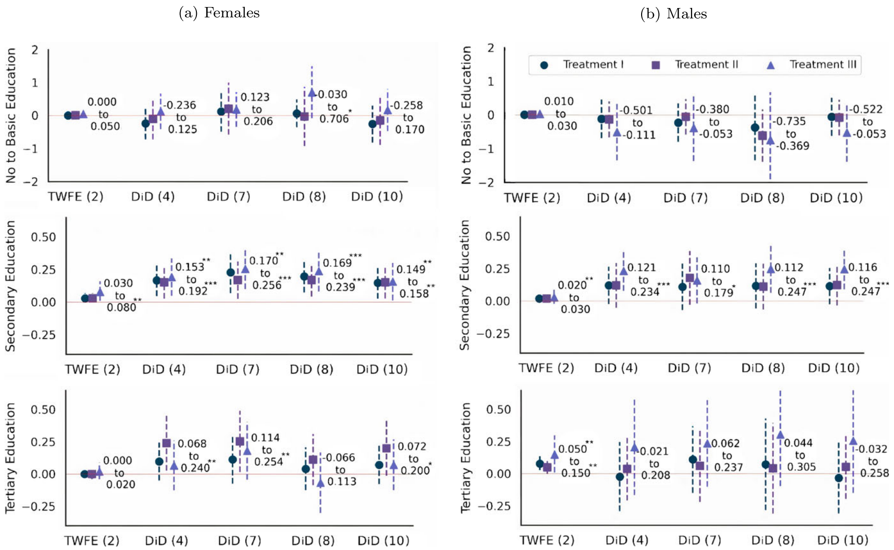


Fig. 11 Positive treatment doses—weekly hours worked by gender and education level. Note: The figure displays coefficient estimates, standard errors, 95% level confidence intervals, and the number of observations ATT and nAVSQ across TWFE model in Section 4.2 (columns 1–2) and the expanded DiD model in Section 4.3 (columns 3–10) for treatment I, II, and III. TWFE(2) model controls for individual and time-fixed effects as well as individual-level characteristics. DiD(4) model controls for individual and time-fixed effects in addition to matching on the (X) individual characteristics. Models DiD(7), DiD(8), and DiD(10) match on both the (X) individual characteristics and district-specific DiD(7), or district-, gender-, and education-specific DiD(8), or district- and industry-specific DiD(10) pre-treatment trends of the dependent variable. Robust standard errors are clustered at the district level. For columns (4–10), pre-trend placebo tests were conducted, and the p-values were calculated using the standard normal distribution. Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

incremental changes at the individual level may suggest a non-trivial enhancement in overall labour supply (along the intensive margin), potentially reflecting shifts in labour market dynamics and productivity.

Further analysis, disaggregated by education level as depicted in Fig. 11, reveals that locals with secondary education are primarily driving the gains in weekly hours worked. Consistent with the previous discussion, results across all model specifications are more robust for females, with coefficients remaining significant in both TWFE and extended DiD models and increasing in magnitude compared to prior results. The estimated increase in hours worked ranges from 0.03 to 0.08 h (1.8 to 4.8 min weekly) for TWFE(2) to 0.15 to 0.19 h (9 to 11.4 min per week) for DiD(4). With the DiD(7, 8, 10) extensions, these figures grow further to 0.15 to 0.26 h or 9 to 15.6 min weekly. The results are less conclusive for male workers, echoing previous findings.

The concentration of positive effects within the secondary education bracket likely reflects the nature of the jobs Ukrainian refugees are taking or the specific demands of the Czech labour market. Individuals with secondary education may occupy roles that complement the positions filled by the incoming workforce, leading to an increase in their hours due to either increased demand or collabourative opportunities. These observed effects can also be directly linked to the profile of the Ukrainian refugee population. Most refugees are female, many of whom are highly educated but face language barriers and unfamiliarity with the Czech labour market. These challenges may lead them to accept jobs requiring secondary or lower levels of education.

Lastly, to ascertain whether the observed increase in working hours across the general population was directly attributable to refugees entering the workforce, we focused our analysis on Czech locals employed in sectors most impacted by the refugee influx. Consistently with previous results, we find consistent patterns among local female workers and not for local male workers. Our findings, reported in Figure B.11, indicate that these sectors experienced significant increases in working hours, particularly among females, across all models. This trend underscores the sector-specific impact of the refugee influx, closely aligned with industries traditionally dominated by, or more adaptable to, female employment. The predominance of female refugees, coupled with their linguistic challenges and unfamiliarity with the Czech labour market, has likely driven this trend, as these individuals typically find employment in sectors facing labour shortages or those more open to new workforce entrants.

5.4 Foreign-born individuals in Czechia

So far, we have focused on the effects on all local workers in the Czech Republic. However, our analysis suggests (in line with the literature) that the influx of refugees has a heterogenous effect on the local labour force, suggesting that certain workers might be more vulnerable to the influx (such as workers in most affected sectors or that match the demographics of the incoming workers). One potentially vulnerable group is foreign-born workers already residing in the host country. We estimate the models for foreign-born workers only, and we find some evidence supporting this conjecture. As summarised in Figure B.12, while the TWFE(2) model identifies no significant effects, the DiD (3, 4) models indicate a slight decrease in employment probability for foreign-born individuals, from −0.009 to −0.014, and an increase in unemployment probability, from 0.011 to 0.016, following a 1% increase in officially employed Ukrainians.

These results suggest that the influx of Ukrainian refugees negatively affected the employment rates and positively the unemployment rates for foreign-born residents in the short term. However, given that foreign-born individuals represent only about 0.04% of our dataset, these findings must be approached with caution as the limited sample size restricts the strength of our conclusions and underscores the importance of conducting further research with a more extensive dataset.

6 Robustness checks

6.1 Secondary effects: local population movements

As is often observed in the literature covering similar refugee or migration events, the effects on locals can be distorted by secondary factors, particularly due to the

Table 6 Analysis of net migration and population stability in (un-)treated districts

Variables	Net migration			Net migration, females		
	(1)	(2)	(3)	(4)	(5)	(6)
Average treatment I	30.59			11.74		
	(54.97)			(24.27)		
Average treatment II		33.71			14.91	
		(66.59)			(29.38)	
Average treatment III			69.49			21.93
			(109.73)			(48.48)
No. of observations	77	77	77	77	77	77
No. of districts	77	77	77	77	77	77

Note: The table presents coefficient estimates and the corresponding standard errors in parentheses. The dependent variables are net migration in Czechia reported in columns (1–3) and net migration among females in Czechia reported in columns (4–6). Data sourced from the Czech Statistical Office (2023d). Significance levels: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

potential movement of locals away from the most affected districts. Although the short time frame of our analysis limits the extent of this issue, we test for this concern by regressing net migration figures (change between 2021 and 2022) by district on the $Average\ Treatment_d^{I,II,\text{ or } III}$. As shown in Table 6, all coefficients are positive and not statistically significant, suggesting that districts have experienced stable net migration similar to that observed in previous years, including the 2021–2022 period. Therefore, we find no conclusive evidence of abnormal population movement into or out of the treated districts.

Regarding the substantial movement of the Ukrainian diaspora in and out of Czechia in 2022, evidence indicates that people did not move away. Refugees under temporary protection are, by definition, temporary residents, and it is quite difficult for them to obtain permanent visas within less than a year. Therefore, it is unlikely that many have switched to permanent status during this period. The number of Ukrainians with permanent residence in Czechia actually increased slightly from 90,776 on December 31, 2021, to 93,545 on December 31, 2022, suggesting that those already residing permanently likely stayed.

Meanwhile, the number of Ukrainians holding temporary visas rose dramatically from 106,099 in 2021 to 542,737 in 2022—an increase of 436,638 (Ministry of the Interior 2023a). As of December 31, 2022, there were 433,071 registered refugees (Ministry of the Interior 2023b), further indicating that the local Ukrainian population did not move away but was joined by a significant number of new arrivals. This suggests that either a small number of Ukrainian refugees managed to switch to permanent residence (approximately 2769 individuals), or there was an influx of Ukrainians who arrived in 2022 but did not register as refugees and instead registered as permanent or temporary residents (approximately 6336 individuals)—a relatively small percentage compared to the 433,071 refugees. Importantly, these individuals should also be considered similar to the refugees, as they all arrived during the crisis and shared the same legal rights regarding access to education, employment, healthcare, and other services.

6.2 Alternative treatment variable: working-age Ukrainians

To ensure the robustness of our findings, we conduct an additional analysis using an alternative treatment variable: the number of working-age Ukrainians, regardless of employment status, across regions and time. We compare districts with earlier arrivals of Ukrainians to those with later arrivals.

We define the alternative treatment variable as

$$\text{Alternative Treatment}_{d,t} = \begin{cases} \dfrac{\text{Refugees of working age 18-65}_{d,t}}{\text{Locals of working age 18-65}_{d,t}} & \text{if } t \geq 2022 \\ 0 & \text{if } t < 2022 \end{cases} \tag{10}$$

where d and t index districts and time (year: quarter), respectively.

Implementing a TWFE model based on this alternative treatment helps verify whether the observed effects remain consistent when the treatment variable is expanded beyond employment to include the broader working-age population. Unfortunately, we cannot incorporate our extended DiD estimator, as the demographic shock was so significant that no district could reasonably be considered untreated. Introducing a random cut-off to signify unaffected areas would be arbitrary. Instead of matching districts on their pre-treatment trends, as done in our main specification using the extended DiD model, we control for local labour market characteristics (unemployment rate and labour market tightness) at the district level, lagged by 1 year. The resulting TWFE regression model is specified as

$$y_{i,d,t} = \alpha + \beta(\text{Alternative Treatment})_{d,t} + \theta' X_{i,d,t} + Z_{d,t-4} + f_i + f_t + \epsilon_{i,d,t}, \tag{11}$$

where i, d, and t index individuals, districts, and time (year: quarter), respectively. The dependent variable, $y_{i,d,t}$, represents the labour market outcome of interest (employment, unemployment, inactivity, and weekly hours worked). The coefficient β on the $AlternamtiveTreatment$ variable is of primary interest. The model accounts for individual– f_i and time-fixed effects f_t, individual-level characteristics (X) used in previous estimations, as well as labour market conditions (Z), proxied by the unemployment rate and labour market tightness lagged by four periods (1 year).

Tables B.6 and B.7 summarise the results for local males and females across different education levels separately. The results align with our main findings: there appears to be a corresponding increase in weekly hours worked, with no consistent statistically significant negative effects identified for the local population.

6.3 DiD: non-normalised treatment effect analysis by dose

For our primary estimator—the extended DiD—we address potential issues from the normalisation of treatment effects. We categorise treated districts based on their average treatment dose, using the same thresholds as those in model 9 ($Average\ Treatment_d^{I,II,\text{ or }III}$). We then recalculate the AVSQ (non-normalised) effect separately for each $Average\ Treatment\ Dose$—1%, 2%, 3%, and $\geq$ 4%—without normalisation.

Additionally, as the treatment period progressed from the 1st to the 4th quarter of 2022, fewer districts remained as controls. This reduction might have hindered our ability to identify significant effects, given the insufficient number of observations to serve as controls later in the year. To address this, we designated districts experiencing 0 to 1% treatment as 'controls', recalculated the $Average\ Treatment\ Dose$ labelling them 'adjusted' and re-estimated the results.

As depicted in Figures B.14–B.21, consistently with the results in the main analysis, among female and male workers, the coefficients for the probability of employment remain insignificant and the coefficients for weekly working hours follow the same pattern, in terms of sign and significance, although the magnitude is somewhat smaller. We find some evidence of statistically significant increase in the probabilities of unemployment and inactivity; however, the results are not consistent throughout the different model specifications, and the economic magnitude is very small.

7 Conclusions

In this paper, we explore the natural experiment of the sudden and forced influx of Ukrainian refugees to rigorously assess the short-run impact on the locals' labour market outcomes in the Czech Republic. On average, we find no (consistently) significant effects on employment, unemployment, and inactivity probabilities for male and female workers. Moreover, we find that, conditional on employment, local workers increased their working hours. Individually, the magnitude of these effects is small. However, the overall effect on labour supply (along the intensive margin) is certainly not negligible.

Our empirical evidence is valuable not only because it is the first to document the effects of the most recent refugee crisis in Europe but also because there are clear policy implications. We identify two groups of workers, particularly vulnerable to the large and sudden influx of workers into the labour market: workers in industries mostly affected by the influx of and foreign-born individuals. We find evidence of a decrease in the probability of employment and an increase in the probability of unemployment for these two groups. However, these results are of very small magnitude. They are also based on relatively small sample sizes, inviting further research focusing on EU-wide analysis to better capture the impact on most affected groups. Furthermore, we believe that this paper's results shed light on the potential outcomes of policies extending the rights to immediate access to the labour market to refugee workers. By doing so, though still in the short run, we contribute to the objective and data-driven body of knowledge, providing insights into the effects of refugees' active participation in labour markets on the local workers.

There is suggestive evidence that the context of the Czech labour market contributed to the null effects identified. At the time of the refugees' arrival, the Czech labour market was exceptionally tight—it had the lowest unemployment rate in the European

Union. Just a month before the refugee inflow began, there were 266,783 open job vacancies reported in the country—largely outnumbering registered job seekers—with the majority requiring only basic education (73%). Employment opportunities were abundant in sectors like retail trade, construction, public administration, and education, which were already facing labour shortages. These sectors became the main employers for most Ukrainian refugees, who often took on low-skilled roles such as product and equipment assemblers, helpers in construction, production, and transport, or stationary machine operators, thereby helping to alleviate the workforce gap.

The combination of a tight labour market and existing shortages in key industries likely mitigated potential disruptions from the influx of refugees, enabling the Czech economy to absorb the new workforce relatively smoothly, at least in the short term. This suggests that the Czech experience may not be directly applicable to countries with different labour market conditions. This context raises important considerations for policy design. The largely neutral outcomes in Czechia could, therefore, support arguments for policies that facilitate refugees or immigrants in filling existing labour shortages, perhaps through targeted matching of their skills with market needs, such as through skilled migration visas, rather than endorsing unrestricted labour access in all contexts.

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Data Availability The primary individual-level data used in this study (LFSS) are not publicly available but can be accessed through appropriate procedures from the Czech Statistical Office.

Declarations

Conflict of Interest The authors declare no competing interests.

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