I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16965

The Effect of Ukrainian Refugees on the Local Labour Markets: The Case of Czechia

Agnieszka Postepska
Anastasiia Voloshyna

APRIL 2024

IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16965

The Effect of Ukrainian Refugees on the Local Labour Markets: The Case of Czechia

Agnieszka Postepska
University of Groningen and IZA

Anastasiia Voloshyna
University of Groningen

APRIL 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Effect of Ukrainian Refugees on the Local Labour Markets: The Case of Czechia*

Following the Russian Federation's invasion of Ukraine on 24th February 2022, over a quarter of the Ukrainian population became displaced, with many seeking refuge across Europe. Czechia emerged as a key destination, granting Temporary Protection to approximately 433 thousand 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 benefits typically reserved for permanent residents, such as unrestricted access to the labour market. This led to a notable increase in the number of Ukrainians officially employed and expanding Czechia's workforce. Using individual micro-level data from sixteen 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 on the labour market outcomes of locals in Czechia. Using 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, noting that we find small negative effects on employment and positive effects on unemployment in sectors that experienced the largest influx of workers. However, we treat these results with caution due to the small sample sizes. 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.

JEL Classification: F22, J15, J21

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

Corresponding author:
Agnieszka Postepska
Faculty of Economics and Business
Department of Economics, Econometrics & Finance
University of Groningen
P.O. Box 800 9700 AV Groningen
The Netherlands

E-mail: a.postepska@rug.nl

* We are particularly grateful to Rob Alessie, Viola Angelini, Max Groneck, and Bertrand Achou for their suggestions on this project. We would also like to thank David Margolis, the participants of the 'Microeconometrics and Policy Evaluation' course at the Paris School of Economics, attendees of the IZA workshop on 'Labour Markets and Innovation during Times of War and Reconstruction', the IUSSP workshop on 'Population and Conflict', and the Groningen University PhD seminar series for their valuable input. All errors and omissions are the sole responsibility of the authors.

1 Introduction

Following the invasion of Ukraine by the Russian Federation on February 24^{th}, 2022, over a quarter of the Ukrainian population became displaced (IOM, 2023b; UNHCR, 2023). By December 2022, the United Nations High Commissioner for Refugees reported that nearly 8 million individuals, mainly women of working age and children, had sought refuge across Europe, with about 5 million registering for Temporary Protection or equivalent national protection programs. This refugee crisis is the largest in Europe since World War II, exceeding the displacement caused by the Yugoslav Wars of the 1990s and the Syrian Civil War.[1]

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

Unlike other unexpected, large-scale migration waves instigated by wars or political upheavals, the Ukrainian refugees almost immediately gained unrestricted access to the host countries' labour markets. In March 2022, the Czech government, alongside other EU nations, adopted the 'Lex Ukraine Act' (European Commission, 2022). This legislative framework temporarily extended benefits, reserved for permanent residents, to Ukrainian citizens, their family members, and other listed categories of individuals. Refugees were granted full access to the labour market, retraining programmes, self-employment opportunities, and unemployment benefits, as well as access to healthcare, education, and living allowances. As a result, by year's end, there was a marked surge in the official employment of Ukrainians, equating to nearly one-third of all registered refugees of working age (18-65 years old).

In this paper, we explore the natural experiment of the sudden and forced influx of Ukrainian refugees, which noticeably expanded Czechia's workforce to assess the short-run impact on the locals' [4] labour market outcomes. Previous research has often leveraged large-scale migration waves triggered by wars or political upheavals to assess the impact of the refugees on the workers in the host countries.[5] However, the decision of the Council of the European Union to activate temporary protection and provide immediate labour market access for Ukrainian refugees stands in stark contrast to the long wait times of several months or even years typically faced by refugees in the EU before gaining such rights.[6] This decision underscores the unique response to the 2022 Ukrainian

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

[2]Czechia, Hungary, Poland, and Slovakia.

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

[4]'Locals' include both Czech nationals and foreign nationals with Czech residency status of 15 years or older, excluding Ukrainian refugees. For definitions of terms such as 'locals', 'refugees', and 'diaspora', see Appendix A.

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

[6]In the EU, the duration for refugees to obtain the right to work has varied (ECRE, 2024); since March 2020, for example, Germany's general rule has been that asylum seekers in initial reception centers are not allowed to take up employment, with

refugee crisis. The lengthy procedures refugees typically endure to access employment opportunities make the influx of workers into the host country's labour markets gradual and no longer exogenous. Due to the 'Lex Ukraine Act', this is not the case for Ukrainian refugees across Europe. A substantial proportion of working-age Ukrainian refugees (18-65 years old) secured official employment by the end of 2022, significantly bolstering the growth of Czechia's workforce. However, the increase was not homogeneous across districts, and we explore this geographical heterogeneity in the increase in workforce size for our identification strategy.

We explore both the extensive margin, considering *employment, unemployment or inactivity statuses* among the locals, and the intensive margin by looking at *the weekly hours worked*. We focus on the impact of the employment surge in 2022 rather than on the overall increase in the Ukrainian population or of Ukrainian employment on the labour market outcomes of locals over the entire panel duration.

We specifically aim to isolate the effects attributable to the employment of Ukrainian refugees only, distinct from the consequences of the Ukrainian diaspora already employed and/or residing in Czechia prior to 2022. The refugees' demographic profile—predominantly higher-educated and female—differs markedly from that of the typical, less-educated, male Ukrainian migrants before 2022. Merging these groups for analysis would obscure these differences and complicate our identification strategy. Focusing on the surge in employment, rather than the general increase in the number of residents due to the refugee influx allows us to address an interesting question: the implications of granting refugees and immigrants immediate and unrestricted access to the labour market, a topic of considerable current societal interest. Lastly, while data on refugees' residence might be compromised by individuals returning to Ukraine, relocating to other countries without deregistering, or unreported stays, the legally mandated official employment figures offer greater degree of accuracy.

Our identification strategy unfolds in several steps. We start by defining 'treatment' variables and identifying districts with significant shifts in Ukrainian employment levels (relative to the districts' labour market size) due to the 2022 refugee influx. Residents in these districts are considered treated, receiving varying 'doses' of treatment based on the intensity of these changes. We then implement a static two-way fixed effects (TWFE) regression. Recognising its potential limitations, such as the risk of not identifying the convex combination of individual treatment effects and the challenge of capturing the dynamic effects of treatment in our complex setting, we turn to an alternative estimator proposed by de Chaisemartin and d'Haultfoeuille (2024). This method, a variant of the extended Difference-in-Difference (DID) estimator, enables the estimation of treatment effects using non-binary, non-staggered treatments and allows dynamic/inter-temporal treatment effect analysis. It also avoids making 'forbidden comparisons' between treated and control individuals, thus overcoming some TWFE regression limitations. We further introduce several extensions implemented to the estimator, such as matching on relevant individual characteristics and on the pre-treatment trends in the dependent variables.

Economic theory offers various predictions concerning the impact of a large-scale immigration

most adults facing a wait of 18 months, and up to 24 months in some Federal States (ECRE, 2023).

event, such as the Ukrainian refugee influx. First, if we treat the labour force as homogeneous, the standard competition framework suggests that an influx of immigrants might exert downward pressure on wages due to the increased labour supply. If wages are sticky (perhaps due to union influences), this can result in rising unemployment. Alternatively, when considering labour as heterogeneous, outcomes depend on whether foreign workers are considered substitutes or complements of native workers. Assuming most immigrants are either unskilled or find it challenging to transfer their skill set to the new market, as with many prior migration waves and in line with the skill-cell approach, skilled natives can be seen as complements to immigrant labour, while unskilled natives may find themselves in more direct competition.

Empirical research often found little to no impact of immigration on the overall employment or wages of locals (see, for example, Card (1990); Friedberg and Hunt (1995); Borjas et al. (1996); Pischke and Velling (1997); Angrist and Kugler (2003); Card (2009)). However, when the analysis is narrowed down to specific demographic groups, particularly those with demographics akin to the immigrants, more pronounced yet varied effects have been observed. For example, adverse effects of immigration have been pinpointed for local low-skilled males and minorities (see, for example, Borjas (1994); Card (2001); Borjas (2003); Dustmann et al. (2005); Borjas and Katz (2007); Lemos and Portes (2008); Ottaviano and Peri (2011); Nickell and Saleheen (2008)) or the influx of female immigrant labour (providing affordable household services) has been linked to (re-)entering the workforce among high potential female earners (see, for example, Cortés and Tessada (2011); Farre et al. (2011); Cortés and Pan (2013)).

Our results are in line with the previous literature. Using microdata from sixteen waves of the Labour Force Sample Survey (LFSS) in the Chech Republic, 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. When considering the most affected industries, we find small negative effects on employment and positive effects on unemployment in sectors that experienced the largest influx of workers, noting that due to the small sample sizes, we treat these results with caution. 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.

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 labour market on the most recent refugee crisis in Europe. 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 refugees' settlement patterns consistent with the literature concerned with the network effects and self-selection of immigrants (Hatton and Williamson, 1998; Woodruff and Zenteno, 2007; Patel and Vella, 2013; Stuart and Taylor, 2021) .

Last but not least, the results of this paper are particularly important for policymakers. First, our results clearly point to groups of workers that are vulnerable to the influx of foreign workers. Second, with public attitudes increasingly polarised over past and future policies on integration &

accommodation of refugees (including financial assistance to Ukrainian refugees) and future EU accession.[7], there is a pressing need for objective, data-driven insights into the effects of refugees' active participation in labour markets. Understanding these effects, though still in the short run, is important for enlarging 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 2022 Ukrainian refugee influx, detailing the demographic characteristics of the Ukrainian refugees, settlement patterns and workforce integration. Section 3 discusses the data and descriptive statistics, while Section 4 outlines the identification strategy. Results and discussion are presented in Section 5, followed by robustness checks in Section 6 and conclusions in Section 7.

2 Contextual Details & Economic Theory: Analysing Potential Labour Market Responses

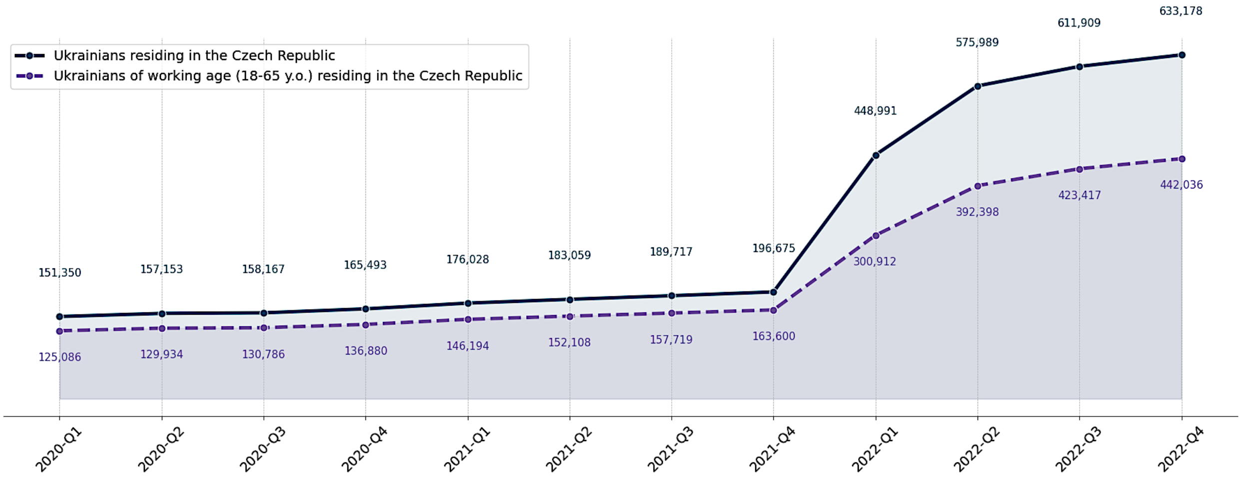
To grasp the economics behind the observed data patterns, we now discuss the Ukrainian refugee influx into Czechia, exploring their settlement patterns, demographic profiles, and integration into the labour market. We identify industries that saw a notable increase in refugee workers, alongside those with a growing demand for local workers to accommodate the significant inflow of displaced Ukrainians. With the relevant theory in mind, we also discuss the potential effects of the refugee influx on the locals' labour market outcomes, focusing on key indicators such as employment, unemployment, inactivity probabilities, and weekly hours worked.

Demographic Characteristics of the Ukrainian Refugees. By 31 December 2022, Czechia had welcomed approximately 433 thousand Ukrainian refugees (Figure 1) - predominantly working-age women and children—a demographic profile distinct from the typical migration patterns common to Czechia.[8] As shown in Table 1, the age distribution of the 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 the 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.

[7] 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 favor 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).

[8] From 2016 to 2021, approximately 57% of immigrants in Czechia were male, primarily from Ukraine, Slovakia, and Russia (Ministry of the Interior, 2023). 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 1,046 by 2021 (Ministry of the Interior, 2022). This group comprised largely younger males from the former Soviet Bloc and countries such as China, Syria, and Ukraine, who were escaping conflicts and crises.

Figure 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 (2023) of Czechia.

Table 1: Demographic Composition: Age and Gender of Ukrainian Refugees Compared to the Czech Population

	Refugees					Locals				
	Overall	Prague	Brno-město	Tachov	Cheb	Overall	Prague	Brno-město	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										
0-5y.o.	8%	8%	7%	4%	7%	5%	5%	6%	5%	5%
6-14y.o.	18%	17%	16%	11%	16%	11%	10%	10%	11%	11%
15-17y.o.	6%	6%	6%	4%	5%	5%	4%	4%	5%	5%
18-64y.o.	64%	65%	67%	79%	67%	59%	62%	61%	61%	58%
65+y.o.	4%	4%	3%	2%	5%	20%	18%	20%	19%	21%

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 (2023) and the 2021 Census (Czech Statistical Office, 2024b). Age categories have been harmonised to ensure comparability.

Table 2: Demographic Composition: Educational attainment of Ukrainian Refugees Compared to the Czech Population

	Refugees			Locals				
	MoLSA (a)	IOM (b)	UNHCR (c)	Overall	Prague	Brno-město	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 (a) the Czech Ministry of Labour and Social Affairs (2022), (b) IOM (2023a), and (c) 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 8 in Appendix B.

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% which is noticeably exceeding the 18% average rate among Czech locals. While this gap was somewhat narrower in urban areas such as Prague and Brno-město, with local tertiary rates at 34% and 32%, respectively, it became more pronounced in smaller, more peripheral districts.

Given the majority of incoming refugees were educated, working-age women and proxying their skills by educational attainment, as in Belot and Hatton (2012), there was a notable increase in medium-to-highly skilled labour in Czechia's labour market. Yet, the transferability of refugees' human capital, especially in the short term, remains a challenge, often leading to underemployment, as highlighted in past studies (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)).

Settlement Patterns & Workforce Integration. The Ukrainian refugee influx led to a significant expansion of Czechia's population (and workforce). By the end of 2022, refugees constituted around 4% of Czechia's residents, the highest per capita number of Ukrainian refugees globally. Notably, each district saw at least a 1% increase in its working-age population (18–65 years old), with Tachov, Plzeň-město, Prague, Cheb, Mladá Boleslav, and Karlovy Vary, among others, experiencing rises from 7% to as much as 13% (see Figure 3a).

Due to the Lex Ukraine Act, 75 thousand Ukrainians secured formal employment by the end of 2022, 79% of whom were women (Ministry of Labour and Social Affairs, 2023a). Another five thousand obtained valid trade licenses, enabling entrepreneurial activities (Ministry of Industry and Trade, 2023). Altogether, this increase in employment equated to nearly one-third of all registered refugees of working age (18-65 years old).[9] As soon as the end of March, nearly 97,120 Ukrainians with temporary protection[10] were working in the Czech Republic, with the highest number of workers in the Central Bohemia Region (16,721), the Plzeň Region (14,514), and the South Moravia Region (10,400).

Surveys by the Czech Ministry of Labour and Social Affairs showed that by the end of 2022, around half of the economically active Ukrainian refugees had found local employment (Ministry of Labour and Social Affairs, 2022). The employment patterns varied considerably on a district-to-district basis (see Figure 3b). Districts like Tachov, Mladá Boleslav, and Prague saw marked workforce increases, with every 3rd, 9th, and 10th employed individual being Ukrainian by year's end,

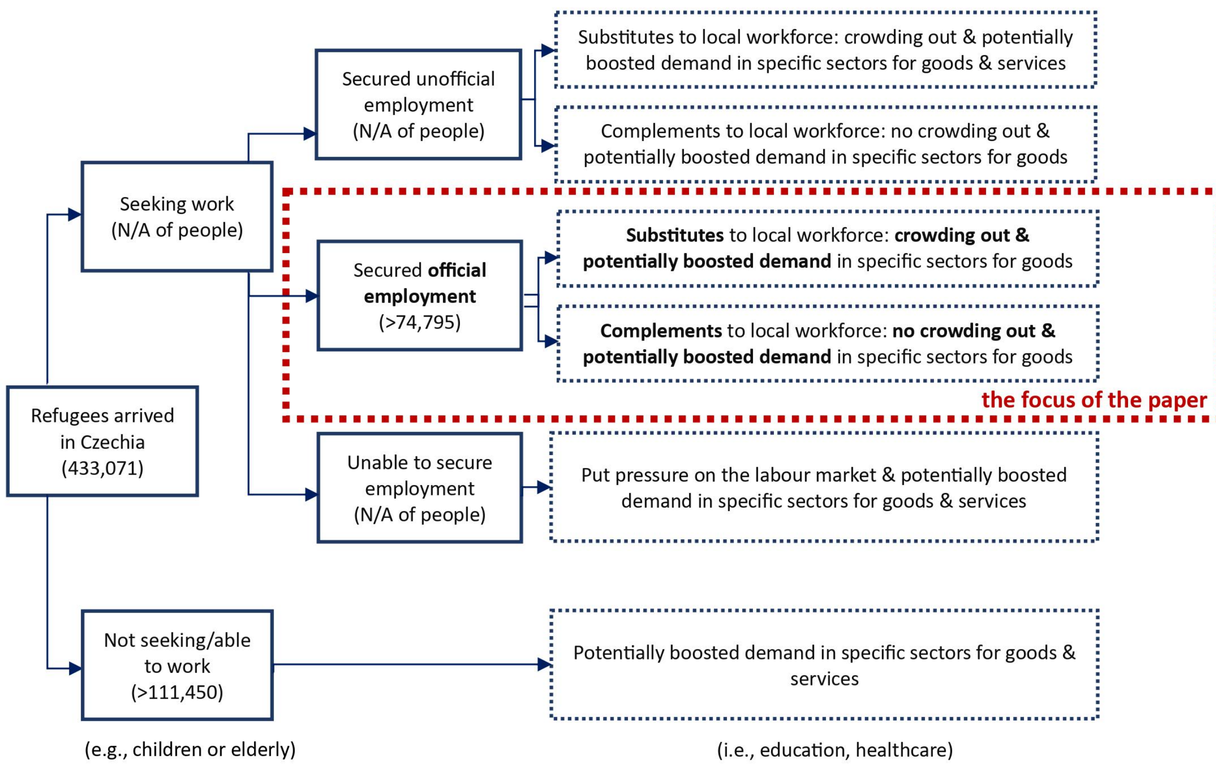
[9] Employment data are reported by citizenship but not by the type of stay permit. Thus, we cannot assert with certainty whether all Ukrainians who joined the Czech workforce in 2022 were refugees or part of the existing diaspora in the country (re-)entering the workforce. However, considering that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

[10] Upon arrival, Ukrainians were encouraged to apply for temporary protection status. The addresses provided on their applications, along with any subsequent updates, have become the primary source for tracking their residential locations.

respectively. In contrast, districts such as Chomutov or Děčín experienced minimal changes. We explore this variation for our identification strategy.

There was also notable variation in employment patterns by gender and industry among refugees. Female refugees primarily secured official employment in Administrative and Support Service Activities (33%) and Manufacturing (29%), with smaller percentages in Accommodation and Food Service Activities (8%), Transportation and Storage (7%), Wholesale and Retail Trade, and Repair of Motor Vehicles and Motorcycles (7%). Male refugees predominantly joined Manufacturing and Construction (31% each), with 19% in Administrative and Support Service Activities. They were most often employed as product and equipment assemblers or helpers in construction, production and transport or as stationary machine operators, noting that these industries were reporting labour shortages (EURES, 2023).

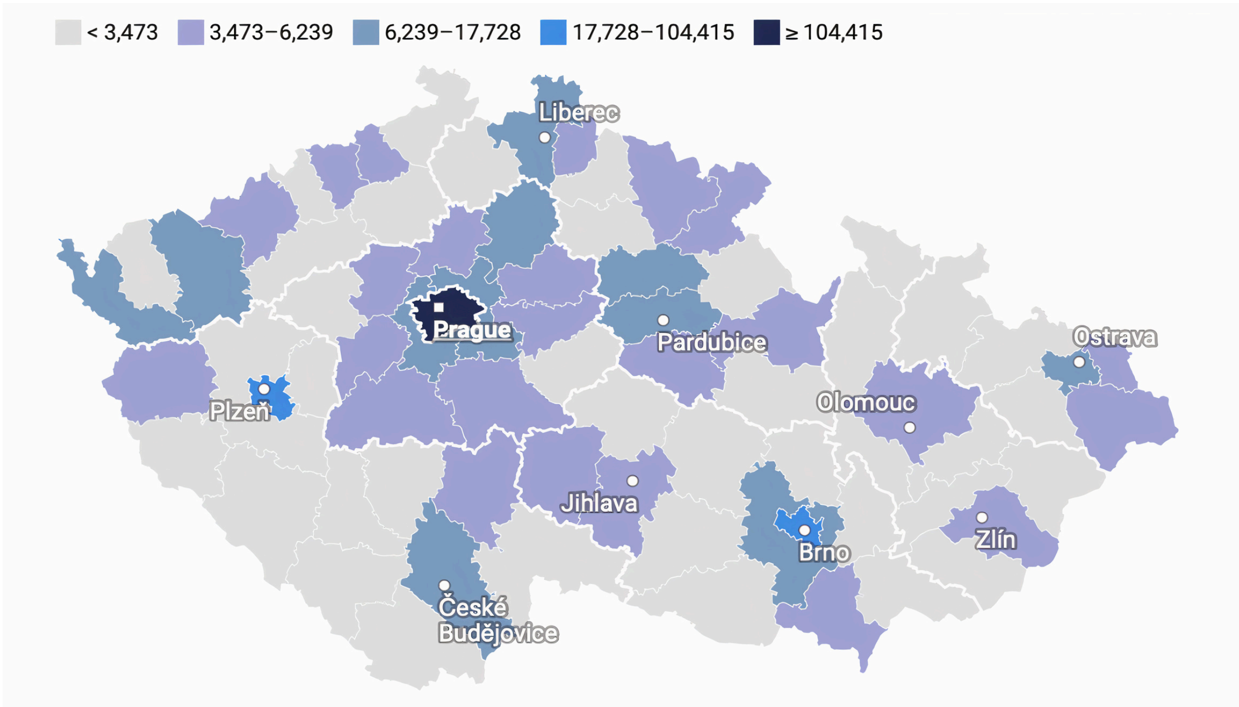
Figure 2: Impact of Refugee Settlement and Employment by District in Czechia



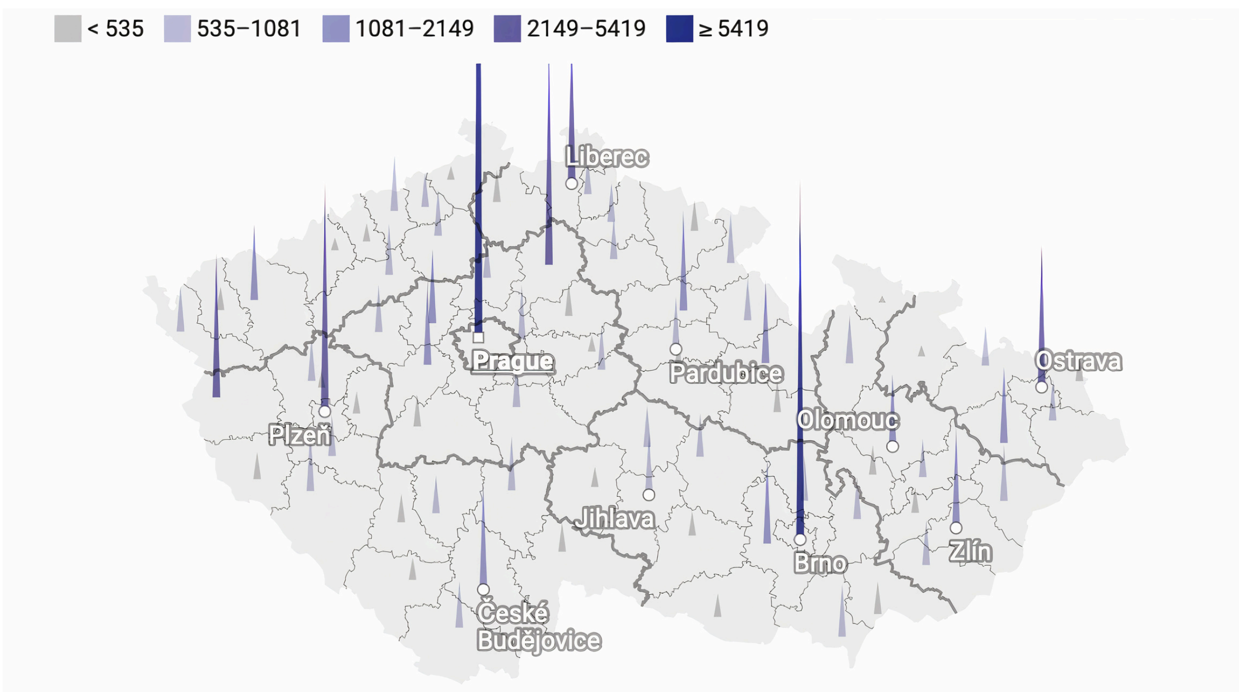
Note: The plot was created by the authors using the data reported by the Ministry of the Interior (2023) and the Ministry of Labour and Social Affairs (2023a) of Czechia. It delineates the central focus of the paper: the impact of Ukrainian refugees securing official employment on the labour market outcomes for the local population (highlighted by the red dotted line).

Despite the favourable conditions on the Czech labour market—being among the tightest in the EU, with an unemployment rate of just 2.22% in 2022, the lowest in the EU, and job vacancies frequently outnumbering job seekers (for details see Appendix C)—many of the Ukrainian workers took on roles that paid less and were below their qualifications compared to jobs they held in Ukraine. This trend was especially true for highly educated refugees and women with only 49% and 29%, respectively, finding jobs aligning with their qualifications. Most refugees, irrespective of their

Figure 3: Geographical Distribution of Ukrainian Refugee Registrations and Employment in Czechia



(a) Settlement



(b) Employment

Note: Panel(a) maps the distribution of refugee settlements in Czech districts as of December 2022; Panel(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 (2023)) and the Ministry of Labour and Social Affairs (2023a)) of Czechia.

qualifications, landed in low-wage manual or auxiliary positions.

Language barriers, identified as a key determinant for successful integration (Tip et al., 2019), posed a significant challenge for Ukrainians. Depending on the source, between 60%-87% self-reported as not able to speak English, and 69%-91% had no Czech skills (Ministry of Labour and Social Affairs, 2022; UNHCR, 2022). However, Czech skills among adults increased throughout the year, as reported in a follow-up study (Ministry of Labour and Social Affairs et al., 2023).

These challenges suggest that Ukrainian refugees often found themselves competing for roles traditionally filled by locals with a lower educational background. In particular, local women with low to medium education might compete with Ukrainian women, especially in sectors already dominated by them. At the same time, an increase in the available labour force could make household services more affordable, potentially motivating locals, especially those with household responsibilities and high market salary expectations, to re-enter the labour market (Cortés and Tessada, 2011; Farre et al., 2011; Cortés and Pan, 2013). The Czech labour market, with its low unemployment rates and more job vacancies than seekers, might have cushioned any potential disruptions from the refugee influx. The arrival of refugees could have even stimulated demand in certain sectors, influenced by the reported needs of the refugees. Accommodation and Food Service Activities, Administrative and Support Service Activities, Other Service Activities, Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles, Human Health and Social Work Activities, Education, and Transportation and Storage sectors might have experienced increased demand potentially linked to the requirements for essential services, such as healthcare and education for refugee families, and the need for basic goods and services, reflecting the broader socio-economic impact of the refugee influx on the Czech labour market.

3 Data and Descriptive Statistics

The primary source of individual micro-level data on the local labour force that we use is the Labour Force Sample Survey (LFSS),[11] compiled and published by the Czech Statistical Office (CZSO). Administered quarterly across all 77 Czech districts, the LFSS is a rotating panel dataset where the same individuals are surveyed for up to five sequential time periods. It is a nationally representative dataset that employs a stratified two-stage cluster sampling design and boasts a large sample size, providing us with detailed information on individuals' socio-demographic characteristics (e.g., age, education, marital status) and their labour market outcomes (e.g., employment status, employment history, industry and occupation, hours worked, and unemployment duration).

We utilise data from sixteen consecutive waves of the LFSS, spanning from the 1st quarter of 2019 to the 4th quarter of 2022, and limit our analysis to locals aged 15 years and older. This results in a sample of 682,757 observations across 77 districts, corresponding to 179,525 individuals.[12] 'Locals'

[11] The Czech Statistical Office allows access to confidential statistical data for scientific research, as detailed in Section 17 'Provision of confidential statistical data' of Act No. 89/1995 relating to the State Statistical Service (Czech Statistical Office, 2023d).

[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

include both Czech nationals and foreign nationals with Czech residency status of 15 years or older, excluding Ukrainian refugees. For definitions of terms such as 'locals', 'refugees', 'diaspora', as well as the description of the variables used, see Appendix A.

Table 3: 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 (2023), 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.

In addition to the primary dataset, we compile several indicators capturing both local and foreign employment levels, along with local demographic patterns. For statistics concerning Ukrainians residing and/or working in the Czech Republic, including both refugees and the Ukrainian diaspora present before 2022, we rely on aggregated district-level datasets provided by the Ministry of the Interior (2023) and the Ministry of Labour and Social Affairs (2023a). Both ministries maintain

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 quarter 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.

detailed records, updated monthly. Furthermore, we source demographic data on the working-age Czech population (18-65 years old) and local employment levels by district, based on the 2021 census, from the public database of the Czech Statistical Office (2024a). Descriptive statistics for key variables are reported in Table 3.

4 Identification Strategy

We explore the natural experiment of the sudden and forced influx of Ukrainian refugees, which noticeably expanded Czechia's workforce to assess the short-run impact on the locals' labour market outcomes. This expansion began in the 1^{st} quarter of 2022 and continues to the present day. Thus, with data available to us, we examine the short-term effects over one year following the onset of the labour market shock, covering the period up to and including the 4^{th} quarter of 2022.

We explore the pronounced variation in the influx of Ukrainians into the workforce across Czech districts for our identification strategy. Our analysis of labour market outcomes among locals considers both the extensive margin, examining statuses of employment, unemployment, or inactivity, and the intensive margin, focusing on the weekly hours worked. Further, we differentiate the estimated effects based on gender, educational attainment, and the country of origin of the Czech residents (foreign-born versus Czech-born).

Our identification strategy unfolds in several steps, starting with defining the 'treatment' variables in Section 4.1. We identify districts experiencing significant increases or decreases in Ukrainian employment levels due to the 2022 refugee influx and calculate the magnitude of these changes relative to the labour market sizes of the districts. Residents in these districts are considered treated, with varying intensities (doses) of treatment assigned to them. Subsequently, we implement a static two-way fixed effects (TWFE) regression in Section 4.2. In Section 4.3, we address the self-selection problem among refugees (also known as sorting gain), a common issue in migration research. We analyse how our study is affected by this and other concerns, such as selection bias, and outline steps taken to mitigate them. We further discuss the assumptions of the TWFE estimator in our context and whether they are satisfied.

Recognising the potential limitations of TWFE regression, such as the risk of not identifying the convex combination of individual treatment effects and the challenge of capturing the dynamic effects of treatment in our complex setting, we explore an alternative in Section 4.4. We utilise the estimators proposed by de Chaisemartin and d'Haultfoeuille (2024). This method, a variant of the extended Difference-in-Difference (DID), enables the estimation of treatment effects using non-binary, non-staggered treatments and allows dynamic/inter-temporal treatment effect analysis. It also avoids making 'forbidden comparisons' between treated and control individuals, thus overcoming some TWFE regression limitations. This section also discusses the assumptions the estimator relies on, testing strategies for these assumptions, and any further extensions implemented to the estimator, such as matching on relevant individual characteristics and on the pre-treatment trends of the dependent variables.

4.1 Defining the Treatment Variables

To analyse the impact of the refugee influx, we identify Czech districts, and the locals within, that experienced notable increases or decreases in Ukrainian employment levels throughout 2022, compared to the 'usual' levels observed among the Ukrainian diaspora, using 2021 as a baseline for 'usual' employment levels. We use 2021 as a baseline because Ukrainian employment levels had returned to pre-COVID-19 figures (Czech Statistical Office, 2023c), providing a stable comparison point. Treatment is assigned to locals at the district level, the most granular level at which the Labour Force Survey Sample (LFSS) reports individuals' residences and all districts are labeled as 'untreated' before 2022 due to the absence of Ukrainian refugees.

As foreign employment data in Czechia is reported by citizenship without detailing the type of stay permit, we can only infer that the employment surge from the first quarter of 2022 is mainly due to the newly arrived refugees rather than established members of the Ukrainian diaspora entering or re-entering employment. This assumption seems reasonable, given the high employment rate (99%) among the Ukrainian diaspora with residence permits as of 31 December 2021. To address the seasonal dip in foreign employment routinely 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 set two benchmarks for 'usual' Ukrainian employment levels: the average 2021 employment level of Ukrainians in Czechia by district (d), as in (1) below; and the actual number of the employment of Ukrainians in Czechia in the 4$^{\text{th}}$ quarter of 2021 by district (d), as in (2) below.

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

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

Since the impact of an influx of, say, 10,000 foreign employees may vary between districts depending on their labour market sizes, we normalise the treatment variable against each district's labour market size, employing two measures: the number of locals employed in 2021 by district (d), as in (3) below; and the number of working-age locals (18-65 years old) by district (d), as in (4) below.[13]

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

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

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

The employment variable in (3), sourced from the 2021 census (Czech Statistical Office, 2021), is anchored to the 2021 values, thus remaining static across time but varying by district. This approach prevents contamination of the treatment variable by subsequent realisations of our outcome variables in 2022, including employment status among locals, which could create a feedback loop. Local employment levels in Czechia for 2021 were consistent with historical norms.[14]

[13] To prevent double-counting, the number of officially employed Ukrainians for (3) and the number of Ukrainians of working age for (4) were subtracted from the total number of locals.

[14] Despite a dip in employment numbers in 2020—5,235 thousand, attributed to the COVID-19 pandemic—the 2021 figure

However, as the census data was gathered in the first half of the year, typically reflecting slightly lower employment levels due to seasonal variations, the inclusion of working-age locals (Czech Statistical Office, 2024b) as a second proxy, as in (4), ensures the robustness of our analysis. Unlike (3), the proxy in (4) varies both by quarter and across districts, ensuring it remains responsive to demographic and labour market size changes without being compromised by subsequent realisations of our outcome variables in 2022, unless significant migration of locals towards or away from impacted by the refugees districts occurs. This scenario was investigated in Section 6, with no evidence found to support it.

Therefore, we employ three variants of the treatment variables, detailed in (5), (6), and (7). Each variant aims to capture the same phenomenon: significant increases or decreases in Ukrainian employment levels during any of the four quarters of 2022 compared to the 'usual' employment levels of the Ukrainian diaspora, resulting from the refugee influx, all normalised by the labour market size of each district.

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

or

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

or

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

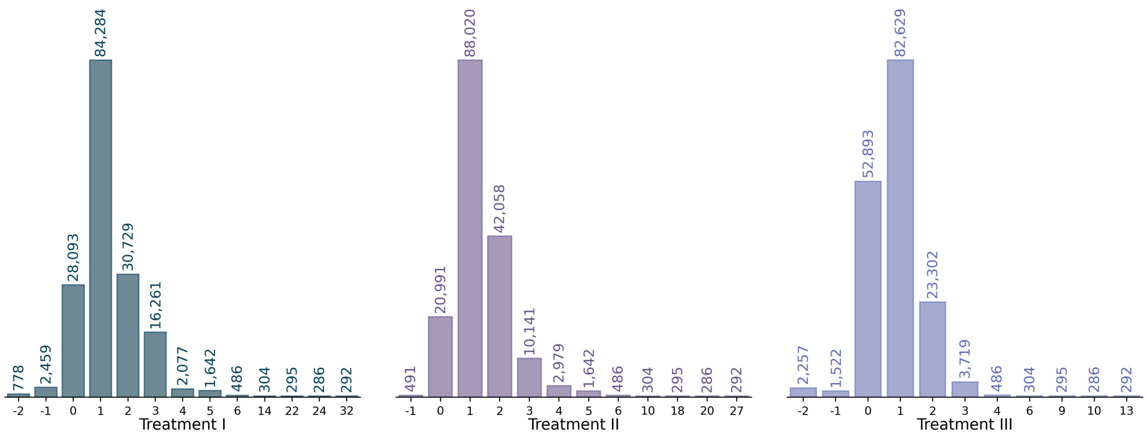
where d and t index districts and time, respectively. We round up the resulting values to the nearest integer, making them discrete, which results in the treatment 'doses' being assigned to individuals residing within each district at each point in time. Each 'dose' reflects a 1% change in Ukrainian 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.

A significant proportion of locals resided in districts that received a positive treatment dose, predominantly between 1% to 4% as documented in Figure 4. In addition, a subset of locals lived in

of 5,290 thousand aligns with pre-pandemic data from 2019 and 2018, which recorded 5,303 thousand and 5,293 thousand, respectively, indicating a labour market recovery (Czech Statistical Office, 2022, 2021).

districts that were unaffected by our treatment. There were also instances of negative treatment doses observed in only one to three districts, depending on the treatment variable specification. These negative doses are largely attributable to the departure of male Ukrainian immigrants.

Figure 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.

Dynamic Treatment Trajectories. The specification of the "treatment" variables results in a complex design where treatment can turn on and off, fluctuate across time periods and turn on at different time periods in different districts.

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’ level of zero. From 2022 onwards, districts exhibit varying treatment trajectories. Districts may experience treatment doses that are either zero, negative, positive, or both. For example, as depicted in Figure 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 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.

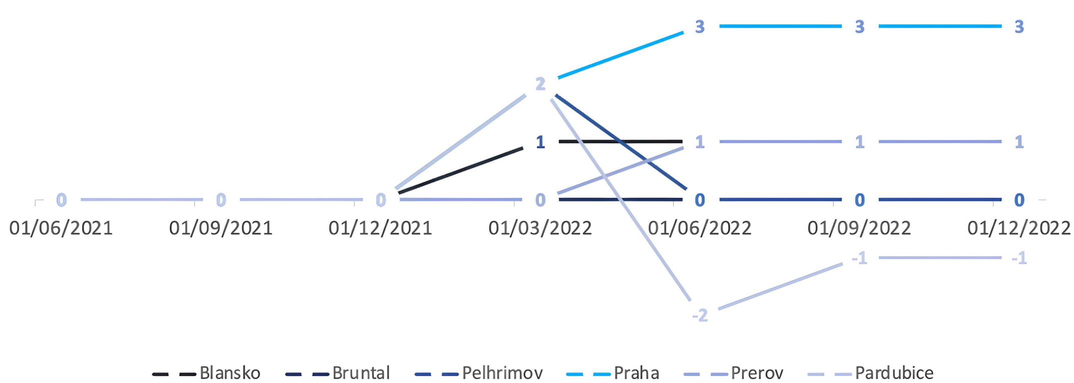
To introduce structure and assist in the identification for further analysis, we categorise districts d for each quarter t as either ’control’, ’switchers in’, or ’switchers out’. See Table 9 in Appendix B for treatment doses according to Treatment^I, Treatment^{II}, and Treatment^{III} by districts 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).

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 and vice versa. 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'.

Figure 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.

4.2 Static Two-Way Fixed Effects (TWFE)

We begin with using the following static two-way fixed effects model:

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

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 on the $\textbf{Treatment}^{I}$, $\textbf{Treatment}^{II}$ or $\textbf{Treatment}^{III}$ variables β, are of primary interest. We always estimate the effects for 'Switchers in' and 'Switchers out' groups separately for each of the treatment variables.The model accounts for individual f_i and time-fixed effects f_t, effectively minimising confounding risks by controlling for individual-specific (but time-invariant) and time-specific (but individual-invariant) unobserved confounders, assuming linear additive effects (Allison, 2009; Wooldridge, 2010).

Drawing on the richness of the LFSS data on locals, our analysis incorporates a range of individual-level characteristics ($\mathbf{X}$).[15] Appendix A provides detailed descriptions of the control variables and how they were calculated.

4.3 Assumptions, Limitations, and Biases of the TWFE Estimator

Refugees' Self-Selection Patterns. In the absence of a randomised experiment, migration research often encounters the self-selection problem (Borjas, 1987; Abowd and Freeman, 1991; Jaeger, 2007). Immigrants with a higher inherent probability of employment, due to specific skill sets or motivation to work, might choose districts with robust economies and a high demand for labour for settlement or job-seeking. On the lookout for such so-called 'sorting gains', Ukrainian refugees, who have the freedom to settle in any district within Czechia, could preferentially select economically thriving areas for settlement and employment, thereby contributing to the growth of foreign employment in these areas rendering then as treated according to our identification strategy. The concentration of established Ukrainian diasporas and refugee reception centres in these central areas may further accentuate the issue of non-random settlement and employment among refugees, potentially making direct comparisons of labour market outcomes of locals between districts with high to low changes in Ukrainian employment levels biased.

Table 4: 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 (2023), 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.

Evidence of these concerns is visible in our adjusted data, showing a significant concentration of refugees in a handful of economically vibrant regions, characterized by higher GDP per capita, wages, and educational attainment levels (Czech Statistical Office, 2023a). Furthermore, refugee

[15] $\mathbf{X}$ includes: age category (15-19, 20-25, ..., 60-65), gender, a dummy for being married, a dummy variable for having a child(ren) younger than 15 years old, a dummy indicating that the individual was born abroad outside of Czechia, thus grouping all foreigners together, both those who reside in Czechia and those who have already naturalized as Czech citizens, categorical variable indicating education level (ISCED), a dummy variable indicating if the person is on pension or has disability status, and a dummy variable for being part-time employed. Additionally, a categorical variable for the NACE-1 industries is used, but only for the weekly hours worked dependent variable.

distribution across districts positively correlates with the presence of active companies, large active companies, and labour market tightness, while inversely relating to unemployment rates (see Table 4). Strong correlation coefficients of 0.99 and 0.81 have also been observed between Ukrainians residing and working in Czechia in 2021 (diaspora) and Ukrainian refugees residing and employed in 2021 by district. This high correlation across districts suggests that those 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). Supporting this finding, a 2022 UNHCR survey indicates that 23% of respondents, the largest percentage of all, chose Czechia as their destination primarily due to the presence of family or friends (UNHCR, 2022). Additionally, refugees may have found employment more readily in these districts, even without personal diaspora connections, potentially due to historical demand for foreign labour.

However, normalisation of our treatment variable(s) by the labour market sizes of each district, mitigates these concerns to an extent. To demonstrate this, we first calculate the $\textbf{Average Treatment}_d^{I,II,\text{ or }III}$ to assign a singular value of treatment dose for each $\textbf{Treatment}_d^{I,II,\text{ or }III}$ for every district during the post-refugee influx shock period (2022). This provides a constant average treatment dose for each district, capturing the intensity level at which each district is treated in 2022. See Appendix E for details on the Average Treatment doses calculations. We then limit our data sample to the pre-refugee influx shock years (2019-2021) and regress $\textbf{Treatment}_d^{I,II,\text{ or }III}$ on the same individual-level characteristics $\mathbf{X}$ used in the TWFE regression (8), in addition to several additional covariates $\mathbf{Z}$—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 the general robustness of the local district economies and labour markets as well as the employed Ukrainian diaspora patterns:

$$\textbf{Average Treatment}_d^{I,II,\text{ or }III} = \alpha + \boldsymbol{\theta}'\mathbf{X}_{i,d,t} + \kappa'\mathbf{Z}_d + \epsilon_{i,d,t}, \tag{9}$$

where i, d, and t index individuals, districts, and time, respectively.

As reported in Table 5, the results reveal no systematic statistically significant association between the variables used to proxy the economic and labour market conditions ($\mathbf{Z}$) of each district for all three specifications of our treatment variables, both when these variables are the only ones the regression controls for (columns 4–6) and when the individual characteristics ($\mathbf{X}$) are also controlled for (columns 7–9). Results suggest that the local economic and labour conditions in 2019-2021 do not predict the intensity of the average treatment each district received in 2022. However, the same cannot be said for the individual characteristics ($\mathbf{X}$), where marital status, foreign origin, and part-time work show statistical significance. This indicates an imbalance regarding those individual characteristics across non-treatment and treated districts in the years preceding 2022. We further account for this in Section 4.4 by matching individuals based on their characteristics ($\mathbf{X}$) to circumvent this potential issue.

Parallel Trends Assumption. While the economic and labour market condition indicators presented in Table 5 provide some reassurance, we cannot definitively rule out the potential for inherent differences between individuals in treated districts and their control counterparts. For example, we observed that districts subject to more intensive treatment exhibited a higher prevalence of part-time employment, foreign-born residents, and married individuals. To address this, the TWFE regression controls for time-invariant and individual-specific selection biases, contingent upon the 'Parallel Trends Assumption'. According to this assumption, the outcomes for treated and control individuals would have followed a similar trajectory in the absence of treatment. Verifying this assumption using TWFE regression alone in our setting is challenging; however, we address and rigorously test it in Section 4.4.

Table 5: Correlation of Treatment Intensity with Local Socioeconomic and labour Market Factors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Individual-level covariates									
Female	-0.02*	-0.02*	-0.01				-0.01*	-0.01	-0.00
	(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.00)
Age	-0.00	-0.00	0.00				-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)				(0.00)	(0.00)	(0.00)
Married	-0.09***	-0.04**	-0.07***				-0.06***	-0.05***	-0.04***
	(0.03)	(0.02)	(0.02)				(0.02)	(0.01)	(0.01)
On pension or disabled	0.04	0.02	0.04				0.05*	0.03	0.04*
	(0.03)	(0.02)	(0.03)				(0.03)	(0.02)	(0.02)
Born abroad	0.59**	0.43**	0.35***				0.34***	0.29***	0.23***
	(0.24)	(0.21)	(0.11)				(0.13)	(0.10)	(0.08)
Part-time employed	0.23***	0.14***	0.17***				0.14**	0.11**	0.11***
	(0.05)	(0.05)	(0.04)				(0.05)	(0.05)	(0.04)
Child(ren) < 15y.o.	0.02	0.02	0.01				0.02	0.01	0.02
	(0.04)	(0.03)	(0.02)				(0.02)	(0.01)	(0.01)
Education level									
No education	-0.16	-0.09	-0.17				0.04	-0.03	-0.02
	(0.15)	(0.09)	(0.13)				(0.09)	(0.07)	(0.08)
Basic education	-0.18	-0.07	-0.20				-0.02	-0.06	-0.07
	(0.21)	(0.14)	(0.14)				(0.08)	(0.07)	(0.07)
Secondary without matriculation	-0.20	-0.07	-0.20				-0.06	-0.07	-0.08
	(0.18)	(0.11)	(0.13)				(0.06)	(0.06)	(0.06)
Secondary with matriculation	-0.09	-0.02	-0.11				-0.02	-0.03	-0.04
	(0.11)	(0.07)	(0.08)				(0.04)	(0.04)	(0.04)
District-level covariates									
No. of employed Ukrainians				-0.00	0.00	-0.00	-0.00	0.00	-0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. of employed locals				-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. active companies				-0.00	-0.00	0.00	-0.00	-0.00	0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. active large companies				0.03	0.02	0.01	0.03	0.02	0.01
				(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Labour market tightness				0.82	0.66	0.30	0.81	0.66	0.29
				(0.58)	(0.49)	(0.29)	(0.58)	(0.49)	(0.29)
Unemployment rate				29.20	16.34	9.30	28.94	16.15	9.17
				(31.14)	(24.92)	(15.80)	(31.03)	(24.84)	(15.74)
No. of observations	514,659	514,659	514,659	514,772	514,772	514,772	514,659	514,659	514,659
No. of districts	77	77	77	77	77	77	77	77	77

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 $\mathbf{X}$; columns (4–6) report the estimates of the regression with covariates added for the district-level characteristics $\mathbf{Z}$; and columns (7–9) report the estimates of the regression when both $\mathbf{X}$ and $\mathbf{Z}$ are controlled for. Robust standard errors clustered at the district level are in parentheses.

Parallel Trends Assumption. While the economic and labour market condition indicators presented in Table 5 provide some reassurance, we cannot definitively rule out the potential for inherent differences between individuals in treated districts and their control counterparts. For example, we observed that districts subject to more intensive treatment exhibited a higher prevalence of part-time employment, foreign-born residents, and married individuals. To address this, the TWFE regression controls for time-invariant and individual-specific selection biases, contingent upon the 'Parallel Trends Assumption'. According to this assumption, the outcomes for treated and control individuals would have followed a similar trajectory in the absence of treatment. Verifying this assumption using TWFE regression alone in our setting is challenging; however, we address and rigorously test it in Section 4.4.

No Anticipation Assumption. The 'No Anticipation' is another crucial assumption of our estimator. It posits that an individual's current outcomes are not influenced by future treatments. Identification problems arise when individuals can adjust their behaviour in anticipation of upcoming treatments (Abbring and van den Berg, 2003; Malani and Reif, 2015). For instance, local Czechs joining the labour force in advance of the refugee crisis to preempt foreign competition. However, given the unexpected influx of Ukrainian refugees, concerns regarding this assumption are minimal. While some individuals might have anticipated the conflict, it is unlikely that locals in Czechia would have significantly altered their labour market behaviours in response.

Self-selection Among the Locals. The third concern is the potential for locals to self-select into a treated or a control group, for example, by purposefully moving to a different district if they expect to benefit from such an action. This would constitute a sorting gain and could also bias our results. Yet, an analysis of local population movements in 2022 indicates no evidence of such strategic migration. See Section 6.

Heterogeneous Treatment Effects across Individuals and Time. The last limitation of the TWFE is its inflexibility under complex settings such as ours. The TWFE regression is often used in empirical research as it is seen as analogous to the difference-in-differences (DID) estimator. The canonical DID model, featuring two periods, a binary treatment variable, and distinct treatment and control groups, allows for the identification of the average treatment effect on the treated (ATT), provided it satisfies the key above-mentioned assumptions; and in this simple setting the ATT can indeed be consistently estimated using the static TWFE regression.

In our case, however, the design of our treatment variable(s) complicates the setting beyond the canonical DID model. Our treatment can turn on or off, fluctuate across time periods, and commence at different times in various districts. Therefore, to ensure our TWFE regression remains unbiased for the ATT in our setting, we must adhere to a stringent assumption: the treatment effect must be constant across individuals and over time. This assumption effectively excludes the possibility of heterogeneous treatment effects, which, as the currently rapidly expanding literature indicates, is improbable in empirical applications.[16] Utilising the test proposed by de Chaisemartin

[16]See for example, de Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021); Imai and Kim (2021); Sun and

and d'Haultfoeuille (2017), we evaluate the influence of negative weights on our treatment effects.[17] The results suggest a potential bias in our Average Treatment on the Treated (ATT) estimates due to negative weights, particularly in relation to weekly hours worked. See Appendix F for the results and explanations of the testing procedure.

4.4 Estimating Heterogeneous Treatment Effects with Extended Difference-in-Difference Estimators (DiD)

To address the limitations of the TWFE estimator, we adopt a heterogeneity-robust estimator proposed by de Chaisemartin and d'Haultfoeuille (2024) which allows for non-binary, non-staggered treatments and facilitates dynamic/inter-temporal treatment effect estimation, making it particularly apt for our context (see Appendix F for details of estimation). Unlike the TWFE regression, this estimator groups individuals in a way that avoids making 'forbidden comparisons,' i.e., comparisons between individuals who are both treated but start receiving treatment at different times. It estimates the actual-versus-status-quo (AVSQ) effect for each treated individual, a variant of ATT.

The initial step involves deducing individual effects for each treated individual over all possible periods. This process involves comparing the evolution of labour market outcomes between treated individuals and a control group, before and after treatment, adjusting for individuals' baseline treatment levels and labour market outcomes. Subsequently, we aggregate these individual effects to derive average effects for all treated individuals, considering variations in treatment intensity. This aggregation is weighted by the number of individuals contributing to each period-specific estimate, ensuring an accurate representation of average effects across the study population. Consequently, to facilitate interpretation and comparison with traditional TWFE regression results, we normalise the aggregated effects.[18] To do it, we divide the estimated average effects by the difference between the actual treatment dose received and the baseline treatment level (zero in our context), yielding a normalised AVSQ (nAVSQ) effect, interpreted as the average total effect per unit of treatment.

Finally, to mitigate potential complications arising from the normalization of effects, we categorise treated districts based on their treatment dose (for **Average Treatment**$_d^{I,II,\text{ or } III}$ as specified in 9), and calculate the AVSQ effect separately for each **Average Treatment Dose** — 1%, 2%, 3%, $\geq$ 4% — without normalization.

A crucial assumption for unbiasedness is the trends for the status-quo outcome, conditional on the baseline treatment, are parallel. We test this assumption using placebo estimators proposed by de Chaisemartin and d'Haultfoeuille (2024). These mimic the actual estimators and compare the outcome evolutions of individuals i before their treatment changes for the first time with the outcome evolution of their respective "control" individuals from the period. This test provides an alternative to visually inspecting the pre-treatment outcomes.

However, the rotating nature of the panel limits us in how many pre-treatment quarters can be

Abraham (2021); de Chaisemartin and d'Haultfoeuille (2022); Borusyak et al. (2024), among others.

[17] Implemented with the Stata command "twowayfeweights". For details, see de Chaisemartin et al. (2023a).

[18] All is implemented with the Stata command "did_multiplegt_dyn". For details, see de Chaisemartin et al. (2023b).

considered to test the parallel trend assumption. Overall, even if the placebos do not clearly indicate a violation of the parallel-trends assumption, they may fail to detect violations of parallel trends large enough to substantially bias the DIDl estimates (Roth, 2022). To minimise the chance of this bias, we extend our baseline model by: (i) allowing for distinct trends across individuals through exact matching on selected individual characteristics, (ii) allowing for distinct trends across Districts through matching on pre-2022 trends of each variable of interest, and (iii) allowing for both distinct trends across individuals and districts.

Allowing for Distinct Trends Across Individuals. Our first extension to the Difference-in-Differences (DiD) estimator involves comparing outcomes between treated and untreated individuals who share selected characteristics, employing the same range of individual-level characteristics ($\mathbf{X}$)[19] as in the TWFE (8) regression. This is akin to exact matching. With this extension, we relax the parallel trends assumption, requiring it to hold within each subset of matched individuals based on shared characteristics rather than universally across all populations. This means we expect the evolution of outcomes—such as weekly hours worked or employment probability—to follow similar trajectories for both treated and untreated individuals when they are matched by age group, gender, marital status, parental status, education level, employment status, foreign status, and industry of employment.

We employ exact matching that pairs individuals with identical observed characteristics due to its stringent control over confounding variables and the substantial size of our sample. This method ensures a like-for-like comparison between treated and control groups, thereby enhancing the credibility of our causal inferences.

Allowing for Distinct Trends Across Districts. Allowing for distinct trends across individuals enhance the reliability of our findings. However, despite matching individuals from treatment and control districts based on characteristics, differences in socio-economic conditions could still influence the variables of interest. For instance, identical demographic groups in different districts might show divergent employment trends due to varying strengths of the local labour markets, potentially leading to biased estimates. To address this, we estimate the seasonally adjusted trend for each of the 77 districts within the Czech Republic separately. We utilise the LFSS data from the first quarter of 2019 to the fourth quarter of 2021, covering the pre-treatment period. This method involves calculating the slope of the variables of interest over time for each district, thus accounting for district-specific temporal trends and controlling for seasonal effects. The slopes are determined by regressing the time variable and season dummies against the variables of interest, with the coefficient value for the time variable serving as our approximation of the slope. Given the continuous nature of this variable, we convert it into a categorical variable through a 'scaled discretisation' process.

[19]$\mathbf{X}$ includes: age category (15-19, 20-25, . . . , 60-65), gender, a dummy for being married, a dummy variable for having a child(ren) younger than 15 years old, a dummy indicating that the individual was born abroad outside of Czechia, thus grouping all foreigners together, both those who reside in Czechia and those who have already naturalized as Czech citizens, categorical variable indicating education level (ISCED), a dummy variable indicating if the person is on pension or has disability status, and a dummy variable for being part-time employed. Additionally, categorical variable for the NACE-1 industries is used, but only for the weekly hours worked dependent variable.

This involves multiplying the continuous variable by a selected factor and rounding the result to the nearest integer to form a categorical variable. We then match control and treated districts that demonstrated a similar trend for the variables of interest before 2022 using the newly created categorical variable.

Choosing a 'scaled discretisation' approach over decimal grouping preserves the inherent variability of our data, enhances the precision of our categorisation, and improves compatibility with the matching algorithms used in further analyses. By multiplying the continuous variable by a factor and rounding to the nearest integer, we maintain more detailed information within each category. This granularity aids in more accurate matching between treated and control groups, allowing for finer distinctions between different levels of the variable. Additionally, this method prevents the arbitrary cutoffs associated with decimal grouping, ensuring that the discretised categories more closely mirror the original data distribution.

Moreover, recognizing that aggregate trends might mask subgroup-specific dynamics, we also calculate the pre-2022 trends separately for each subgroup within the districts, defined by (i) gender, education level, and (ii) gender, industry of employment according to NACE level 1. This ensures our analysis accounts for socio-economic factors that might affect specific groups differently.

This extension ensures comparisons are made only between comparable groups, minimizing potential bias. A more detailed account of the trend calculation and categorization process is available in Appendix G.

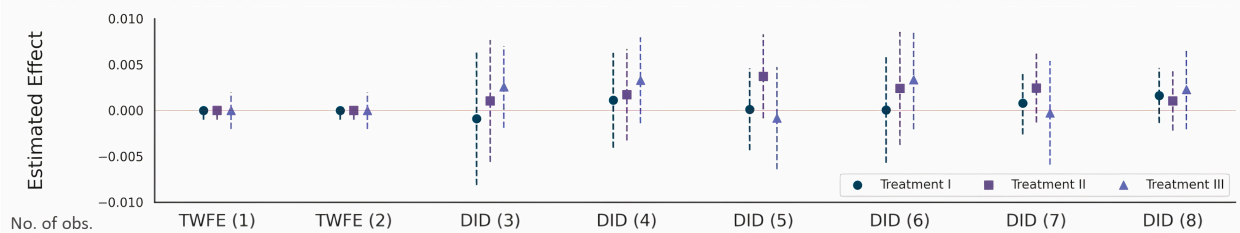
Allowing for Distinct Trends Across Individuals and Districts. Finally, we incorporate the mix of the two extensions in our DID estimation. We estimate the treatment effects while matching on both the individual characteristics ($\mathbf{X}$) as well as the generated pre-2022 trends for each variable of interest. Thus, we allow for distinct trends across individuals and districts.

5 Results

Throughout the results section, we report results from all the models outlined in Section 4. 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.

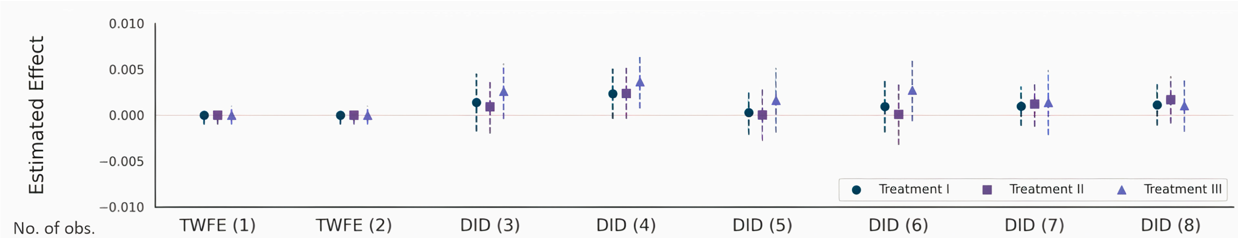
Each figure reports the average treatment effects on the treated (ATTs), as estimated by the TWFE model in Section 4.2 (columns 1-2), alongside normalised actual-versus-status-quo (nAVSQ) effects, calculated by the extended DiD model in Section 4.4 (columns 3-10*), for Treatment^I,

Figure 6: Positive Treatment Doses—Probability of Inactivity by Gender



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	361,537	340,550	67,535	61,412	50,880	52,113	41,137	28,990
Treatment II	362,748	341,511	67,825	62,953	47,995	51,135	40,418	29,502
Treatment III	360,670	339,899	66,813	63,271	56,247	58,819	47,189	34,563

(a) Females



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	317,510	299,812	58,882	53,554	44,446	43,498	35,588	24,331
Treatment II	318,556	300,635	59,103	54,681	41,721	45,213	34,860	23,459
Treatment III	316,741	299,209	58,106	55,098	48,862	50,523	40,659	28,800

(b) Males

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, confidence intervals and observation counts for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) pre-treatment trends of the dependent variable. Models DID(7 and 8) match on both the ($\mathbf{X}$) individual characteristics and pre-treatment trends as in DID(5 and 6), respectively. Robust standard errors are clustered at the district level. For columns (3-8), the p-values were calculated using the standard normal distribution.

Treatment^{II} and Treatment^{III}, noting that the full set of results are presented in Appendix B.[20] Since the number of districts experiencing negative treatment doses is very small, we focus on districts experiencing positive treatment doses only in our discussion.[21]

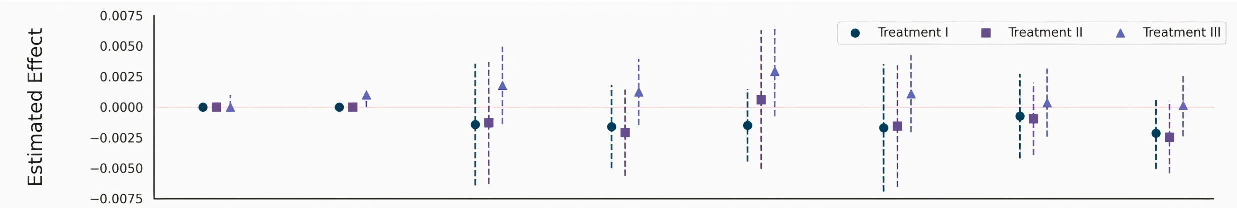
Probability of Unemployment & Inactivity. We start our analysis by looking at how the sudden and large influx of workers affected unemployment and inactivity among local workers. Results are presented in Figures 7 and 6 and show no significant correlation between treatment doses and unemployment or inactivity 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

[20] Assuming the underlying assumptions for each estimator are met, the reported coefficients can be interpreted as an average total effect per unit of treatment—a.k.a, the short-term effects of 1% increase in officially employed Ukrainians relative to the local labour market size on labour market outcomes of Czech locals.

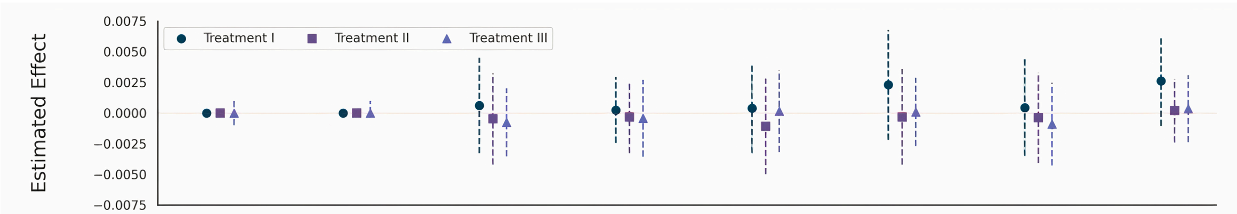
[21] Negative treatment doses were observed in one to three districts—Pardubice, Praha-východ, and Praha-západ—depending on the treatment variable specification. These doses are largely attributable to the departure of male Ukrainian immigrants. Results concerning these districts are available upon request.

Figure 7: Positive Treatment Doses—Probability of Unemployment by Gender



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	361,537	340,550	67,535	61,412	55,244	65,035	44,129	48,945
Treatment II	362,748	341,511	67,825	62,953	58,282	64,580	48,164	50,940
Treatment III	360,670	339,899	66,813	63,271	62,730	65,265	55,237	54,360

(a) Females



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	317,510	299,812	58,882	53,554	48,170	57,470	38,260	40,635
Treatment II	318,556	300,635	59,103	54,681	50,740	58,017	41,033	40,547
Treatment III	316,741	299,209	58,106	55,098	54,532	57,008	47,707	47,713

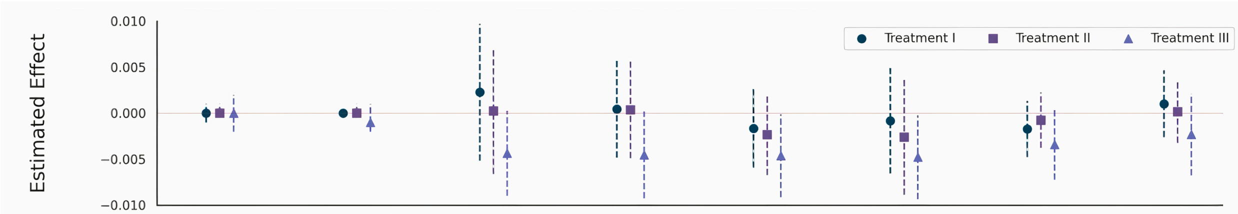
(b) Males

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, confidence intervals and observation counts for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) pre-treatment trends of the dependent variable. Models DID(7 and 8) match on both the ($\mathbf{X}$) individual characteristics and pre-treatment trends as in DID(5 and 6), respectively. Robust standard errors are clustered at the district level. For columns (3-8), the p-values were calculated using the standard normal distribution.

control groups were following a similar trend before the intervention, which is critical for the DiD method's validity. The p-value from these tests measures the likelihood that any observed pre-treatment differences between the groups occurred by chance. Parallel trends 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 11 and 12. 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.

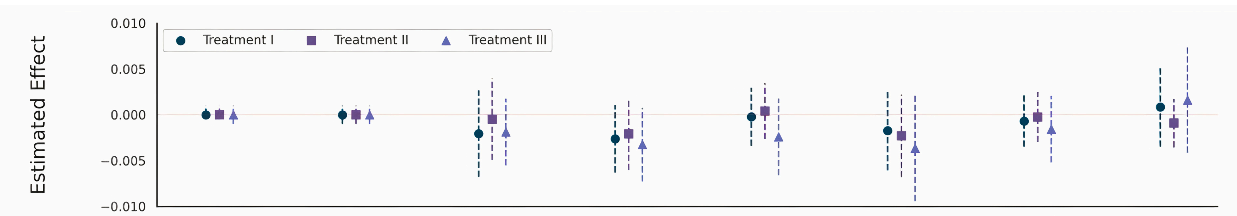
Moreover, by including all three variations of the treatment variable, we significantly enhance the robustness of our findings. Treatments I and II typically show minimal differences in estimated effects, instilling confidence in the method employed to quantify Ukrainian employment within Czechia. Treatment 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

Figure 8: Positive Treatment Doses—Probability of Employment by Gender



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	361,537	340,550	67,535	61,412	47,424	51,728	39,194	28,328
Treatment II	362,748	341,511	67,825	62,953	51,086	53,489	41,073	27,473
Treatment III	360,670	339,899	66,813	63,271	53,561	57,927	45,632	33,785

(a) Females



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (7)	DID (8)
Treatment I	317,510	299,812	58,882	53,554	41,486	46,309	33,899	24,396
Treatment II	318,556	300,635	59,103	54,681	44,539	47,095	35,260	24,038
Treatment III	316,741	299,209	58,106	55,098	46,676	52,386	39,395	28,828

(b) Males

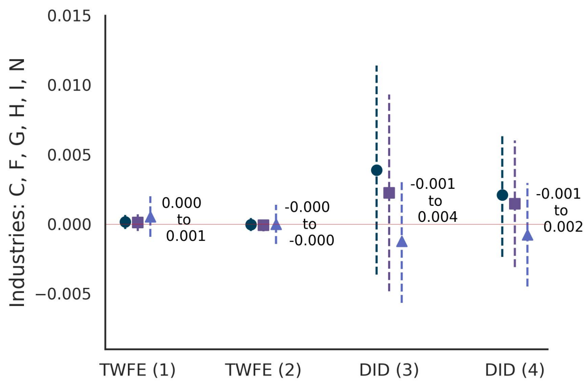
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, confidence intervals and observation counts for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) pre-treatment trends of the dependent variable. Models DID(7 and 8) match on both the ($\mathbf{X}$) individual characteristics and pre-treatment trends as in DID(5 and 6), respectively. Robust standard errors are clustered at the district level. For columns (3-8), the p-values were calculated using the standard normal distribution.

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 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.

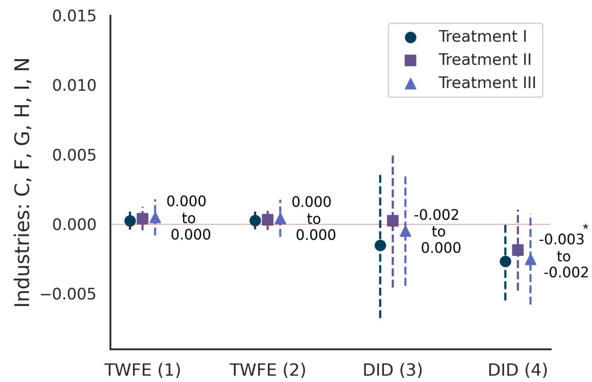
Further examination by education level (shown in Figures 14 and 15 in Appendix B), found no significant effects, indicating that a 1% rise in officially employed Ukrainians does not affect the unemployment or inactivity rates of Czech men and women.

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 (Figure 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 11 and 12. This supports our Difference-in-Differences (DiD) assumptions and validates our methodology. Further analysis by education level (reported in Figure 13 in Appendix B), 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.

Figure 9: Positive Treatment Doses—Probability of Employment by Gender & Most Affected Industries



(a) Treatment I: Female



(b) Treatment I: Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. The sample is limited to locals employed in industries such as Manufacturing (C), Construction (F), Wholesale and Retail Trade (G), Transportation and Storage (H), Accommodation and Food Service Activities (I), and Administrative and Support Service Activities (N), or those not employed. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

When examining sectors most impacted by the refugee influx,[22] the trend among females remains consistent with previous results. However, for local male workers, the DiD(4) estimator indicated a potential decrease in employment probability. A sector-specific analysis revealed that this effect is entirely due to a small (-0.003), but significant, decrease in employment probability in the manufacturing sector, noting that the sample size is small.[23] Notably, one-third of all male and some female refugees have secured employment in this sector suggesting that, at least in the short-run, workers in most affected sectors may have faced a direct competition from Ukrainian refugees.

Weekly Hours Worked. Our results along the extensive margin show no effect of Ukrainian refugees on local workers. Next, we turn to the intensive margin and consider weekly working hours. Figure 10 summarizes the results and shows a statistically significant positive correlation between the treatment doses and the weekly hours worked by both Czech women and men, implying that a

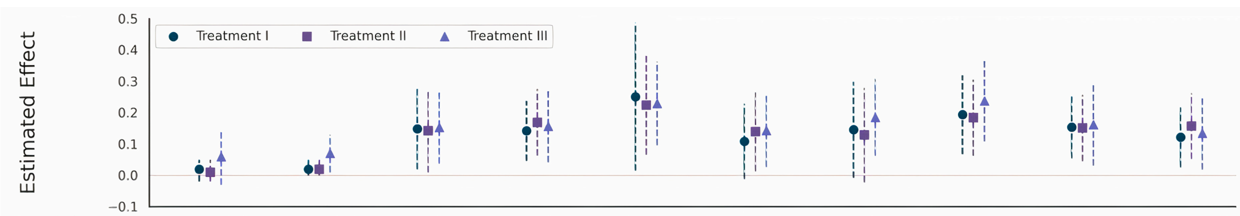
[22]The sectors with the highest refugee employment are: N-Administrative and Support Service Activities (30%), C-Manufacturing (29%), H-Transportation and Storage (7%), I-Accommodation and Food Service Activities (7%), G-Wholesale and Retail Trade (6%), and F-Construction (6%).

[23]Detailed results are available upon request.

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.

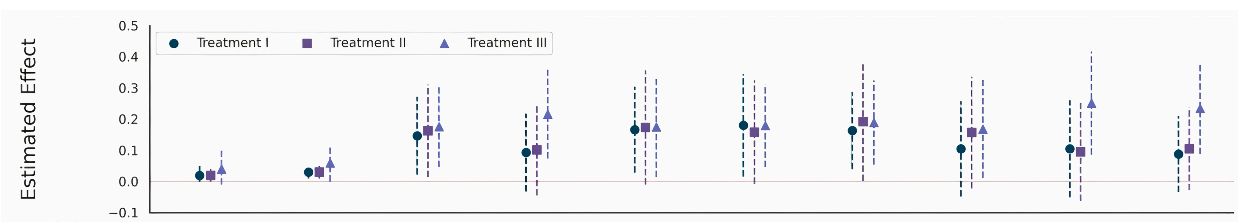
While for females, the coefficients are significant across all models, reinforcing the reliability of the observed treatment effects, for male workers, the significance in DiD models diminishes after controlling for individual characteristics, district-specific factors, and pre-treatment trends specific 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 moth matching on individual characteristics as well as 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 10.

Figure 10: Positive Treatment Doses—Weekly Hours Worked by Gender



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (9*)	DID (7)	DID (8)	DID (10*)
Treatment I	163,795	157,128	29,347	16,012	26,650	27,253	29,081	10,150	10,322	14,797
Treatment II	164,379	157,601	29,512	16,370	26,273	27,023	29,293	10,488	10,376	15,172
Treatment III	163,339	156,777	29,087	18,286	27,625	28,629	29,056	12,462	12,376	16,800

(a) Females



No. of obs.	TWFE (1)	TWFE (2)	DID (3)	DID (4)	DID (5)	DID (6)	DID (9*)	DID (7)	DID (8)	DID (10*)
Treatment I	187,358	179,956	33,838	19,427	30,705	31,901	33,626	12,485	12,847	17,973
Treatment II	187,983	180,459	33,990	19,883	30,159	31,809	33,855	12,740	13,087	18,504
Treatment III	186,894	179,590	33,438	22,472	31,843	32,923	33,347	15,490	15,782	20,891

(b) Males

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, confidence intervals and observation counts for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-10*) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)), or district- and industry-specific (DID(9* pre-treatment trends of the dependent variable. Models DID(7, 8, and 10*) match on both the (**X**) individual characteristics and pre-treatment trends as in DID(5, 6, 9*), respectively. Robust standard errors are clustered at the district level. For columns (3-10*), the p-values were calculated using the standard normal distribution.

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 hours worked the previous year. This is equivalent to an additional 0.03 to 0.06 hours (or approximately 1.8 to 3.6 minutes) 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 hours in 2021, which translates to an additional 0.02 to 0.07 hours (or roughly 1.2 to 4.2 minutes) weekly.

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 hours (or 5.4 to 13.2 minutes). 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 minutes) 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.[24]

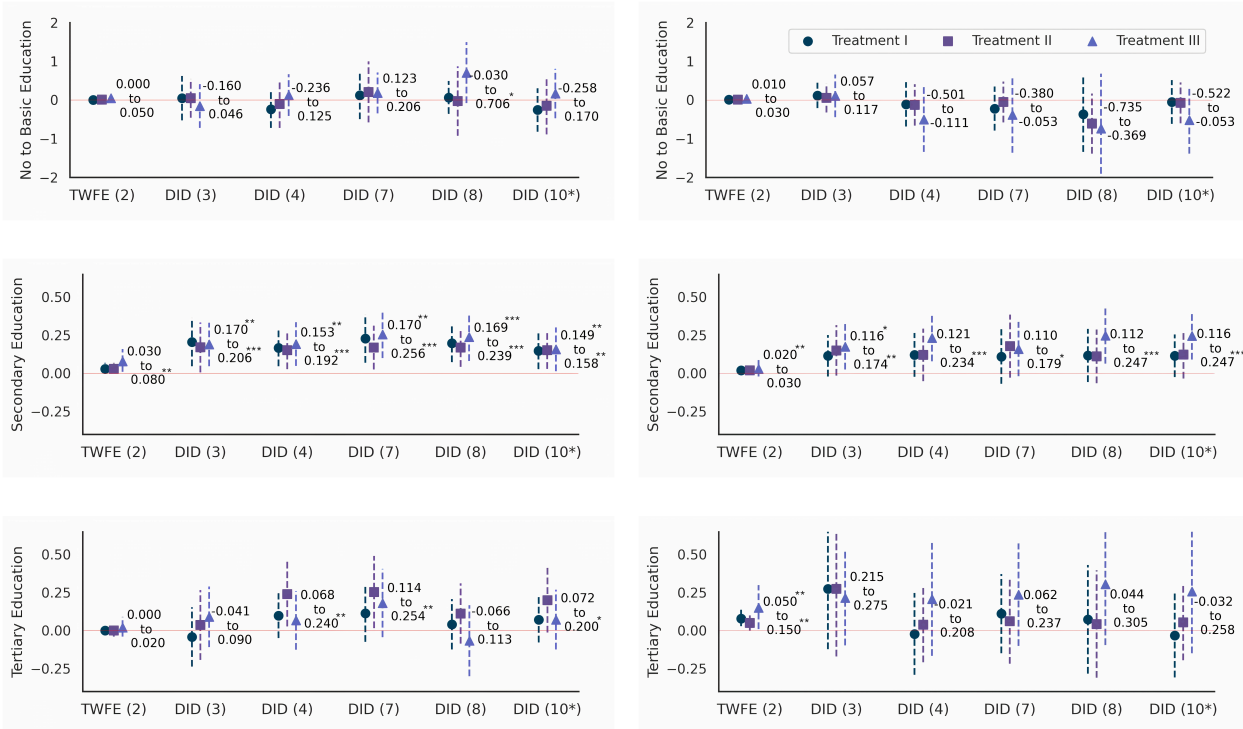
Individually, these increases amount to a relatively modest change in weekly working hours. The larger effects observed in the DiD model, compared to the TWFE, can be attributed to the DiD model's ability to capture dynamic treatment effects over time. In aggregate terms, though, even small percentage increases in average weekly hours worked can accumulate to a substantial impact across the workforce. These 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 Figure 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 hours (1.8 to 4.8 minutes weekly) for TWFE(2), to 0.15 to 0.19 hours (9 to 11.4 minutes per week) for DiD(4). With the DiD(7, 8, 10*) extensions, these figures grow further to 0.15 to 0.26 hours, or 9 to 15.6 minutes 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

[24] 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.

Figure 11: Positive Treatment Doses—Weekly Hours Worked by Gender & Education Level



(a) Female

(b) Male

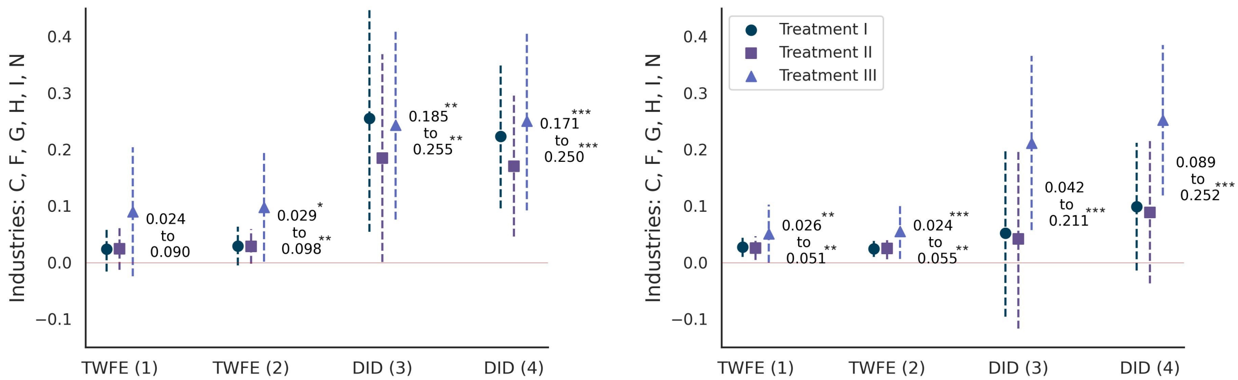
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-10*) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on both the ($\mathbf{X}$) 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 (3-10*), the p-values were calculated using the standard normal distribution.

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 12, 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.

Foreign-Born Individuals in Czechia. So far, we have focused on the effects on all local workers in the Czech Republic. However, our analysis reveals (in line with the literature) that the influx

Figure 12: Positive Treatment Doses—Weekly Hours Worked by Gender & Most Affected Industries



(a) Treatment I: Female

(b) Treatment I: Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. The sample is limited to locals employed in industries such as Manufacturing (C), Construction (F), Wholesale and Retail Trade (G), Transportation and Storage (H), Accommodation and Food Service Activities (I), and Administrative and Support Service Activities (N), or those not employed. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

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 summarized in Figure 16, 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.[25]

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 Check

To ensure robustness of our results and address potential issues from effect normalisation, we categorised treated districts based on their **Average Treatment**$_d^{I,II,\text{ or } III}$ doses. We then calculated the AVSQ effect for each **Average Treatment Dose** — 1%, 2%, 3%, $\geq 4\%$ — without normalization.

Additionally, as the treatment period progressed from the 1[st] to the 4[th] quarter of 2022, fewer districts remained as controls. This reduction might have hindered our ability to identify significant

[25]We find no significant results for weekly hours worked.

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 18—25 in Appendix B, 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.

We also acknowledge that the the identified effects of the treatment on labour market outcomes for locals might have been distorted by secondary effects, primarily due to the potential movement of locals away from the most affected districts. To adress this point, we regress the 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 of the coefficients are positive andnot statistically significant suggesting that the districts have been experiencing stable net migration similar to that in the 2021-2022 period in the previous years as well. Therefore, we see no conclusive patterns of abnormal population movement in or out of the treated districts.

Table 6: Local Population Movements Analysis

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: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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, 2023b).

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.

References

Abbring, J. H. and van den Berg, G. J. (2003). The nonparametric identification of treatment effects in duration models. *Econometrica*, 71(5):1491–1517.

Abowd, J. M. and Freeman, R. B. (1991). *Immigration, Trade, and the Labor Market*. University of Chicago Press.

Allison, P. D. (2009). *Fixed Effects Regression Models*. Quantitative Applications in the Social Sciences. SAGE Publications, Inc.

Angrist, J. D. and Kugler, A. D. (2003). Protective or counter-productive? Labour market institutions and the effect of immigration on eu natives. *The Economic Journal*, 113(488):F302–F331.

Aydemir, A. and Kırdar, M. G. (2017). Quasi-experimental impact estimates of immigrant labor supply shocks: The role of treatment and comparison group matching and relative skill composition. *European Economic Review*, 98(C):282–315.

Aydemir, A. and Skuterud, M. (2005). Explaining the deteriorating entry earnings of Canada's immigrant cohorts, 1966 - 2000. *The Canadian Journal of Economics / Revue canadienne d'Economique*, 38(2):641–671.

Belot, M. V. K. and Hatton, T. J. (2012). Immigrant selection in the OECD. *The Scandinavian Journal of Economics*, 114(4):1105–1128.

Bevelander, P. and Nielsen, H. S. (2001). Declining employment success of immigrant males in Sweden: Observed or unobserved characteristics? *Journal of Population Economics*, 14(3):455–471.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *The American Economic Review*, 77(4):531–553.

Borjas, G. J. (1994). The economics of immigration. *Journal of Economic Literature*, 32(4):1667–1717.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics*, 118(4):1335–1374.

Borjas, G. J., Freeman, R. B., and Katz, L. F. (1996). Searching for the effect of immigration on the labor market. *American Economic Review*, 86:246–251.

Borjas, G. J. and Friedberg, R. M. (2009). Recent Trends in the Earnings of New Immigrants to the United States. NBER Working Papers 15406, National Bureau of Economic Research, Inc.

Borjas, G. J. and Katz, L. F. (2007). *The Evolution of the Mexican-Born Workforce in the United States*, pages 13–55. University of Chicago Press.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, page rdae007.

Card, D. (1990). The impact of the mariel boatlift on the Miami labor market. *Industrial and Labor Relations Review*, 43(2):245–257.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D. (2009). Immigration and inequality. *American Economic Review*, 99(2):1–21.

Carrington, W. J. and de Lima, P. J. F. (1996). The impact of 1970s repatriates from Africa on the Portuguese labor market. *Industrial and Labor Relations Review*, 49(2):330–347.

Ceritoğlu, E., Gürcihan Yüncüler, B., Torun, H., and Tumen, S. (2017). The impact of Syrian refugees on natives' labor market outcomes in turkey: evidence from a quasi-experimental design. *IZA Journal of Labor Policy*, 6(1):1–28.

Chiswick, B. R. and Miller, P. W. (2008). Why is the payoff to schooling smaller for immigrants? *Labour Economics*, 15(6):1317–1340.

Chiswick, B. R. and Miller, P. W. (2010). *Educational Mismatch: Are High-Skilled Immigrants Really Working at High-Skilled Jobs and the Price They Pay If They Aren't?*, pages 111–154. Number 4280 in IZA Discussion Paper No. 4280. American Enterprise Institute Press, Washington D.C.

Cohen-Goldner, S. and Paserman, M. D. (2011). The dynamic impact of immigration on natives' labor market outcomes: Evidence from Israel. *European Economic Review*, 55(8):1027–1045.

Cortés, P. and Pan, J. (2013). Outsourcing household production: Foreign domestic workers and native labor supply in Hong Kong. *Journal of Labor Economics*, 31(2):327–371.

Cortés, P. and Tessada, J. (2011). Low-skilled immigration and the labor supply of highly skilled women. *American Economic Journal: Applied Economics*, 3(3):88–123.

Czech Statistical Office (2021). Results of census 2021. https://www.scitani.cz/results. Accessed: 2023-09-05.

Czech Statistical Office (2022). Labor market in the czech republic - time series - 1993–2021. https://www.czso.cz/csu/czso/trh-prace-v-cr-casove-rady-1993-2021. Published on: 01/08/2022; Accessed: 2023-09-05.

Czech Statistical Office (2023a). Czech statistical office database of national accounts. https://apl.czso.cz/pll/rocenka/rocenka.indexnu_en. Accessed: 2023-07-05.

Czech Statistical Office (2023b). Population status and movement in the Czech Republic / stav a pohyb obyvatelstva v Čr. https://www.czso.cz/csu/czso/stav-a-pohyb-obyvatelstva-v-cr. Accessed: 2024-03-10.

Czech Statistical Office (2023c). Preliminary data published by the directorate of foreign police service. https://www.czso.cz/csu/cizinci/predbezne-udaje-zverejnovane-rs-cp. Accessed: 2023-10-03.

Czech Statistical Office (2023d). Provision of confidential statistical data for scientific research purposes - principles and conditions. https://www.czso.cz/csu/czso/provision_of_microdata_for_scientific_research_purposes_principles_and_conditions. Accessed: 2023-07-05.

Czech Statistical Office (2023e). Public database: Employment, unemployment. https://vdb.czso.cz/vdbvo2/faces/en/index.jsf?page=statistiky#katalog=30853. Accessed: 2023-12-06.

Czech Statistical Office (2024a). Public database. https://vdb.czso.cz/vdbvo2/faces/en/index.jsf. Accessed: 2024-03-05.

Czech Statistical Office (2024b). Public database: Population. https://www.czso.cz/csu/czso/population. Accessed: 2024-03-05.

de Chaisemartin, C. and d'Haultfoeuille, X. (2017). Fuzzy Differences-in-Differences. *The Review of Economic Studies*, 85(2):999–1028.

de Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

de Chaisemartin, C. and d'Haultfoeuille, X. (2022). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey. *The Econometrics Journal*, 26(3):C1–C30.

de Chaisemartin, C. and d'Haultfoeuille, X. (2024). Difference-in-Differences Estimators of Intertemporal Treatment Effects. *The Review of Economics and Statistics*, pages 1–45.

de Chaisemartin, C., D'Haultfoeuille, X., and Deeb, A. (2023a). Twowayfeweights: Stata module to estimate the weights and measure of robustness to treatment effect heterogeneity attached to two-way fixed effects regressions.

de Chaisemartin, C., D'Haultfoeuille, X., Malézieux, M., and Sow, D. (2023b). DID_MULTIPLEGT_DYN: Stata module to estimate event-study Difference-in-Difference (DID) estimators in designs with multiple groups and periods, with a potentially non-binary treatment that may increas. Statistical Software Components, Boston College Department of Economics.

DGP (2023). Poles less willing to help Ukraine [latest poll] / olacy mniej chętni, by pomagać ukrainie [najnowszy sondaż]. *Dziennik Gazeta Prawna*. Author: Paweł Sikora; Accessed: 2024-03-05.

Dustmann, C., Fabbri, F., and Preston, I. (2005). The Impact of Immigration on the British Labour Market. *The Economic Journal*, 115(507):F324–F341.

ECRE (2023). Access to the Labour Market: Germany. https://asylumineurope.org/reports/country/germany/reception-conditions/employment-and-education/access-labour-market. Asylum Information Database; Accessed: 2023-04-06.

ECRE (2024). Mapping asylum procedures, reception conditions, detention and content of protection in Europe. https://asylumineurope.org. Accessed: 2024-01-10.

EURES (2023). Labour market information: Czechia. https://eures.ec.europa.eu/living-and-working/labour-market-information/labour-market-information-czechia_en. Accessed: 2023-09-05.

European Commission (2022). Czech republic: "Lex Ukraine" law package enters into force. https://migrant-integration.ec.europa.eu/library-document/czech-republic-lex-ukraine-law-package-enters-force_en. Accessed: 2023-04-05.

European Commission (2023a). Eu challenges and priorities in 2023. https://europa.eu/eurobarometer/surveys/detail/3092. Fieldwork: August 2023; Accessed: 2023-12-27.

European Commission (2023b). Standard eurobarometer 99 - spring 2023. https://europa.eu/eurobarometer/surveys/detail/3052. Fieldwork: May 2023 - June 2023; Accessed: 2023-11-27.

Eurostat (2023). Unemployment statistics. https://ec.europa.eu/eurostat/statistics-explained. Accessed on 02.10.2023.

Farre, L., Gonzalez, L., and Ortega, F. (2011). Immigration, family responsibilities and the labor supply of skilled native women. *The B.E. Journal of Economic Analysis & Policy*, 11(1):1–48.

Forsal (2023). Our attitude towards helping Ukrainians is changing: Surprising results [survey] / zmienia się nasze nastawienie do pomocy dla ukraińców. zaskakujące wyniki [sondaŻ]. *Forsal.pl*. Author: Krzysztof Maciejewski; English translation; Accessed: 2023-11-27.

Friedberg, R. (2001). The impact of mass migration on the Israeli labor market. *The Quarterly Journal of Economics*, 116(4):1373–1408.

Friedberg, R. M. (2000). You can't take it with you? Immigrant assimilation and the portability of human capital. *Journal of Labor Economics*, 18(2):221–251.

Friedberg, R. M. and Hunt, J. (1995). The impact of immigrants on host country wages, employment and growth. *Journal of Economic Perspectives*, 9(2):23–44.

Glitz, A. (2012). The labor market impact of immigration: A quasi-experiment exploiting immigrant location rules in Germany. *Journal of Labor Economics*, 30(1):175–213.

GLOBSEC (2023). Ukrainian refugees in Visegrad countries: Societal attitudes and challenges of accommodating people fleeing the war. https://www.globsec.org/what-we-do/publications/ukrainian-refugees-visegrad-countries-societal-attitudes-and-challenges.

GMF (2023). Transatlantic trends 2023. https://www.gmfus.org/news/transatlantic-trends-2023. Accessed: 2023-11-27.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277. Themed Issue: Treatment Effect 1.

Hatton, T. and Williamson, J. G. (1998). *The Age of Mass Migration: Causes and Economic Impact*. Oxford University Press.

Hunt, J. (1992). The impact of the 1962 repatriates from Algeria on the French labor market. *Industrial and Labor Relations Review*, 45(3):556–572.

Imai, K. and Kim, I. S. (2021). On the use of two-way fixed effects regression models for causal inference with panel data. *Political Analysis*, 29(3):405–415.

IOM (2023a). Dtm Czechia — Displacement surveys with refugees from Ukraine and TCNs, annual report (15 jun–31 dec 2022). https://dtm.iom.int/reports/czechia-displacement-surveys-refugees-ukraine-and-tcns-annual-report-15-jun-31-dec-2022. Accessed: 2024-01-05.

IOM (2023b). Ukraine — Internal displacement report — General population survey round 12 (16 - 23 january 2023). https://dtm.iom.int/reports/ukraine-internal-displacement-report-general-population-survey-round-12-16-23-january-2023.

Jaeger, D. A. (2007). Green cards and the location choices of immigrants in the United States, 1971-2000. *Research in Labor Economics*, 27:131–184. IZA DP No. 2145.

Lemaitre, G. and Liebig, (2007). *Labour Market Integration in Australia, Denmark, Germany and Sweden. Jobs for Immigrants*, volume 1. OECD.

Lemos, S. and Portes, J. (2008). New labour? The impact of migration from Central and Eastern European countries on the UK labour market.

Lubotsky, D. (2007). Chutes or ladders? A longitudinal analysis of immigrant earnings. *Journal of Political Economy*, 115(5):820–867.

Malani, A. and Reif, J. (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, 124:1–17.

Mansour, H. (2010). The effects of labor supply shocks on labor market outcomes: Evidence from the Israeli-Palestinian conflict. *Labour Economics*, 17(6):930–939.

Maystadt, J.-F. and Verwimp, P. (2014). Winners and losers among a refugee-hosting population. *Economic Development and Cultural Change*, 62(4):769–809.

Ministry of Industry and Trade (2023). Numbers of entrepreneurs by citizenship doing business in the Czech Republic. https://www.mpo.cz/cz/podnikani/zivnostenske-podnikani/statisticke-udaje-o-podnikatelich/pocty-podnikatelu-dle-obcanstvi-podnikajicich-v-ceske-republice--151024/. Accessed: 2024-03-10.

Ministry of Labour and Social Affairs (2021). Structure of applicants and vacancies / Struktura uchazečů a volných míst. https://data.mpsv.cz/web/data/struktura-uchazecu-a-volnych-mist. Accessed: 2024-03-03.

Ministry of Labour and Social Affairs (2022). The situation of a refugee from Ukraine (Situace uprchliku z Ukrajiny). https://migrant-integration.ec.europa.eu/library-document/situation-refugees-ukraine_en. Accessed: 2023-07-20.

Ministry of Labour and Social Affairs (2023a). Employment of foreign nationals. https://data.mpsv.cz/web/data/otevrena-data9. Accessed: 2023-09-21.

Ministry of Labour and Social Affairs (2023b). Statistics. https://www.mpsv.cz/web/cz/z-uzemniho-hlediska. Accessed: 2024-02-03.

Ministry of Labour and Social Affairs, PAQ Research, and ISAS (2023). Voice of Ukrainians: Work, housing, poverty and knowledge of the Czech language (hlas ukrajinců: Práce, bydlení, chudoba a znalost češtiny). Technical report, Czech Ministry of Labour and Social Affairs in collaboration with PAQ Research and Institute of Sociology of the Czech Academy of Sciences. Accessed: 2023-09-20.

Ministry of the Interior (2022). International protection. https://www.mvcr.cz/clanek/mezinarodni-ochrana-253352.aspx. Accessed: 2023-12-27.

Ministry of the Interior (2023). Statistics related to the war in Ukraine - archive. https://www.mvcr.cz/clanek/statistika-v-souvislosti-s-valkou-na-ukrajine-archiv. Accessed: 2023-07-05.

Nickell, S. and Saleheen, J. (2008). The impact of immigration on occupational wages: evidence from Britain. *Federal Reserve Bank of Boston*.

OECD (2020). OECD economic surveys: Czech Republic - overview. https://www.oecd.org/economy/surveys/Czech-Republic-2020-OECD-economic-survey-overview.pdf.

Ottaviano, G. I. P. and Peri, G. (2011). Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, 10:152–197.

Patel, K. and Vella, F. (2013). Immigrant networks and their implications for occupational choice and wages. *Review of Economics and Statistics*, 95(4):1249–1277.

Pischke, J.-S. and Velling, J. (1997). Employment effects of immigration to Germany: An analysis based on local labor markets. *Review of Economics and Statistics*, 79:594–604.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights*, 4(3):305–22.

Schaafsma, J. and Sweetman, A. (2001). Immigrant earnings: Age at immigration matters. *Canadian Journal of Economics*, 34(4):1066–1099.

Sharaf, M. F. (2013). Job–education mismatch and its impact on the earnings of immigrants: Evidence from recent arrivals to Canada. *ISRN Economics*, 2013:14. Article 452358.

Stuart, B. A. and Taylor, E. J. (2021). Migration networks and location decisions: Evidence from US mass migration. *American Economic Journal: Applied Economics*, 13(3):134–175.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199. Themed Issue: Treatment Effect 1.

Tip, L. K., Brown, R., Morrice, L., Collyer, M., and Easterbrook, M. J. (2019). Improving refugee well-being with better language skills and more intergroup contact. *Social Psychological and Personality Science*, 10(2):144–151.

UNHCR (2022). Lives on hold: Intentions and perspectives of refugees from ukraine 2. https://data.unhcr.org/en/documents/details/99600. Accessed on 02.12.2023.

UNHCR (2023). Syria emergency. https://www.unhcr.org/emergencies/syria-emergency. Accessed on 02.10.2023.

UNHCR (2023). Ukraine refugee situation. https://data.unhcr.org/en/situations/ukraine. Accessed on 02.10.2023.

USCRI (1998). U.S. committee for refugees world refugee survey 1998 - Yugoslavia. https://www.refworld.org/reference/annualreport/uscri/1998/en/15855. Accessed on 02.11.2023.

Warman, C. (2010). The portability of human capital of male temporary foreign workers: You can bring it with you. In McDonald, T., Ruddick, E., Sweetman, A., and Worswick, C., editors, *Canadian Immigration: Economic Evidence for a Dynamic Policy Environment*, chapter 8. McGill–Queen's University Press.

Warman, C. and Worswick, C. (2004). Immigrant earnings performance in Canadian cities: 1981 through 2001. *Canadian Journal of Urban Research*, 13(1):62–84.

Weiss, Y., Sauer, R., and Gotlibovski, M. (2003). Immigration, search, and loss of skill. *Journal of Labor Economics*, 21(3):557–591.

Woodruff, C. and Zenteno, R. (2007). Migration networks and microenterprises in Mexico. *Journal of Development Economics*, 82:509–528.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*, volume 1 of *MIT Press Books*. The MIT Press.

A Appendix: Overview of the Variables Used in the Analysis

In this appendix, we provide an overview of the terminology used throughout the paper, describe the variables used in the analysis and state their sources. Refer to Table 7 for the information on the variables.

Table 7: Description and Sources of the Variables Used in the Analysis

Variables	Description & Source
Variables of Inerest (all sourced from the Labour Force Survey (LFSS))	
Employed Status	Binary: 1 if the worker is employed, 0 otherwise.
Unemployed Status	Binary: 1 if the worker is without work but actively seeking employment, 0 otherwise.
Inactive Status	Binary: 1 if the worker is not actively involved in job search or employment, 0 otherwise.
Hours worked	Continuous: Total hours usually worked in a typical week.
X: Individual Characteristics (all sourced from the Labour Force Survey (LFSS))	
Age	Categorical: Age groups (15-19, 20-25, ..., 60-65).
Gender	Binary: 0 if male, 1 if female.
Marital status	Binary: 1 if married, 0 otherwise.
On pension or disabled	Binary: 1 if on pension or has disability status, 0 otherwise.
Part-time employed	Binary: 1 if part-time employed, 0 otherwise.
Born abroad	Binary: 1 for individuals born outside of Czechia (includes residents and naturalized citizens), 0 otherwise.
Child(ren) < 15y.o.	Binary: indicator for having child(ren) under 15; 1 if yes, 0 otherwise.
Education level	Categorical: 1 for no education (ISCED 0); 2 for basic education (ISCED 1,2); 3 for secondary without matriculation (ISCED 3b); 4 for secondary with matriculation (ISCED 3a); 5 for university (ISCED 5,6).
Industry of Employment	Categorical: NACE Rev. 2, categories 21 industries from A to U.
Treatment Variables Components	
Employed Ukrainians $_{d,\ \text{Average in 2021}}$	Discrete: Average number of employed Ukrainians in Czechia in 2021, by district. Sourced from the Ministry of Labour and Social Affairs (2023).
Employed Ukrainians $_{d,\ \text{4th quarter in 2021}}$	Discrete: Number of employed Ukrainians in Czechia in the 4th quarter of 2021, by district. Sourced from the Ministry of Labour and Social Affairs (2023).
Employed Locals $_{d,\ \text{Census 2021}}$	Discrete: Number of employed locals, excluding Ukrainians, according to the 2021 census, by district. Sourced from the Czech Statistical Office (2023).
Locals of Working Age $_{d,\ t}$	Discrete: Number of locals aged 18-65, by district. Sourced from the Czech Statistical Office (2023).
Additional Variables for the Extended DiD Models	
District-specific pre-treatment trends	Categorical: Seasonally adjusted pre-treatment employment slope in each district, as calculated by the authors using LFSS for employment, unemployment, inactivity rates, and weekly hours worked.
District-, gender-, and education-specific pre-treatment	Categorical: Gender and education-specific seasonally adjusted pre-treatment employment slope in each district, as determined by the authors using LFSS for employment, unemployment, inactivity rates, and weekly hours worked.
District- and industry-specific pre-treatment	Categorical: Industry sector and gender-specific seasonally adjusted pre-treatment slope for weekly hours worked in each district, calculated by the authors using LFSS.
Z: Proxies for the General Robustness of Local District Economies and Labour Markets	
Employed Locals $_{d,\ \text{Census 2021}}$	Discrete: As previously defined.
Employed Ukrainians $_{d,\ t}$	Discrete: Average number of employed Ukrainians in Czechia, by district. Sourced from the Ministry of Labour and Social Affairs (2023).
Number of Active Companies	Discrete: Total number of active firms in the district. Sourced from the Czech Statistical Office (2023).
Number of Active Large Companies	Discrete: Total number of firms in the district with more than 250 employees. Sourced from the Czech Statistical Office (2023).
Labour Market Tightness	Continuous: Calculated by the autors, defined as number of job openings devided by the number of job seekers. Sourced from the Czech Statistical Office (2023).
Unemployment Rate	Continuous: Sourced from the Czech Statistical Office (2023).

Terminology Used Throughout the Paper:

'Locals' – This group comprises Czech nationals and foreign nationals with permanent residency, excluding Ukrainian refugees. The age range for this demographic is 15 years or older.

'Refugees' – Individuals who were forced to leave Ukraine following the Russian Federation's invasion on February 24^{th}, 2022. This includes all individuals protected under the Temporary Protection scheme.

'Diaspora' – Ukrainian nationals residing in Czechia under temporary or permanent legal statuses who arrived in the country prior to the 2020 refugee wave.

B Appendix: Auxiliary Figures and Tables

Table 8: Educational Attainment of Ukrainian Refugees Compared to the Czech Population

	Refugees			Locals				
	MoLSA (a)	IOM (b)	UNHCR (c)	Overall	Prague	Brno-město	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: Data on locals is sourced from the 2021 Census (Czech Statistical Office, 2021); data on the socio-economic profiles of Ukrainian refugees comes primarily from three surveys: (a) conducted by the Ministry of Labour and Social Affairs (2022) in July with 50,236 respondents, (b) the IOM (2023a) survey , conducted from June to December 2022 with 4,284 responses across all Czech regions, and (c) the UNHCR (2022) survey, conducted from May to September 2022, yielding 4,800 global responses and 721 responses specific to Czechia. The non-representative nature of the last two surveys suggests that their results are indicative rather than conclusive. Please refer to the original reports for detailed methodologies. To compare educational attainment across the surveys, some categories were merged. "No Education" remains unchanged. "Primary/Basic" combines "Primary" (UNHCR), "Basic" (MoLSA), "Lower Secondary" (IOM), and "Lower secondary/primary education" (CR). "Secondary" encompasses "Secondary" (UNHCR), "High school without diploma" (MoLSA), "High school with high school diploma" (MoLSA), "Upper secondary/Vocational" (IOM), and "Secondary, incl. vocational (no graduation)" (CR). "Post-Secondary" merges "Technical/Vocational" (UNHCR), "Post/Upper secondary/Vocational" (IOM), "Higher Professional" (MoLSA), "Upper/post-secondary education", and "Post-secondary professional education, Conservatoire" (CR). "Tertiary" includes "Doctorate", "Master", "Bachelor" (UNHCR), "PhD", "Tertiary" (IOM), "University"(MoLSA), and "Tertiary education" (CR). "Not Identified" comprises "Prefer not to answer" (UNHCR) and "Not identified" (CR).

Table 9: Treatment Doses According to Treatment^{I}, Treatment^{II}, and Treatment^{III} by Districts and Time.

District	Q1 2022			Q2 2022			Q3 2022			Q4 2022		
	T I	T II	T III	T I	T II	T III	T I	T II	T III	T I	T II	T III
Benešov	1	1	0	1	1	1	1	2	1	2	2	1
Beroun	1	2	1	1	2	1	2	2	2	3	3	2
Blansko	1	1	1	1	1	1	1	1	1	1	1	1
Břeclav	1	1	1	1	2	1	1	2	1	1	2	1
Brno-město	1	1	1	2	2	2	3	3	2	3	3	3
Brno-venkov	1	1	0	1	1	0	1	1	1	1	1	1
Bruntál	0	0	0	0	0	0	0	0	0	0	0	0
Česká Lípa	0	0	0	0	1	0	1	1	0	1	1	1
České Budějovice	1	1	0	1	1	1	1	1	1	2	2	1
Český Krumlov	3	3	2	2	2	1	2	2	1	2	3	2
Cheb	3	2	2	2	1	1	3	2	2	4	3	2
Chomutov	2	2	1	0	0	0	1	1	0	0	1	0
Chrudim	1	2	1	1	1	0	1	1	0	0	1	0
Děčín	0	0	0	0	0	0	1	0	0	0	0	0
Domažlice	1	2	0	0	1	0	0	2	0	1	2	0
Frýdek-Místek	0	0	0	0	0	0	1	1	0	1	1	0
Havlíčkův Brod	1	1	0	1	1	1	1	1	1	1	1	1
Hlavní město Praha	2	1	1	3	2	2	3	2	2	3	2	2
Hodonín	0	1	0	1	1	1	1	1	0	1	1	0
Hradec Králové	0	0	0	1	1	1	2	2	1	2	2	2
Jablonec nad Nisou	0	0	0	1	1	0	1	1	1	1	1	1
Jeseník	0	0	0	1	1	1	1	1	1	1	1	1
Jičín	0	1	0	1	1	1	2	2	1	2	2	1
Jihlava	2	1	1	1	1	1	2	2	1	2	2	1
Jindřichův Hradec	1	0	0	1	1	1	1	1	1	1	1	1
Karlovy Vary	1	1	1	2	2	1	2	2	2	3	3	2
Karviná	0	0	0	0	0	0	0	0	0	0	0	0
Kladno	1	1	0	1	1	1	1	1	1	1	1	1
Klatovy	1	1	1	2	2	1	2	3	2	3	3	2
Kolín	1	1	0	1	1	1	1	1	1	1	1	0
Kroměříž	0	0	0	1	1	1	1	1	1	1	1	1
Kutná Hora	2	2	1	2	2	1	2	2	2	2	2	1
Liberec	0	1	0	2	3	1	2	3	1	2	3	2
Litoměřice	0	0	0	1	1	1	1	1	1	1	1	1
Louny	0	1	0	0	1	0	1	2	1	1	2	1
Mělník	1	1	0	1	1	1	1	1	1	1	1	1
Mladá Boleslav	2	3	2	3	4	2	5	5	3	6	6	4
Most	0	0	0	0	0	0	1	1	0	1	1	0
Náchod	0	0	0	1	1	1	2	2	1	2	2	1

District	Q1 2022			Q2 2022			Q3 2022			Q4 2022		
	T I	T II	T III	T I	T II	T III	T I	T II	T III	T I	T II	T III
Nový Jičín	1	1	1	1	1	1	1	1	1	2	2	1
Nymburk	1	2	1	1	2	1	1	2	1	1	1	0
Olomouc	0	0	0	1	1	1	1	1	1	1	1	1
Opava	0	0	0	1	1	0	1	1	0	1	1	0
Ostrava-město	0	0	0	1	1	1	1	1	1	2	1	1
Pardubice	2	4	1	-2	1	-2	-1	1	-2	-1	2	-2
Pelhřimov	2	3	1	0	1	0	0	1	0	0	1	0
Písek	1	2	1	1	2	1	2	2	1	2	2	1
Plzeň-jih	5	5	3	2	2	1	4	4	2	3	3	1
Plzeň-město	2	2	1	3	3	2	4	4	3	5	5	3
Plzeň-sever	1	1	1	1	1	0	1	1	1	2	2	1
Prachatice	0	2	0	0	1	0	1	2	0	0	2	0
Praha-východ	4	4	2	0	0	-1	1	1	0	2	2	0
Praha-západ	2	2	1	-1	-1	-1	-1	0	-1	0	1	0
Přerov	0	0	0	1	1	1	1	1	1	1	1	1
Příbram	1	1	1	1	1	0	1	1	0	1	1	1
Prostějov	0	0	0	1	1	1	1	1	1	1	1	1
Rakovník	0	0	0	1	1	1	2	3	2	2	3	2
Rokycany	1	2	1	0	2	0	1	2	0	1	2	0
Rychnov nad Kněžnou	1	1	0	1	2	1	2	2	1	1	2	1
Semily	1	1	1	2	2	1	2	2	1	2	2	1
Sokolov	0	0	0	1	1	1	1	1	1	1	1	1
Strakonice	2	2	1	1	1	0	1	2	1	1	2	1
Šumperk	1	1	1	1	1	1	1	1	1	1	1	1
Svitavy	1	1	0	1	1	0	1	1	0	1	1	0
Tábor	1	1	1	1	1	1	1	2	1	2	2	1
Tachov	32	27	13	14	10	6	22	18	9	24	20	10
Teplice	0	0	0	1	1	1	1	1	1	1	2	1
Třebíč	0	0	0	1	1	0	1	1	1	1	1	1
Trutnov	0	0	0	1	1	1	1	1	1	1	1	1
Uherské Hradiště	1	1	0	1	1	1	1	1	1	1	1	1
Ústí nad Labem	0	0	0	1	1	1	1	1	1	1	1	1
Ústí nad Orlicí	1	1	1	2	2	2	2	2	2	2	2	2
Vsetín	0	1	0	1	1	1	1	1	1	1	1	1
Vyškov	0	1	0	1	1	1	1	1	1	1	1	1
Žďár nad Sázavou	0	0	0	1	1	1	1	1	1	1	1	1
Zlín	1	1	0	1	1	1	1	1	1	2	2	1
Znojmo	1	1	0	1	1	1	1	1	1	1	1	0

- Switchers in or control

- Switchers out

Note: The table presents treatment doses across districts for all four quarters of 2022, under three different treatment specifications—Treatment^{I}, Treatment^{II}, and Treatment^{III}. '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 and vice versa. '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'.

Table 10: Summary of the Results: Positive Treatment Doses—Weekly Hours Worked by Gender

	(1)			(2)			(3)			(4)			(5)			(6)			(9*)			(7)			(8)			(10*)		
	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
	Weekly hours usually worked: Conditional on weekly hours usually worked being greater than 0.																													
Treatment	0.02	0.01	0.06	0.02*	0.02*	0.07*	0.15**	0.14**	0.15**	0.14***	0.17***	0.16***	0.25**	0.22***	0.23***	0.11*	0.14**	0.14**	0.15*	0.13*	0.18***	0.19***	0.18***	0.24***	0.15***	0.15***	0.16**	0.12**	0.16***	0.13**
	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)	(0.03)	(0.07)	(0.07)	(0.06)	(0.05)	(0.05)	(0.06)	(0.12)	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y										Y	Y	Y	Y	Y	Y			
District pre-treatment trends													Y	Y	Y							Y	Y	Y						
District, gender and education pre-treatment trends																Y	Y	Y	Y	Y	Y				Y	Y	Y	Y	Y	Y
No. of observations	163,795	164,379	163,339	157,128	157,601	156,777	29,347	29,512	29,087	16,012	16,370	18,286	26,650	26,273	27,625	27,253	27,023	28,629	29,081	29,293	29,056	10,150	10,488	12,462	10,322	10,376	12,376	14,797	15,172	16,800
No. of switchers x periods	32,843	35,071	26,861	26,961	28,891	21,923	20,073	20,587	17,318	10,495	11,006	10,808	18,477	18,282	16,605	18,207	18,270	17,099	19,839	20,407	17,301	6,421	6,820	7,203	6,547	6,832	7,119	9,664	10,194	9,869
Parallel trends test p-value	-	-	-	-	-	-	0.68	0.51	0.29	0.75	0.80	0.19	0.99	0.23	0.43	0.75	0.78	0.39	0.67	0.44	0.12	0.76	0.83	0.46	0.87	0.95	0.43	0.55	0.59	0.11
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

(a) Females

	(1)			(2)			(3)			(4)			(5)			(6)			(9*)			(7)			(8)			(10*)		
	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
	Weekly hours usually worked: Conditional on weekly hours usually worked being greater than 0.																													
Treatment	0.02*	0.02*	0.04	0.03***	0.03***	0.06**	0.15**	0.16**	0.18***	0.09	0.1	0.22***	0.17 **	0.17*	0.18**	0.18 **	0.16*	0.18***	0.16***	0.19**	0.19***	0.11	0.16*	0.17**	0.11	0.1	0.25***	0.09	0.11	0.23***
	(0.01)	(0.01)	(0.03)	0.01	0.01	0.03	0.06	0.08	0.07	0.06	0.07	0.07	0.07	0.09	0.08	0.08	0.08	0.07	0.06	0.1	0.07	0.08	0.09	0.08	0.08	0.08	0.08	0.06	0.07	0.08
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y										Y	Y	Y	Y	Y	Y			
District pre-treatment trends													Y	Y	Y							Y	Y	Y						
District, gender and education pre-treatment trends																Y	Y	Y	Y	Y	Y				Y	Y	Y	Y	Y	Y
No. of observations	187,358	187,983	186,894	179,956	180,459	179,590	33,838	33,990	33,438	19,427	19,883	22,472	30,705	30,159	31,843	31,901	31,809	32,923	33,626	33,855	33,347	12,485	12,740	15,490	12,847	13,087	15,782	17,973	18,504	20,891
No. of switchers x periods	37,386	39,959	30,347	30,905	33,159	24,902	23,181	23,759	19,889	12,611	13,345	13,146	21,301	20,980	19,107	21,900	22,025	19,750	23,007	23,653	19,829	7,844	8,310	8,853	8,068	8,432	9,079	11,676	12,426	12,212
Parallel trends test p-value	-	-	-	-	-	-	0.84	0.58	0.10	0.50	0.24	0.20	0.98	0.15	0.29	0.85	0.72	0.13	0.76	0.62	0.07	0.60	0.21	0.36	0.78	0.68	0.19	0.84	0.24	0.18
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

(b) Males

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table displays coefficient estimates, standard errors (in parentheses), observation counts, classifications of the extensions, and the p-values from placebo tests for the parallel trends assumption for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-10*) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) or district-, and industry-specific DID(9*)) pre-treatment trends of the dependent variable. Models DID(7, 8, 10*) match on both the ($\mathbf{X}$) individual characteristics and pre-treatment trends as in DID(5, 6, 9*), respectively. Robust standard errors are clustered at the district level. For columns (3-10*), the p-values were calculated using the standard normal distribution.

Table 11: Summary of the Results: Positive Treatment Doses—Probability of Employment, Unemployment & Inactivity for Females

	(1)			(2)			(3)			(4)			(5)			(6)			(7)			(8)		
	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
Employment probability: Dummy = 1 if individual is employed.																								
Treatment	0.000	0.000*	-0.000	-0.000	-0.000	-0.001	0.002	0.000	-0.004*	0.000	0.000	-0.005*	-0.002	-0.002	-0.005**	-0.001	-0.003	-0.005**	-0.002	-0.001	-0.003*	0.001	0.000	-0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	361,537	362,748	360,670	340,550	341,511	339,899	67,535	67,825	66,813	61,412	62,953	63,271	47,424	51,086	53,561	51,728	53,489	57,927	39,194	41,073	45,632	28,328	27,473	33,785
No. of switchers x periods	72,931	77,939	59,572	58,961	63,266	47,911	46,162	47,293	39,594	41,693	43,764	37,645	30,913	34,514	32,172	33,603	35,944	35,642	25,546	27,603	27,254	17,681	17,375	19,940
Parallel trends test p-value	-	-	-	-	-	-	0.40	0.08	0.31	0.63	0.40	0.53	0.14	0.07	0.87	0.12	0.01	0.12	0.10	0.10	0.54	0.52	0.13	0.21
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Unemployment probability: Dummy = 1 if individual is unemployed.																								
Treatment	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001	0.002	-0.002	-0.002	0.001	-0.001	0.001	0.003	-0.002	-0.002	0.001	-0.001	-0.001	0.000	-0.002	-0.002	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	361,537	362,748	360,670	340,550	341,511	339,899	67,535	67,825	66,813	61,412	62,953	63,271	55,244	58,282	62,730	65,035	64,580	65,265	44,129	48,164	55,237	48,945	50,940	54,360
No. of switchers x periods	72,931	77,939	59,572	58,961	63,266	47,911	46,162	47,293	39,594	41,693	43,764	37,645	36,442	39,449	38,557	44,086	44,351	38,652	27,649	31,880	34,169	32,435	34,731	32,953
Parallel trends test p-value	-	-	-	-	-	-	0.83	0.94	0.67	0.85	0.88	0.40	0.12	0.34	0.24	0.88	0.92	0.65	0.45	0.70	0.21	0.95	0.79	0.96
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Inactivity probability: Dummy = 1 if individual is inactive in the labour market.																								
Treatment	-0.000	-0.000*	0.000	-0.000	-0.000	0.000	-0.001	0.001	0.003	0.001	0.002	0.003	0.000	0.004	-0.001	0.000	0.002	0.003	0.001	0.002	-0.000	0.002	0.001	0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	361,537	362,748	360,670	340,550	341,511	339,899	67,535	67,825	66,813	61,412	62,953	63,271	50,880	47,995	56,247	52,113	51,135	58,819	41,137	40,418	47,189	28,990	29,502	34,563
No. of switchers x periods	72,931	77,939	59,572	58,961	63,266	47,911	46,162	47,293	39,594	41,693	43,764	37,645	34,126	32,030	33,900	33,666	34,064	36,928	27,016	27,133	27,972	17,933	19,073	20,153
Parallel trends test p-value	-	-	-	-	-	-	0.61	0.03	0.58	0.78	0.21	0.95	0.90	0.04	0.32	0.90	0.12	0.65	0.21	0.06	0.90	0.81	0.70	0.64
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

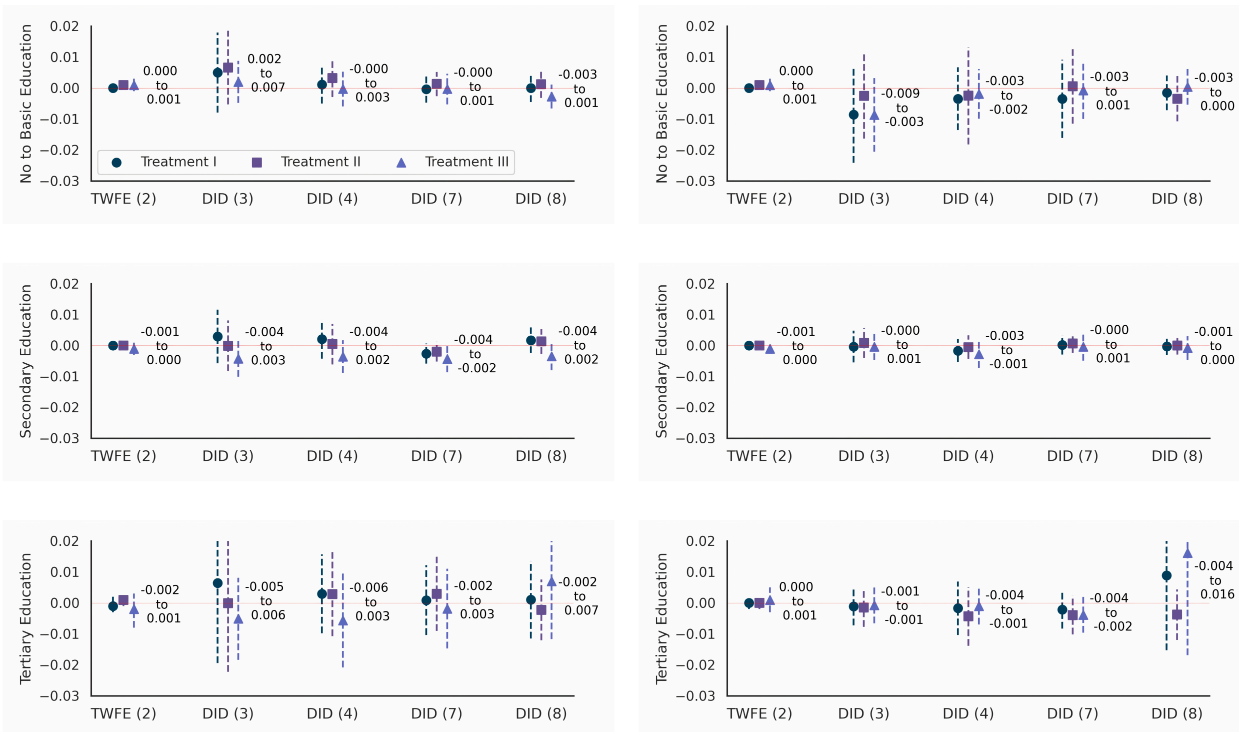
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table displays coefficient estimates, standard errors (in parentheses), observation counts, classifications of the extensions, and the p-values from placebo tests for the parallel trends assumption for ATT and nAVSQ across TWFE model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) pre-treatment trends of the dependent variable. Models DID(7 and 8) match on both the ($\mathbf{X}$) individual characteristics and pre-treatment trends as in DID(5 and 6), respectively. Robust standard errors are clustered at the district level. For columns (3-8), the p-values were calculated using the standard normal distribution.

Table 12: Summary of the Results: Positive Treatment Doses—Probability of Employment, Unemployment & Inactivity for Males

	(1)			(2)			(3)			(4)			(5)			(6)			(7)			(8)		
	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
Employment probability: Dummy = 1 if individual is employed.																								
Treatment	0.000	0.000	0.000	0.000	0.000	-0.000	-0.002	-0.000	-0.002	-0.003	-0.002	-0.003	-0.000	0.000	-0.002	-0.002	-0.002	-0.004	-0.001	-0.000	-0.002	0.001	-0.001	0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	317,510	318,556	316,741	299,812	300,635	299,209	58,882	59,103	58,106	53,554	54,681	55,098	41,486	44,539	46,676	46,309	47,095	52,386	33,899	35,260	39,395	24,396	24,038	28,828
No. of switchers x periods	63,725	68,090	51,741	51,698	55,468	41,689	40,075	41,079	34,251	36,264	37,911	32,577	26,958	29,971	27,879	30,159	31,294	31,948	21,973	23,505	23,459	15,171	15,386	16,064
Parallel trends test p-value	-	-	-	-	-	-	0.41	0.63	0.12	0.29	0.40	0.22	0.17	0.21	0.26	0.30	0.26	0.32	0.05	0.23	0.31	0.07	0.18	0.22
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Unemployment probability: Dummy = 1 if individual is unemployed.																								
Treatment	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.001	-0.000	-0.001	0.000	-0.000	-0.000	0.000	-0.001	0.000	0.002	-0.000	0.000	0.000	-0.000	-0.001	0.003	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	317,510	318,556	316,741	299,812	300,635	299,209	58,882	59,103	58,106	53,554	54,681	55,098	48,170	50,740	54,532	57,470	58,017	57,008	38,260	41,033	47,707	40,635	40,547	47,713
No. of switchers x periods	63,725	68,090	51,741	51,698	55,468	41,689	40,075	41,079	34,251	36,264	37,911	32,577	31,616	34,235	33,314	39,345	40,427	33,894	23,868	26,857	29,298	26,156	26,565	29,120
Parallel trends test p-value	-	-	-	-	-	-	0.85	0.75	0.67	0.95	0.98	0.99	0.77	0.78	0.39	0.60	0.92	0.37	0.85	0.88	0.99	0.98	0.83	0.93
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Inactivity probability: Dummy = 1 if individual is inactive in the labour market.																								
Treatment	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.001	0.001	0.003*	0.002*	0.002*	0.004**	0.000	0.000	0.002	0.001	0.000	0.003	0.001	0.001	0.001	0.001	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distric FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics				Y	Y	Y				Y	Y	Y							Y	Y	Y	Y	Y	Y
District pre-treatment trends													Y	Y	Y				Y	Y	Y			
District, gender and education pre-treatment trends																Y	Y	Y				Y	Y	Y
No. of observations	317,510	318,556	316,741	299,812	300,635	299,209	58,882	59,103	58,106	53,554	54,681	55,098	44,446	41,721	48,862	43,498	45,213	50,523	35,588	34,860	40,659	24,331	23,459	28,800
No. of switchers x periods	63,725	68,090	51,741	51,698	55,468	41,689	40,075	41,079	34,251	36,264	37,911	32,577	29,748	27,769	29,274	27,137	29,284	30,207	23,255	23,221	23,975	14,688	14,094	16,498
Parallel trends test p-value	-	-	-	-	-	-	0.36	0.65	0.28	0.22	0.51	0.20	0.26	0.56	0.75	0.16	0.12	0.20	0.98	0.44	0.94	0.02	0.15	0.45
No. of effects estimated	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table displays coefficient estimates, standard errors (in parentheses), observation counts, classifications of the extensions, and the p-values from placebo tests for the parallel trends assumption for ATT and nAVSQ across TWFE model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)), in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)), or matching on district-specific (DID(5)), or district-, gender-, and education-specific (DID(6)) pre-treatment trends of the dependent variable. Models DID(7 and 8) match on both the (**X**) individual characteristics and pre-treatment trends as in DID(5 and 6), respectively. Robust standard errors are clustered at the district level. For columns (3-8), the p-values were calculated using the standard normal distribution.

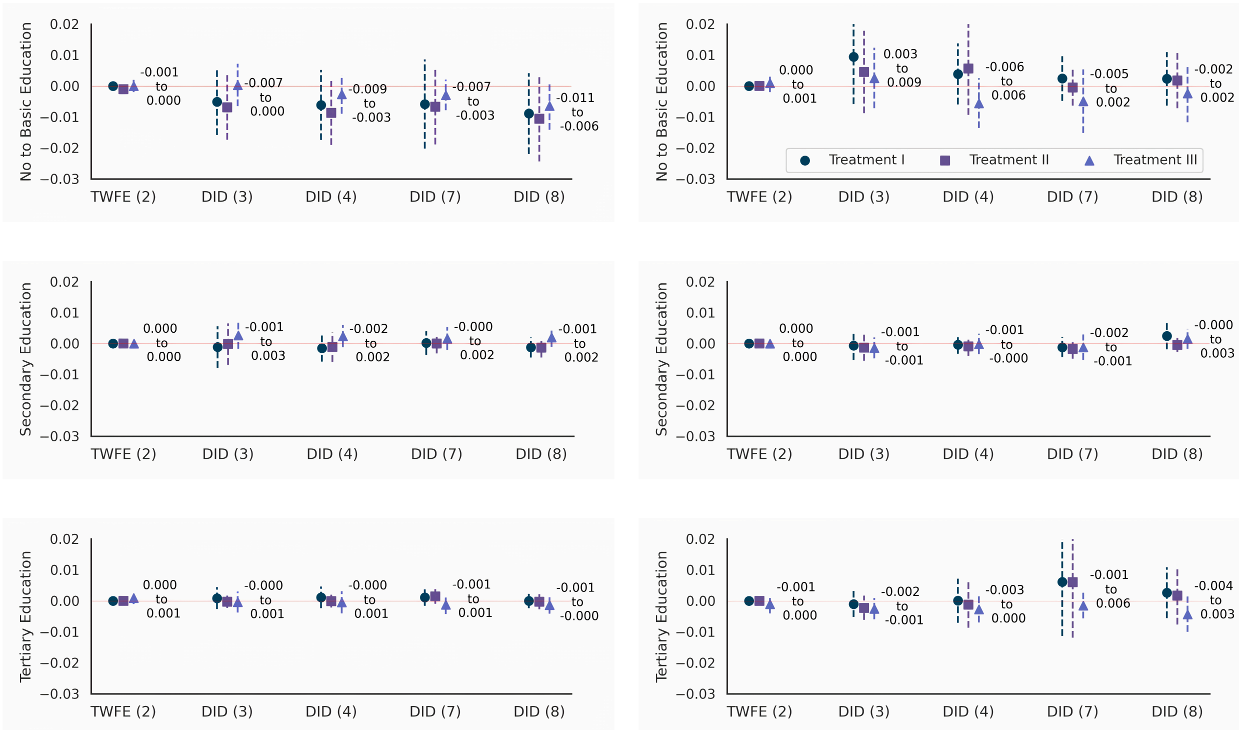
Figure 13: Positive Treatment Doses—Probability of Employment by Gender & Education Level



(a) Female (b) Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)), or matching 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 (3-8), the p-values were calculated using the standard normal distribution.

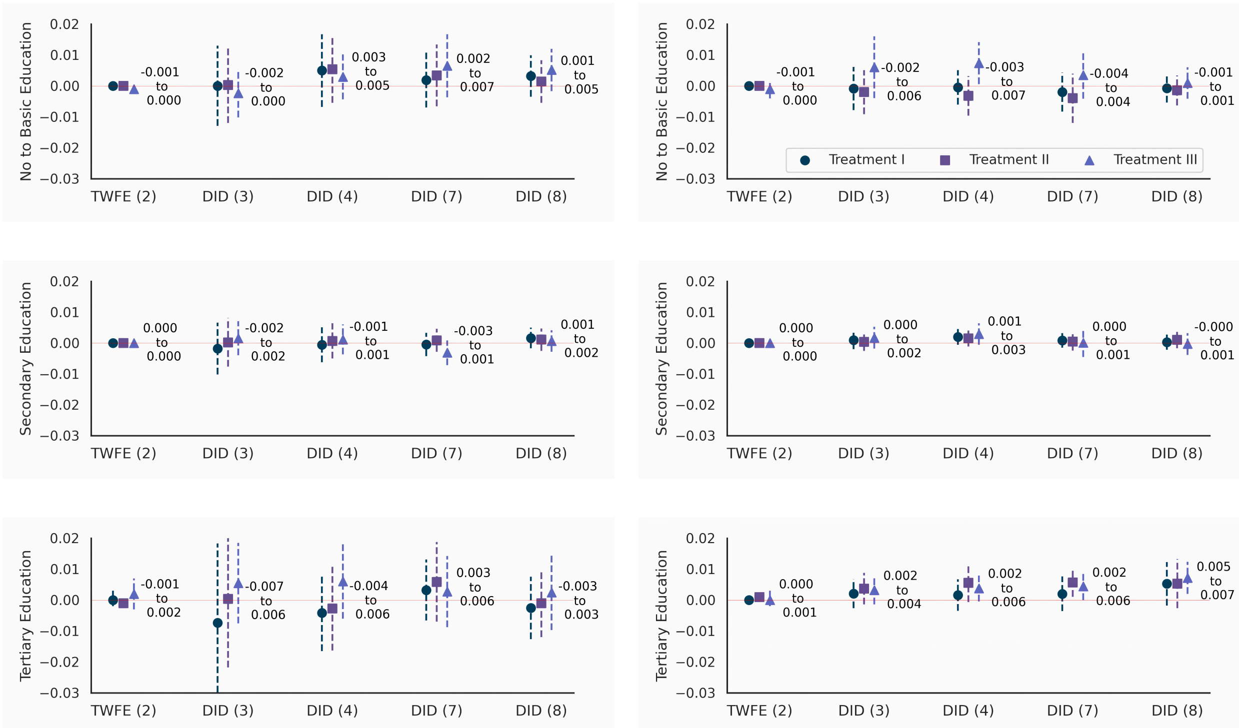
Figure 14: Positive Treatment Doses—Probability of Unemployment by Gender & Education Level



(a) Female (b) Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)), or matching 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 (3-8), the p-values were calculated using the standard normal distribution.

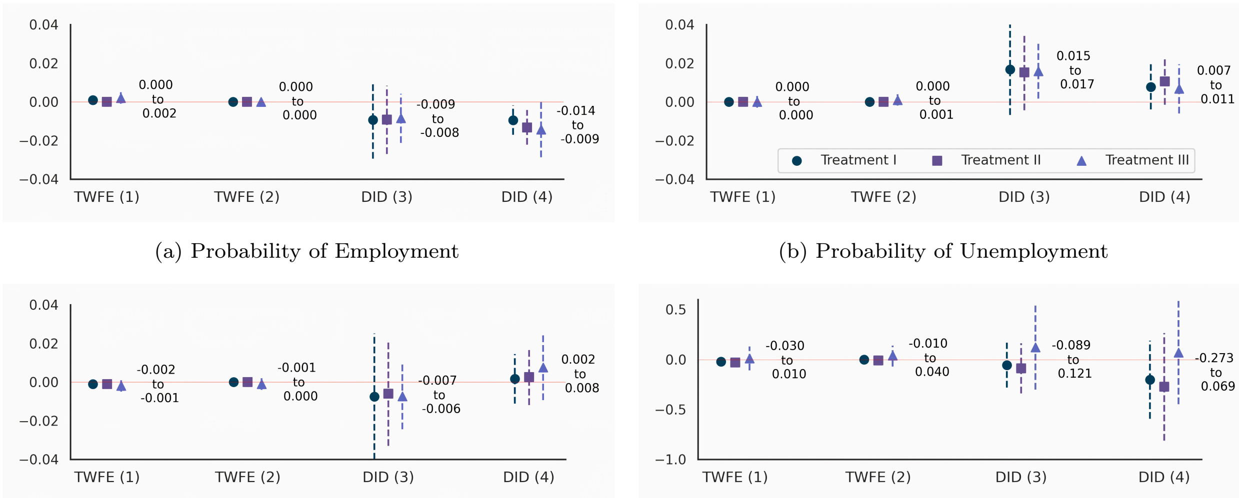
Figure 15: Positive Treatment Doses—Probability of Inactivity by Gender & Education Level



(a) Female (b) Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-8) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)), or matching on both the ($\mathbf{X}$) 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 (3-8), the p-values were calculated using the standard normal distribution.

Figure 16: Labour Market Outcomes: Positive Treatment Doses—Among Foreign Born Individuals Residing in Czechia



(a) Probability of Employment

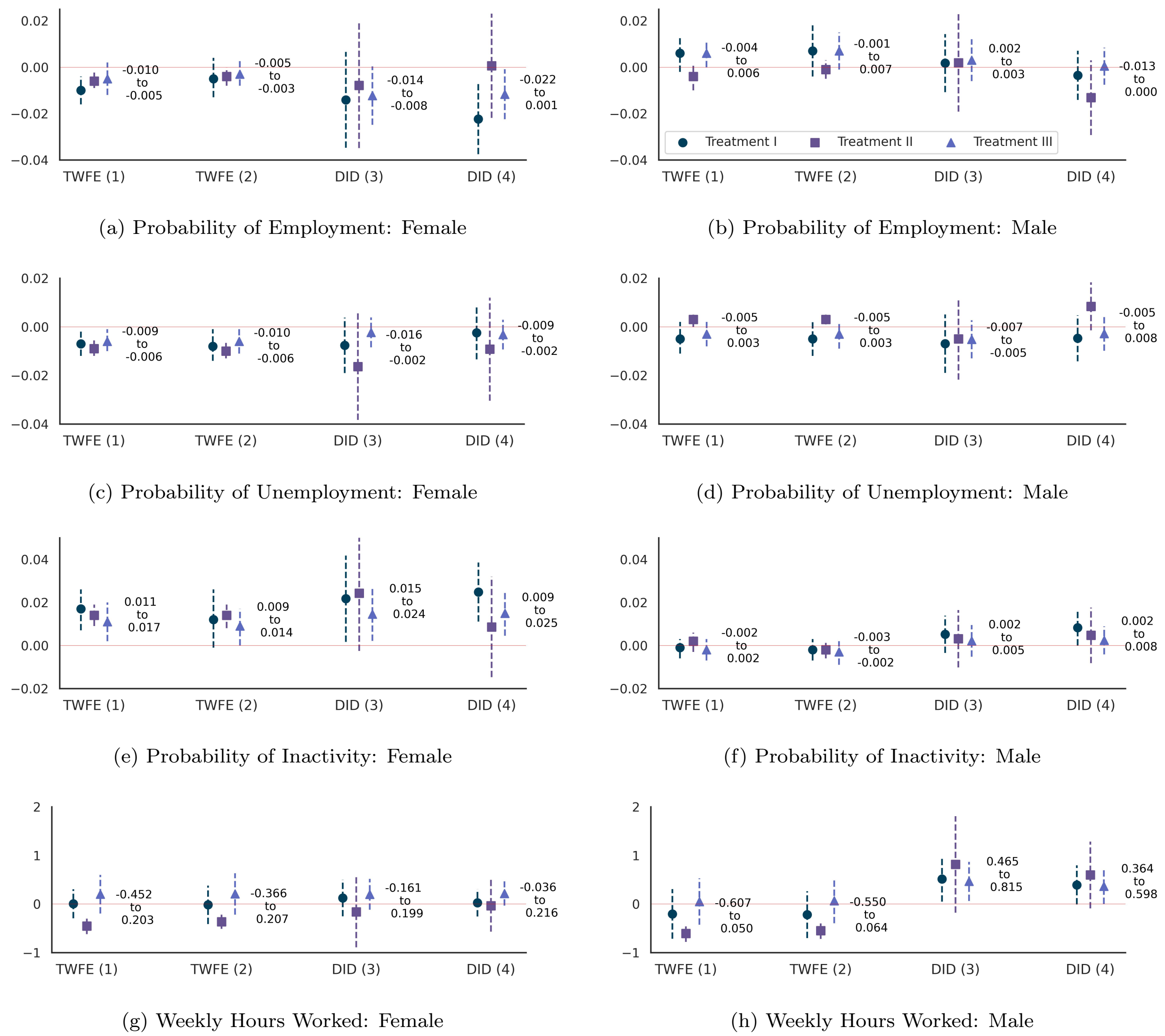
(b) Probability of Unemployment

(c) Probability of Inactivity

(d) Weekly Hours Worked

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 1-2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)) in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

Figure 17: Summary of the Results: Negative Treatment Doses—Probability of Employment, Unemployment, Inactivity & Weekly Hours Worked by Gender



(a) Probability of Employment: Female

(b) Probability of Employment: Male

(c) Probability of Unemployment: Female

(d) Probability of Unemployment: Male

(e) Probability of Inactivity: Female

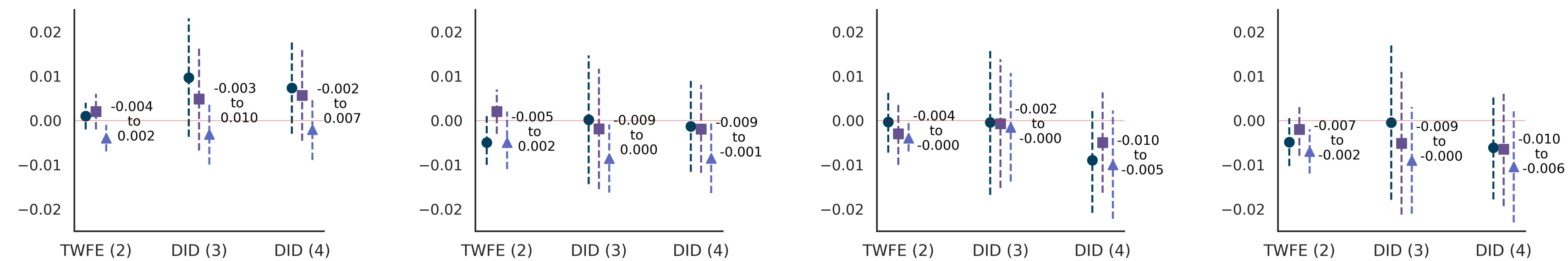
(f) Probability of Inactivity: Male

(g) Weekly Hours Worked: Female

(h) Weekly Hours Worked: Male

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 1-2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. TWFE models control for: individual and time-fixed effects (TWFE(1)) in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

Figure 18: Positive Treatment Doses—Probability of Employment for Females by Original & Adjusted Doses of Treatment

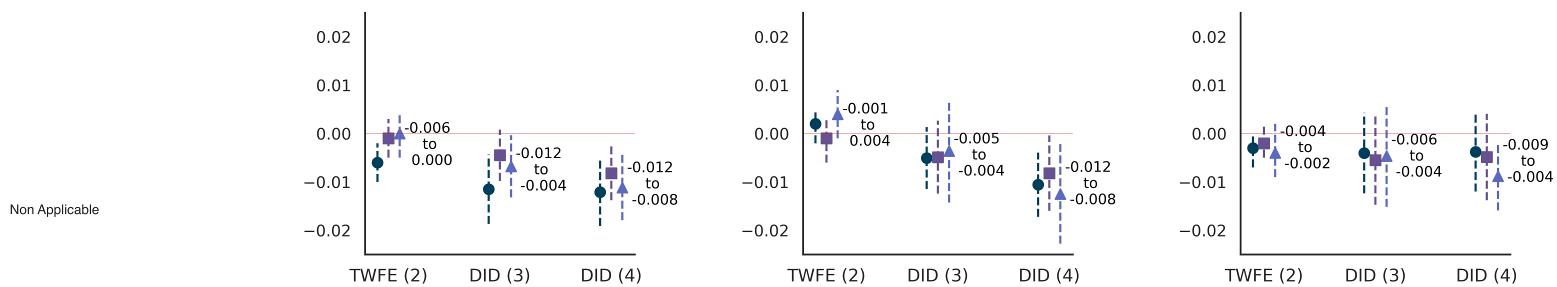


(a) Dose 1%

(b) Dose 2%

(c) Dose 3%

(d) Dose $\geq$ 4%



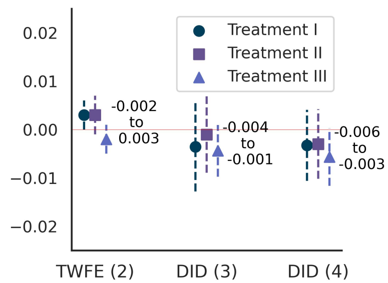
(e) Adjusted Dose 2%

(f) Adjusted Dose 3%

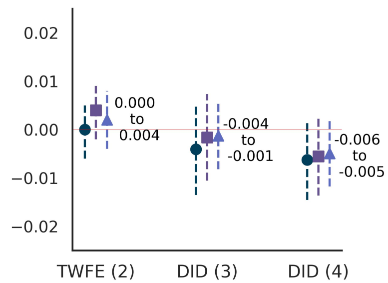
(g) Adjusted Dose $\geq$ 4%

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

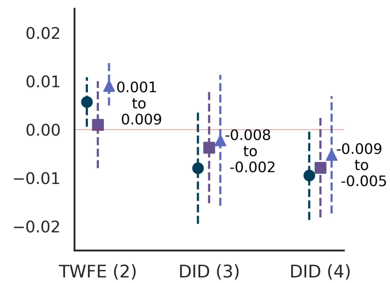
Figure 19: Positive Treatment Doses—Probability of Employment for Males by Original & Adjusted Doses of Treatment



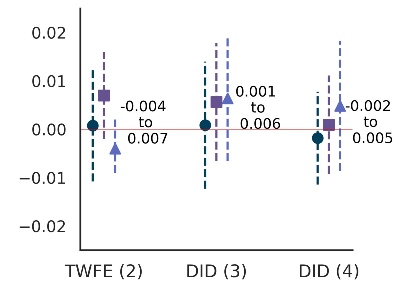
(a) Dose 1%



(b) Dose 2%



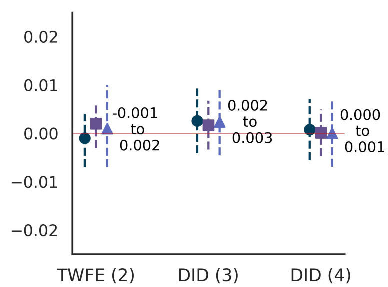
(c) Dose 3%



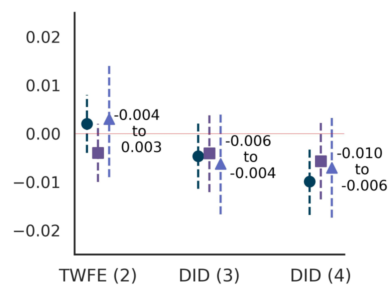
(d) Dose $\geq$ 4%

Non Applicable

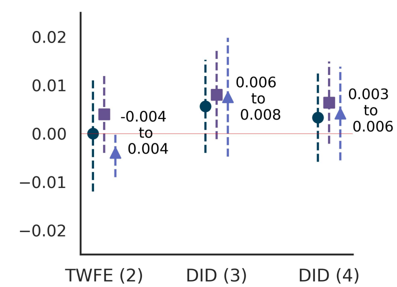
(e) Probability of employment



(f) Adjusted Dose 2%



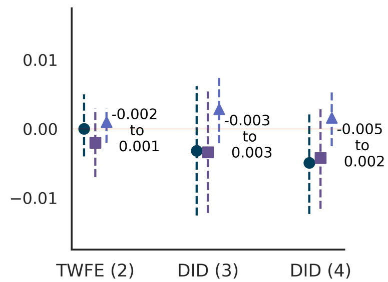
(g) Adjusted Dose 3%



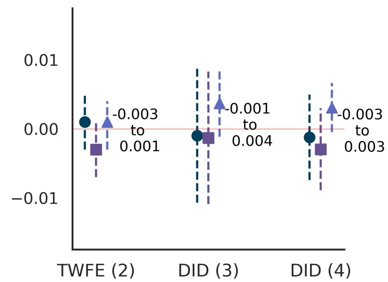
(h) Adjusted Dose $\geq$ 4%

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

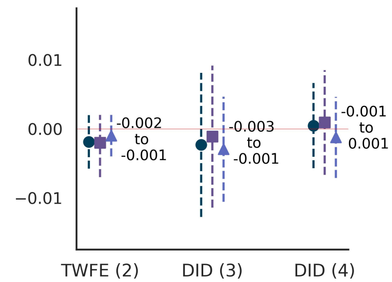
Figure 20: Positive Treatment Doses—Probability of Unemployment for Females by Original & Adjusted Doses of Treatment



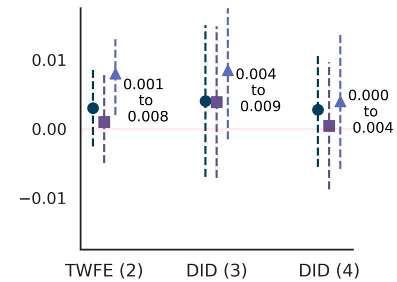
(a) Dose 1%



(b) Dose 2%

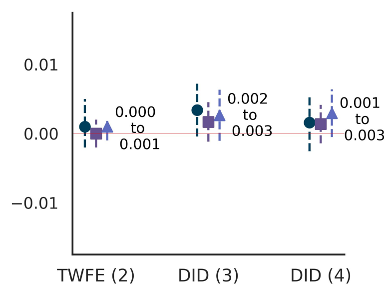


(c) Dose 3%

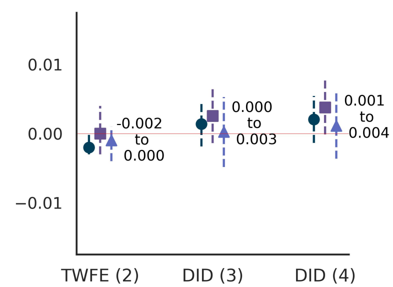


(d) Dose $\geq$ 4%

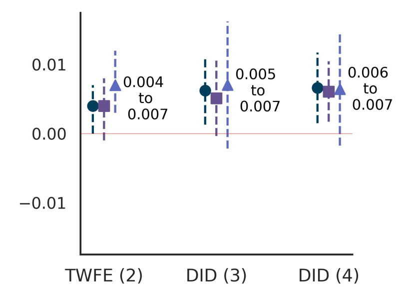
Non Applicable



(e) Adjusted Dose 2%



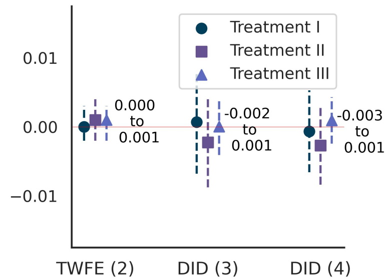
(f) Adjusted Dose 3%



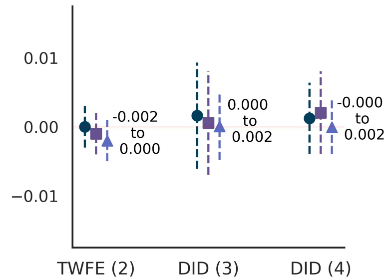
(g) Adjusted Dose $\geq$ 4%

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

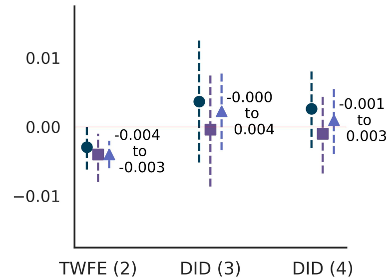
Figure 21: Positive Treatment Doses—Probability of Unemployment for Males by Original & Adjusted Doses of Treatment



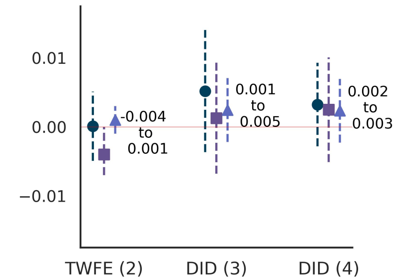
(a) Dose 1%



(b) Dose 2%

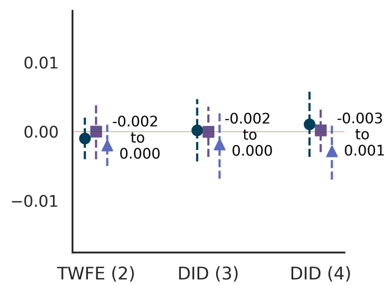


(c) Dose 3%

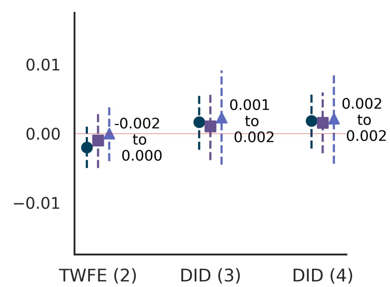


(d) Dose ≥ 4%

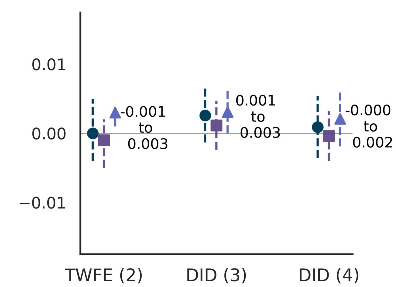
Non Applicable



(e) Adjusted Dose 2%



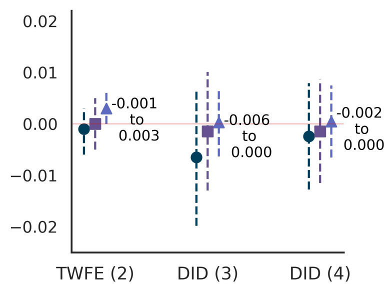
(f) Adjusted Dose 3%



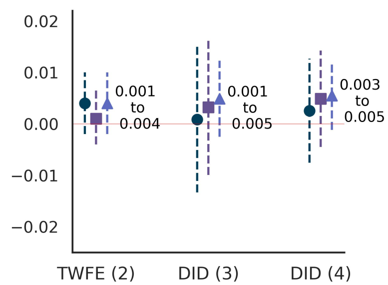
(g) Adjusted Dose ≥ 4%

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

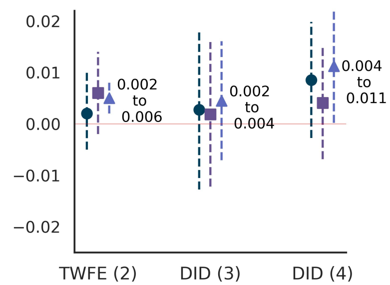
Figure 22: Positive Treatment Doses—Probability of Inactivity for Females by Original & Adjusted Doses of Treatment



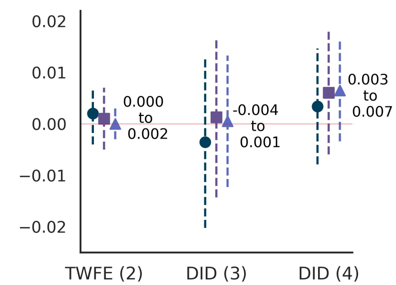
(a) Dose 1%



(b) Dose 2%

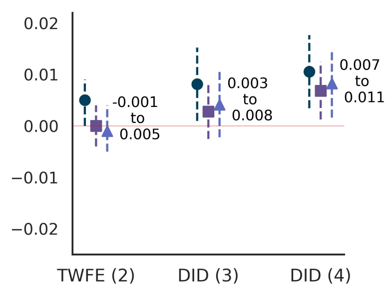


(c) Dose 3%

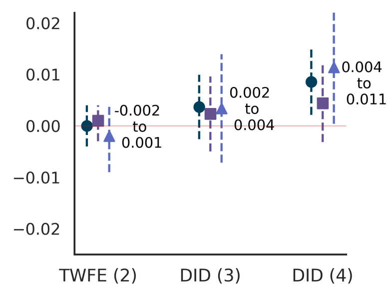


(d) Dose $\geq 4\%$

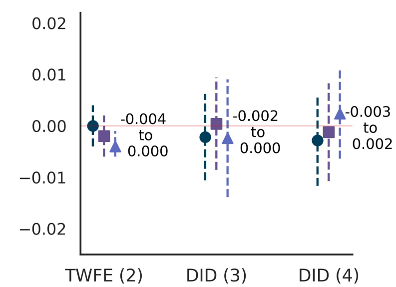
Non Applicable



(e) Adjusted Dose 2%



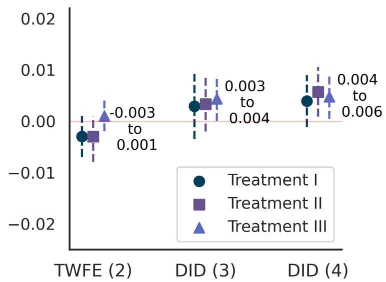
(f) Adjusted Dose 3%



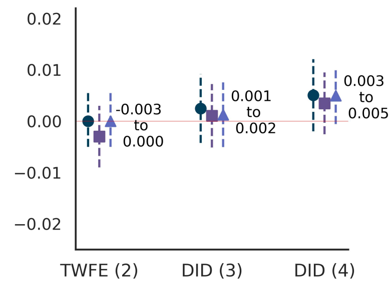
(g) Adjusted Dose $\geq 4\%$

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

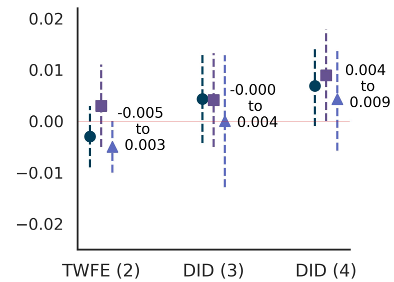
Figure 23: Positive Treatment Doses—Probability of Inactivity for Males by Original & Adjusted Doses of Treatment



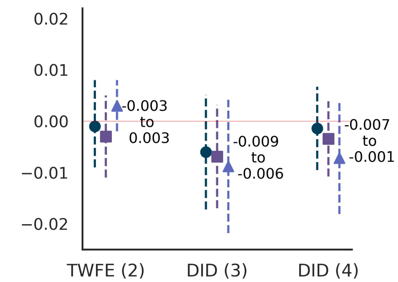
(a) Dose 1%



(b) Dose 2%

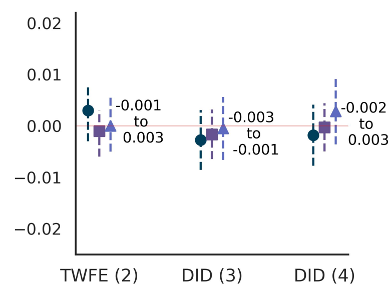


(c) Dose 3%

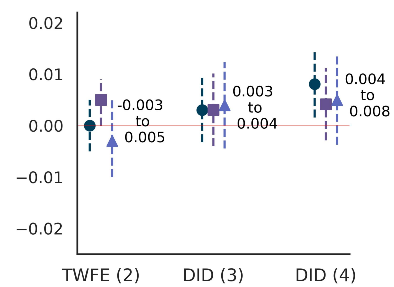


(d) Dose ≥ 4%

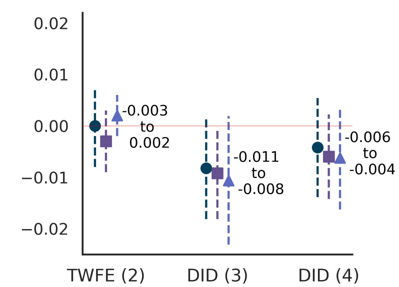
Non Applicable



(e) Adjusted Dose 2%



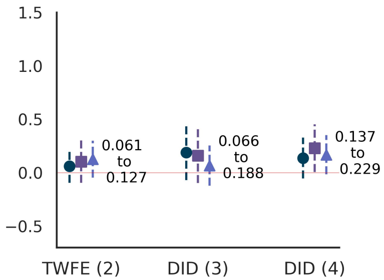
(f) Adjusted Dose 3%



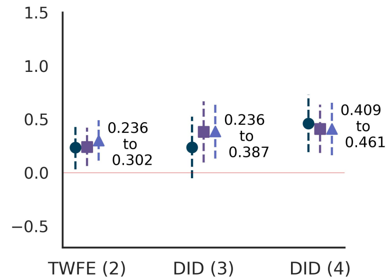
(g) Adjusted Dose ≥ 4%

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

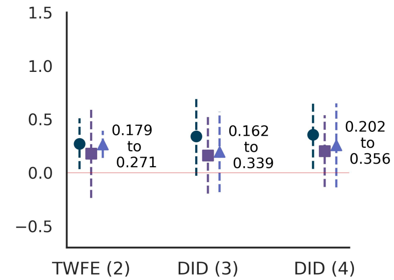
Figure 24: Positive Treatment Doses—Weekly Hours Worked for Females by Original & Adjusted Doses of Treatment



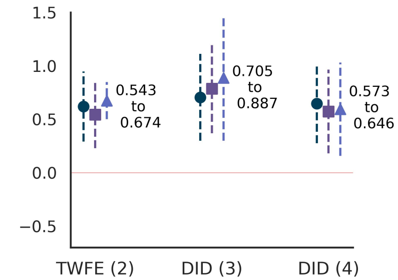
(a) Dose 1%



(b) Dose 2%

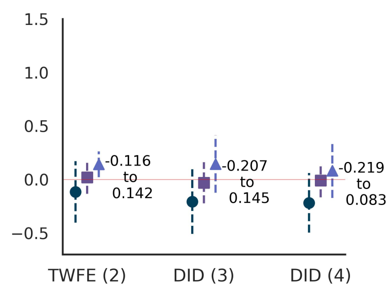


(c) Dose 3%

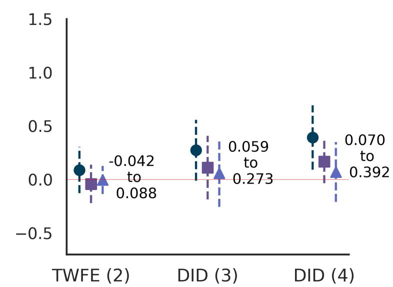


(d) Dose $\geq 4\%$

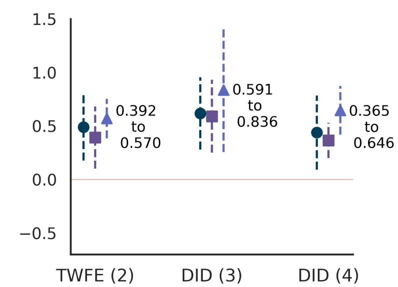
Non Applicable



(e) Adjusted Dose 2%



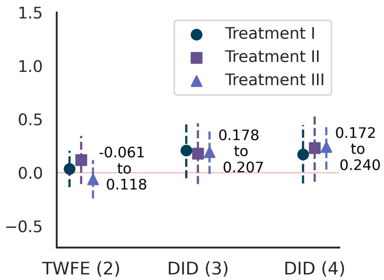
(f) Adjusted Dose 3%



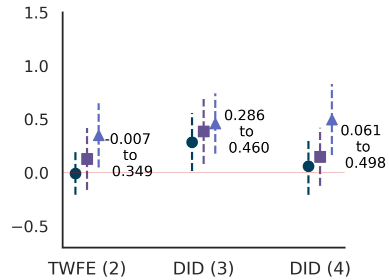
(g) Adjusted Dose $\geq 4\%$

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the (**X**) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

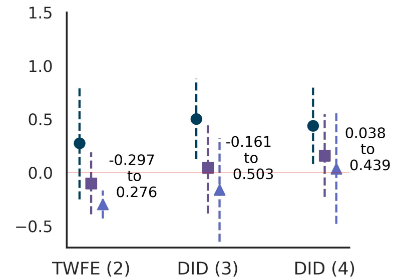
Figure 25: Positive Treatment Doses—Weekly Hours Worked for Males by Original & Adjusted Doses of Treatment



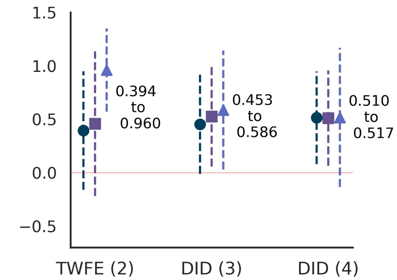
(a) Dose 1%



(b) Dose 2%

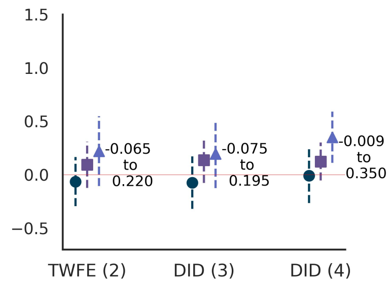


(c) Dose 3%

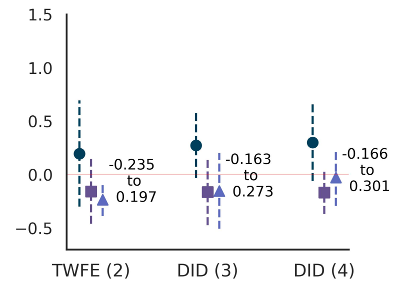


(d) Dose $\geq 4\%$

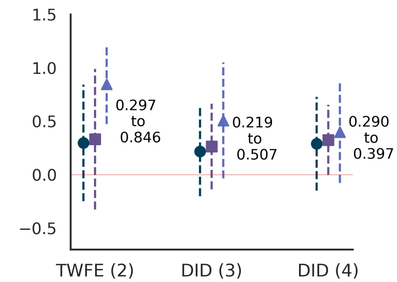
Non Applicable



(e) Adjusted Dose 2%



(f) Adjusted Dose 3%



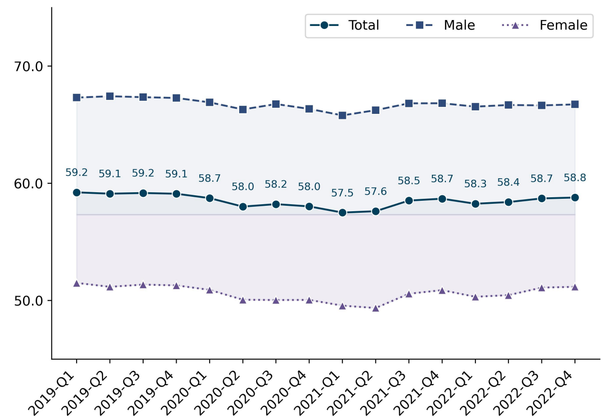
(g) Adjusted Dose $\geq 4\%$

Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.4 (columns 3-4) for Treatment I, II, and III. Reported are the estimated effects separately for each **Average Treatment Dose**. The first row reports the results for the 'original' treatment doses. The second row presents the 'adjusted' treatment doses, for which we designated districts experiencing 0% to 1% treatment as 'controls'. TWFE models accounts for: individual and time-fixed effects in addition to individual-level characteristics (TWFE(2)). DiD models control for: individual and time-fixed effects (DID(3)), in addition to matching on the ($\mathbf{X}$) individual characteristics (DID(4)). Robust standard errors are clustered at the district level. For columns (3-4), the p-values were calculated using the standard normal distribution.

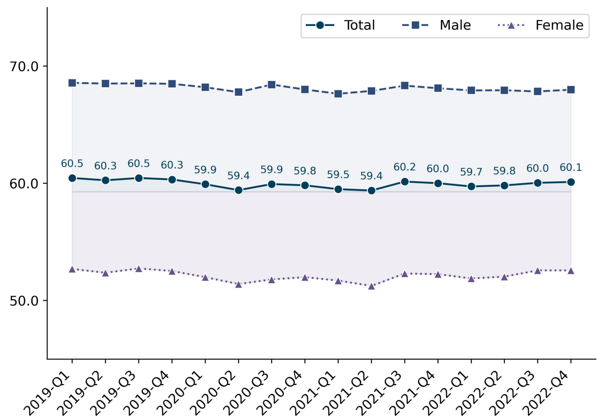
C Appendix: Labour Market Conditions in Czechia

At the beginning of 2022, the Czech labour market was among the tightest in the EU. By the end of 2022, the unemployment rate, albeit marginally higher than the previous year's 2.20%, stood at 2.22% — the lowest within the EU with the average recorded at 6% (Ministry of Labour and Social Affairs, 2023b; Eurostat, 2023). Refer to Figure 26d. There was notable regional heterogeneity, especially concerning central and more peripheral districts. The unemployment rate peaked at 8.47% in Karviná in 2021 and at 6.89% in Bruntál in 2022 over the years 2019-2022.

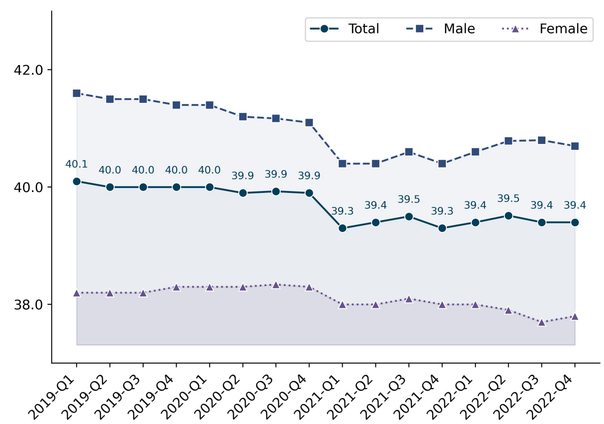
Figure 26: Snapshot of Czechia's Labour Market Conditions



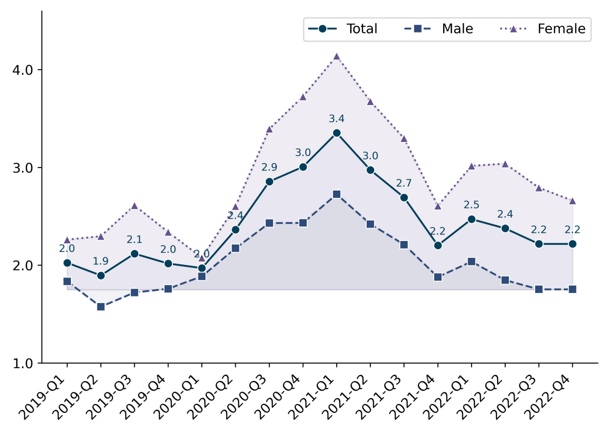
(a) Employment Rate



(b) Participation Rate



(c) Weekly Hours Worked



(d) Unemployment Rate

Note: The plot was created by the authors using the data reported by the Czech Statistical Office (2021, 2023e).

Despite global economic challenges, such as the COVID-19 pandemic, Czechia maintained relatively stable employment and participation rates throughout these years (Figures 26a and 26b). Although the employment data from 2020, registering 5,235 thousand locals, reveal a dip — likely a consequence of the COVID-19 pandemic — the 2021 census data, standing at 5,290 thousand locals, resembled the figures from the pre-pandemic years of 2019 and 2018, signalling recovery. These stood at 5,303 thousand and 5,293 thousand, respectively (Czech Statistical Office, 2022, 2021).

The demand for labour remained high in the years leading up to and including 2022, with the number of job vacancies often surpassing job seekers. By December 2021, there were a total of 266,783 open vacancies, the vast majority of which required only basic education (including uncompleted) - 73%, followed by 21% requiring secondary education and 6% tertiary or higher education levels (Ministry of Labour and Social Affairs, 2021). Employment opportunities were most prevalent in sectors such as retail trade, specialised construction activities, public administration, and education, among others. The highest demand for new employees was noted in Prague and the Central Bohemia Region, with significant vacancies in building construction, forklift operation, and assembly work, suitable for both local and foreign candidates (EURES, 2023).

However, the labour market in Czechia is not without its challenges. Certain demographic groups, such as women (particularly those with young children), older workers, low-skilled labourers, and individuals with disabilities, consistently show low employment rates (OECD, 2020). Specifically, women's employment rates are on average about 15% lower than men's, highlighting a significant disparity.

D Appendix: Deterministic & Probabilistic LFSS Data Matching

Due to regulatory changes 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 those in Q2 and earlier. We restored the panel structure of the data through a two-step matching process:

(i) First, deterministic matching was employed to identify unique pairs of individuals based on available time-invariant variables.

These variables included the sequence number of the observation period for each individual in the rotating panel (1^{st}, 2^{nd}, 3^{rd}, 4^{th} or 5^{th} wave), gender, year of birth, country of birth, and employment status from all previously observed periods, which are always reported at each wave for each individual, as well as district of residence. We treated the district of residence as a time-invariant variable, considering that in the dataset where unique identifiers for individuals were available, only 111 out of approximately 130,000 individuals changed their district of residence over a span of four years. While acknowledging that this approach could introduce a slight bias—especially if individuals were more prone to moving in the last two quarters—our analysis of population movements between 2021 and 2022, discussed in Section 6, revealed no significant increase in migration. This confirms that the bias is minimal, enabling us to successfully match around 67% of the observations in Q3 and Q4 2022 with their corresponding observations from the previous quarter.

(ii) Second, for the remaining 33% of observations, where duplicates arose due to individuals having identical time-invariant characteristics, we employed probabilistic matching.

We utilised a Random Forest model, which is highly suitable for this classification task, to calculate the likelihood of two individuals being a match. At this stage, we included most of the remaining time-variant variables, such as the highest level of education achieved, the year of achieving the highest education level, type of degree, education field code, industry of employment (NACE) with 778 unique categories, weekly hours worked, marital status, parental status, and others. Previously, these variables could not be relied upon for deterministic matching since some might change within a quarter. However, with over 200 variables in our dataset, using probabilistic matching to distinguish between a few duplicate individuals became straightforward. This approach is feasible because their time-invariant variables are usually very different and, on average, remain constant over time, such as the level of education, for example.

For the Random Forest model, we first prepared our data by taking the LFSS dataset, which provided unique identifiers for individuals from 1Q 2019 to 2Q 2022, and transformed it to include rows listing all variables for the same individual across two adjacent waves of the LFSS. We generated interaction terms between gender and marital status, age and marital status, age and weekly hours worked, gender and weekly hours worked, and marital status and weekly hours worked for each wave separately. We then calculated the rate of change for each variable; for continuous variables, we subtracted the later value from the earlier value for the same variable. For categorical variables, we generated a binary variable: 1 if the category had changed and 0 otherwise. This process yielded 844,094 'correct' matches and the rate of change for their variables between two adjacent quarters.

A 'false' dataset was generated in a similar manner as for the correct matches, but in this case, we paired individuals who, based on their IDs, were not the same people, yet shared the same time-invariant variables. This method produced 509,232 'false' matches and the rate of change for their variables between two adjacent quarters. The datasets for both 'correct' and 'false' matches were then merged and reshuffled.

To build, train and employ the Random Forest model for our probabilistic matching task, we split our dataset into predictor variables X, consisting of rates of change for various variables, and a target variable y, a binary indicator where 1 represents a 'correct' match and 0 a 'false' match. The data was further divided into a training set, comprising 70% of the data, and a testing set, comprising the remaining 30%. This standard division allowed us to train the Random Forest model on a substantial portion of the data while retaining a significant subset for evaluation, ensuring the model was not tested on the data it was trained on to avoid overfitting and overly optimistic performance estimates.

An extensive grid search for hyperparameter tuning was conducted, focusing on adjustable parameters that control the model's training process. The search was critical for fine-tuning the model to enhance its prediction accuracy. The best parameters, selected based on their performance in cross-validation, are reported in Table 13.

Table 13: Best Parameters from the Grid Search

Parameter	**Range**
n_estimators	[100, 200, <u>300</u>, 400, 600]
max_depth	[None, 20, 40, <u>60</u>, 80, 100]
min_samples_split	[2, 5, <u>10</u>, 15, 25]
min_samples_leaf	[1, 2, <u>4</u>, 6, 10]
max_features	[<u>sqrt</u>, 'log2', None]
bootstrap	[<u>True</u>, False]
criterion	[<u>gini</u>, 'entropy']

Note: The best parameters are underscored. The table reports the range of values explored during the grid search process.

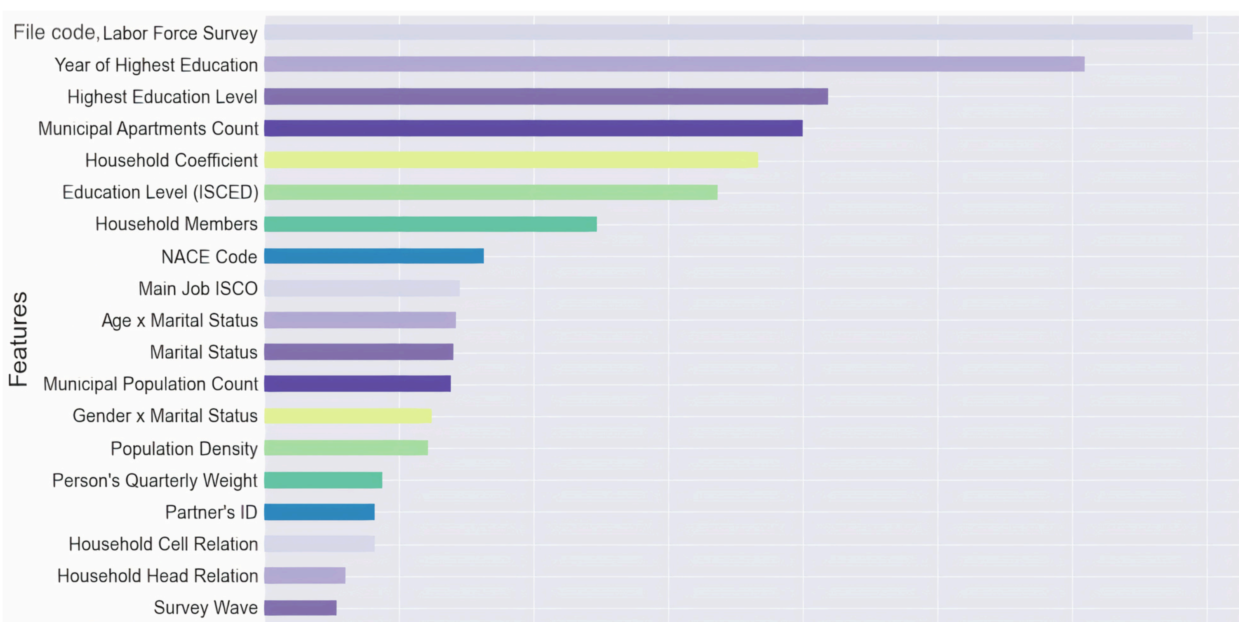
Evaluating the model on the test set involved metrics such as accuracy, ROC AUC score, F1 score, precision, and recall. These metrics collectively provided a succinct overview of the model's robustness and predictive precision, detailed in Table 14. The model achieved high performance across all metrics, indicating its strong predictive capability. An accuracy of 99.58% and a ROC AUC score of 99.59% suggest that the model is highly effective in distinguishing between 'correct' and 'false' matches. The high F1 score of 99.48% illustrates a balanced precision-recall trade-off, with precision at 99.33% and recall at 99.63%, showcasing the model's accuracy and sensitivity.

Table 14: Predictive Performance Metrics (Out of Sample)

Metric	Value
Accuracy	0.9958
ROC AUC Score	0.9959
F1 Score	0.9948
Precision	0.9933
Recall	0.9963
Support	
Correct Match	67454
False Match	101365

To mitigate the risk of data leakage, we performed a feature importance analysis, identifying the features that significantly contributed to the model's predictions and ensuring that the high performance was not due to leaked information. The visualization, as shown in Figure 27, ranks the features by their relative importance, highlighting those crucial in the model's decision-making process. Notably, the file code assigned by the CZSO to each individual was a highly effective predictor, with 281 unique values and remaining constant for the same individual in 93.01% of cases in the subset of data where IDs were provided. Other significant predictors included the year of highest education, highest education level, and municipal apartment counts—variables that tend not to change frequently within a single quarter.

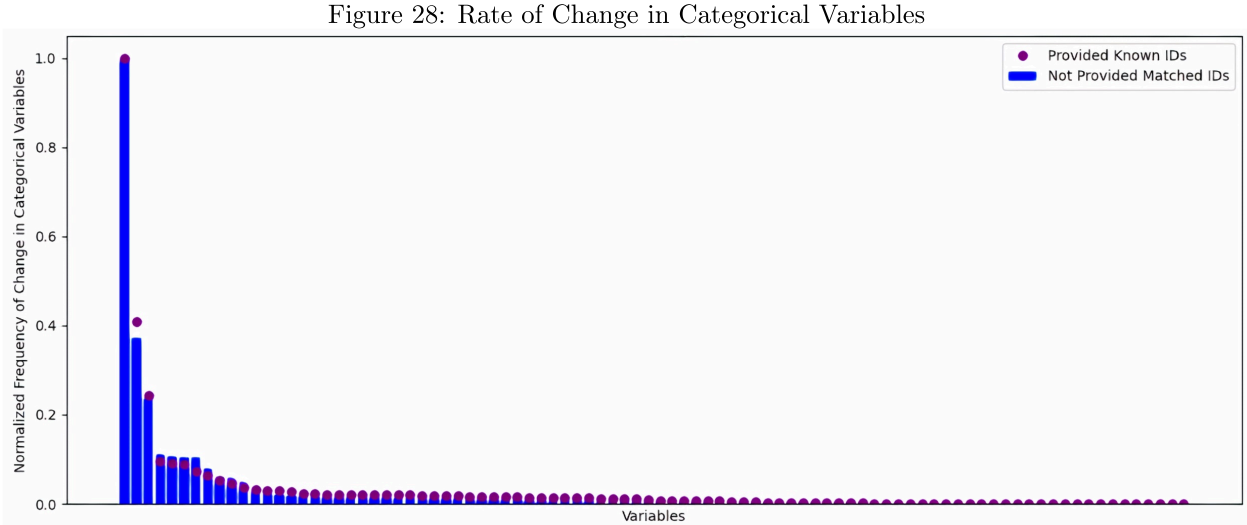
Figure 27: Top 20 Feature Importances in the Random Forest Model



Note: This figure visualizes the relative importance of the top 20 features used by the Random Forest model. Features are ranked based on their impact on model performance, offering insights into the variables most predictive of match accuracy.

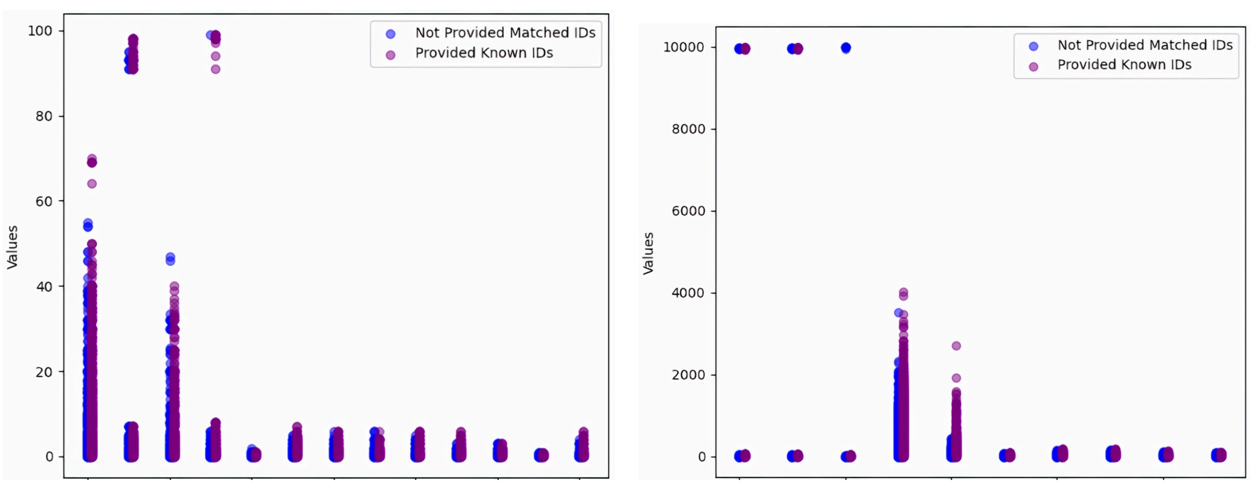
The best parameters from the grid search were then applied to predict the likelihood of 'correct' matches for individuals without an ID. Consequently, we successfully matched the remaining observations from the deterministic matching step, with only 0.8% of observations unmatched in Q3 and 2.2% in Q4 2022.

Figure 28: Rate of Change in Categorical Variables



This figure contrasts the rates of change in categorical variables—each column represents a variable—for matched individuals with known IDs against those without IDs. This comparison serves as a quality check, indicating the high accuracy of the matching process.

Figure 29: Rate of Change in Continuous Variables



(a) Low Variance Variables

(b) High Variance Variables

Note: This figure contrasts the rates of change in continuous variables—each column represents a variable—for matched individuals with known IDs against those without IDs. Panel (a) reports on variables with low variance, and panel (b) focuses on those with high variance. We report them separately because combining them would obscure the trends in variables with low variance. This comparison serves as a quality check, indicating the high accuracy of the matching process.

To evaluate the accuracy of our matching for individuals without known IDs, we compared the rate of change in variables against those from 'correct' matches. This comparative analysis for continuous and categorical variables, presented in Figures 29 and 28 respectively, showed that the distributions of variable changes for matched individuals were remarkably similar to those in the 'correct' matches dataset. Any slight variances in continuous variables were likely due to the smaller sample size of matched individuals, less than 10% of the 'correct' matches dataset. This comparison serves as a quality check, reassuring us that the matching process was highly accurate.

E Appendix: Calculating the Average Treatment

We calculate the **Average Treatment**$_d^{I,II,\text{ or } III}$ as the mean treatment dose received by each district during the third and fourth quarters of 2022. This method provides a consistent average treatment dose for each district, capturing the intensity level at which it is treated. The decision to average the doses over the last two quarters, rather than all four quarters of 2022, more accurately differentiates between districts that maintained consistent treatment levels and those whose treatments were discontinued in the latter half of the year. Tables 15 to 17 list the districts categorised by their average treatment doses for Average Treatment$^{I,II,\text{ or } III}d, respectively.$

Table 15: Districts by Average Treatment Doses^I

Average Treatment I			
Dose 1%	Dose 2%	Dose 3%	Dose ≥ 4%
Blansko	Benesov	Beroun	Cheb
Breclav	Ceske Budejovice	Brno-mesto	Mlada Boleslav
Brno-venkov	Cesky Krumlov	Karlovy Vary	Plzen-jih
Chomutov	Hradec Kralove	Klatovy	Plzen-mesto
Chrudim	Jicin	Praha	Tachov
Domazlice	Jihlava	Beroun	Cheb
Havlickuv Brod	Kutna Hora	Brno-mesto	Mlada Boleslav
Jindrichuv Hradec	Liberec	Karlovy Vary	Plzen-jih
Kladno	Nachod	Klatovy	Plzen-mesto
Kolin	Novy Jicin	Praha	Tachov
Melnik	Ostrava-mesto		
Nymburk	Pisek		
Pribram	Plzen-sever		
Rokycany	Praha-vychod		
Strakonice	Rakovnik		
Sumperk	Rychnov nad Kneznou		
Svitavy	Semily		
Uherske Hradiste	Tabor		
Znojmo	Usti nad Orlici		
	Zlin		

Table 16: Districts by Average Treatment Doses^{II}

Average Treatment II			
Dose 1%	Dose 2%	Dose 3%	Dose ≥ 4%
Blansko	Benesov	Beroun	Mlada Boleslav
Brno-venkov	Breclav	Brno-mesto	Plzen-jih
Chomutov	Ceske Budejovice	Cesky Krumlov	Plzen-mesto
Chrudim	Domazlice	Cheb	Tachov
Havlickuv Brod	Hradec Kralove	Karlovy Vary	
Hodonin	Jicin	Klatovy	
Kladno	Jihlava	Liberec	
Kolin	Kutna Hora	Rakovnik	
Melnik	Louny		
Pelhrimov	Nachod		
Praha-zapad	Novy Jicin		
Pribram	Nymburk		
Sumperk	Pardubice		
Svitavy	Pisek		
Uherske Hradiste	Plzen-sever		
Vsetin	Prachatice		
Vyskov	Praha		
Znojmo	Praha-vychod		
	Rokycany		
	Rychnov nad Kneznou		
	Semily		
	Strakonice		
	Tabor		
	Teplice		
	Usti nad Orlici		
	Zlin		

Table 17: Districts by Average Treatment Doses^{III}

Average Treatment III			
Dose 1%	Dose 2%	Dose 3%	Dose ≥ 4%
Benesov	Beroun	Brno-mesto	Mlada Boleslav
Blansko	Cesky Krumlov	Plzen-mesto	Tachov
Breclav	Cheb		
Jihlava	Hradec Kralove		
Novy Jicin	Karlovy Vary		
Nymburk	Klatovy		
Pisek	Kutna Hora		
Plzen-sever	Liberec		
Pribram	Plzen-jih		
Semily	Praha		
Strakonice	Rakovnik		
Sumperk	Usti nad Orlici		
Tabor			

F Appendix: Overview of the Extended Difference-in-Difference Estimators (DiD)

Testing for Potential Bias from Negative Weights in TWFE Regression Treatment Effects. Utilising the test proposed by de Chaisemartin and d'Haultfoeuille (2017), we evaluate the influence of negative weights on our treatment effects.[26] This command calculates weights and sensitivity measures for the fixed-effects regression under the common trends assumption, indicating potential bias in our Average Treatment on the Treated (ATT) estimates due to negative weights, particularly with regard to weekly hours worked.

In the case of "employment status" and considering only a sub-sample of the data experiencing positive treatment doses, the ATT is the weighted sum of 106 999, 114 948, and 86 576 effects for $Treatment^{I}$, $Treatment^{II}$, and $Treatment^{III}$, respectively. Here, 53 572 (53 373 and 58 822) effects receive positive weights, while 53 427 (61 575 and 27 754) receive negative weights. The total negative weight is -0.1519 (-0.1899 and -0.1541), affecting the overall ATT, given that all weights sum to unity. The TWFE coefficient (β_{fe}) is noted as -0.0000 (0.0001 and -0.0005), suggesting a negligible negative average effect of the treatment on the treated. The minimum standard deviation ($\sigma(\Delta)$) compatible with both a zero average treatment effect ($\Delta_{TR} = 0$) and an average treatment effect of a different sign is 0.0000 (0.0000 and 0.0002), and 0.0000 (0.0001 and 0.0008), respectively, indicating that minor heterogeneity in treatment effects could cause the TWFE coefficient to deviate from the ATT. Despite the predominance of positive weights, the slight negative influence highlighted by β_{fe} suggests a potentially adverse average effect of the treatment, albeit minimal. The findings for "unemployment and inactivity statuses" follow a similar pattern.

Concerning the "weekly hours worked status", the situation becomes even more pronounced. For instance, Treatment I shows a nearly even division between positive (28 355) and negative (28 314) weights, leading to a modestly positive TWFE coefficient ($\beta_{fe} = 0.0262$). The minimum standard deviations ($\sigma(\Delta)$) needed to correspond with a non-existent average treatment effect ($\Delta_{TR} = 0$) and one of an opposing sign are relatively low at 0.0074 and 0.0389, respectively, highlighting slight yet notable heterogeneity in treatment effects. Treatment II features more negative (32,830) than positive weights (28 011), with a TWFE coefficient of 0.0253. The minimum $\sigma(\Delta)$ for a null effect and for an effect of a different sign are 0.0069 and 0.0325, suggesting that even minimal variations in treatment effects could alter the observed positive TWFE coefficient. Treatment III is distinguished by a larger number of positive weights (31 082) compared to negative ones (14 703), and the TWFE coefficient increases to 0.0630, indicating a significantly positive treatment effect. The necessary $\sigma(\Delta)$ for a null effect and for one of a different sign are notably higher at 0.0201 and 0.0986, demonstrating greater heterogeneity in treatment effects for this group.

These results, especially the considerable proportion of negative weights, underline the importance of closely examining the TWFE coefficients' sensitivity to treatment effect heterogeneity. Such a balance of weights could reflect underlying differences in the treatment's effectiveness across various

[26] Implemented with the Stata command "twowayfeweights". For details, see de Chaisemartin et al. (2023a).

sub-populations and periods. Based on the assumption of uniform treatment effects, which might not align with reality, these variances could challenge the causal interpretation of β_{fe}.

The Extended Difference-in-Difference Estimators (DiD) in our Setting. The notation used below aligns with that of de Chaisemartin and d'Haultfoeuille (2024), with slight modifications for compatibility with the TWFE section of our paper. We observe labour market outcomes for an individual ('local'), denoted as i, in district d, across multiple quarters t, as reported by the LFSS dataset. Since the LFSS is a rotating panel, only data from the 1$^{\text{st}}$ quarter of 2021 to the 4$^{\text{th}}$ quarter of 2022 are used to estimate the AVSQ effects of the 2022 Ukrainian refugees' employment on the labour market outcomes for Czech locals. The LFSS tracks an individual for up to five consecutive periods, allowing us to estimate the AVSQ effect by observing the same individual at least once pre-treatment and once during the treatment period. Individuals begin treatment at the earliest in the 1$^{\text{st}}$ quarter of 2022; therefore, data on individuals recorded before the 1$^{\text{st}}$ quarter of 2021 are disregarded as their observations would not coincide with the treatment period. Consequently, we utilise data from the 1$^{\text{st}}$ quarter of 2021 to the 4$^{\text{th}}$ quarter of 2022, resulting in a sample of 338,627 observations across 77 districts. Treatment is assigned to locals at the district level d, meaning all individuals within a district receive identical treatment doses at time t. To simplify notation, we exclude d and denote treatment as $D_{i,t}$ for individual i at time t.

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

$$\mathrm{DID}_{i,\ell} = Y_{i,F_i-1+\ell} - Y_{i,F_i-1} - \frac{1}{N^i_{F_i-1+\ell}} \sum_{i':D_{i',1}=D_{i,1},F_{i'}>F_i-1+\ell} \left(Y_{i',F_i-1+\ell} - Y_{i',F_i-1}\right), \qquad (10)$$

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

The pre-treatment period (or baseline treatment) for an individual i begins sometime before 2022, depending on when i is observed for the first time in the rotating panel. In our setting, it is always zero. This period continues until i experiences the first change in treatment. For instance, an individual might have been experiencing a treatment corresponding to 0% of refugees employed in their respective district for multiple quarters. Only when this treatment level changes for the first time does the individual begin to receive the "treatment" whose effect we aim to estimate. The timing of this change can vary among individuals. The DiD estimator then compares the F_i-1-to-$F_i-1+\ell$ outcome evolution of individual i, for whom the treatment changes, to the average outcome evolutions of individuals i' with the same baseline treatment level as i, who are either never treated or whose treatment has not changed yet by $F_i - 1 + \ell$. We can estimate the instantaneous, dynamic and inter-temporal effects of the treatment for all feasible $\ell \in \{1, \dots, \max(\ell)\}$ periods. In our setting, $\max(\ell)$ is 4 periods, i.e., from the 1st to the 4th quarter of 2022. But for those individuals who start receiving the treatment later than the 1st quarter of 2022, it is less.

Using the individual AVSQ effects estimated by DID for each individual i and location ℓ, we calculate the average effects for all treated individuals, distinguishing between 'Switchers in' and 'Switchers out'. 'Switchers in' are defined as districts where, at a specific time, the treatment level increases for the first time from zero to a positive value or remains above the baseline in subsequent periods. Conversely, 'Switchers out' refer to districts that have experienced a reduction in treatment dose at any point.

The estimated values for each individual and location are aggregated and then averaged across all individuals for each location, taking into account the total number of individuals the estimates were derived from. This process involves summing the individual effects and weighting them by the total number of individuals, adjusting the sign of the estimated effect based on whether the district is classified as 'Switchers in' (positive sign) or 'Switchers out' (negative sign).

Under such specification, the estimator does not distinguish between individuals treated more or less intensely. TTo compare the estimated average AVSQ effects for each location with results from the TWFE regression, we follow a suggested by de Chaisemartin and d'Haultfoeuille (2024) and divide the estimated effects obtained with $\text{DID}_{i,\ell}$ by the difference between the total treatment dose received by individual i from F_i to $F_i - 1 + \ell$, and the total treatment dose he/she would have received in the status-quo counterfactual.

For instance, if the maximum number of periods under consideration is 4, the normalization involves calculating the total treatment dose received by an individual over these periods and comparing it to the baseline scenario where no treatment was administered. This comparison yields the normalized actual-versus-status-quo (nAVSQ) effect, which we interpret as an average total effect per unit of treatment, as suggested in the literature.

G Appendix: Calculating the Pre-Treatment Trends for the Variables of Interest

We estimate the seasonally adjusted trends of weekly hours worked, the employment rate, the unemployment rate, and the inactivity rate for each of the 77 districts within the Czech Republic. The analysis utilises LFS panel data limited to the pre-treatment period from the first quarter of 2019 to the fourth quarter of 2021. The approach involves estimating the slope of weekly hours worked over time for each district separately, allowing for district-specific temporal trends and controlling for seasonal effects. The econometric model used to estimate these slopes, adjusted for seasonal variations, is specified as follows:

$$y_{i,d,t} = \alpha_d + \beta_d \cdot t + \sum_{q=1}^{4} \gamma_{d,q} \cdot \mathrm{I}(Q_t = q) + \epsilon_{i,d,t}, \quad t \in \{1\mathrm{Q}\ 2019, \ldots, 4\mathrm{Q}\ 2021\}, \tag{11}$$

where $y_{i,d,t}$ represents the outcome of interest for individual i in district d at time t, indicating one of the four variables of interest: hours worked, employment, unemployment, and inactivity rates. The model is estimated separately for each variable of interest. The parameter α_d is the district-specific intercept, and β_d signifies the slope of the respective outcome over time, delineating the temporal trend within each district for that particular labour market variable. The quarter fixed effects, $\gamma_{d,q}$, adjust for seasonal variations, ensuring the trend represented by t accurately reflects the underlying changes. The error term, $\epsilon_{i,d,t}$, captures unobserved factors affecting each outcome for individual i in district d at time t, over the specified period.

The resulting variable is continuous. We transform it into a categorical variable through 'scaled discretisation', which involves multiplying the continuous variable by a selected factor and rounding the result to the nearest integer to create categories. Tables 18 to 21 report the generated categories, with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts categorised into the same category cell.

Table 18: District-Specific Pre-Treatment Trends for Unemployment Rate

District-specific pre-treatment trends	Min	Max	Observ	Mean	Std. dev.	Average Unemployment
-2	-0.002	-0.002	4,332	-0.002	-	0.013
-1	-0.001	-0.001	73,190	-0.001	0.000	0.016
0	-0.000	0.000	246,052	0.000	0.000	0.010
1	0.001	0.001	296,321	0.001	0.000	0.013
2	0.002	0.002	56,654	0.002	0.000	0.020
3	0.004	0.004	5,349	0.004	-	0.024

Note: This figure depicts district-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 19: District-Specific Pre-Treatment Trends for Employment Rate

District-specific pre-treatment trends	Min	Max	Observ	Mean	Std. dev.	Average Employment
-6	-0.013	-0.011	15,945	-0.012	0.001	0.515
-5	-0.009	-0.009	4,376	-0.009	-	0.463
-4	-0.009	-0.008	42,222	-0.008	0.000	0.502
-3	-0.006	-0.005	85,565	-0.006	0.000	0.530
-2	-0.005	-0.003	124,699	-0.004	0.001	0.509
-1	-0.003	-0.001	115,069	-0.002	0.001	0.531
0	-0.001	0.000	168,186	-0.000	0.000	0.518
1	0.001	0.002	86,365	0.002	0.000	0.512
2	0.003	0.004	28,351	0.004	0.000	0.513
3	0.006	0.006	6,788	0.006	-	0.489
4	0.014	0.014	4,332	0.014	-	0.500

Note: This figure depicts district-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 20: District-Specific Pre-Treatment Trends for Inactivity Rate

District-specific pre-treatment trends	Min	Max	Observ	Mean	Std. dev.	Average Inactivity
-4	-0.012	-0.012	4,332	-0.012	-	0.488
-3	-0.007	-0.007	6,788	-0.007	-	0.502
-2	-0.005	-0.003	35,096	-0.004	0.001	0.497
-1	-0.003	-0.001	138,580	-0.002	0.001	0.464
0	-0.001	0.001	99,182	-0.000	0.001	0.469
1	0.001	0.003	183,833	0.002	0.001	0.467
2	0.003	0.005	119,243	0.004	0.001	0.464
3	0.006	0.007	32,301	0.006	0.001	0.462
4	0.007	0.009	37,991	0.008	0.001	0.493
5	0.009	0.011	18,214	0.010	0.001	0.472
6	0.011	0.011	6,338	0.011	-	0.461

Note: This figure depicts district-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 21: District-Specific Pre-Treatment Trends for Weekly Hours Worked

District-specific pre-treatment trends	Min	Max	Observ	Mean	Std. dev.	Average Weekly Hours Worked
-3	-0.28	-0.27	11,964	-0.28	0.00	41.04
-2	-0.20	-0.16	59,259	-0.18	0.02	39.84
-1	-0.14	-0.05	354,403	-0.10	0.03	39.41
0	-0.05	0.03	210,027	-0.01	0.02	39.36
1	0.06	0.12	40,662	0.09	0.02	39.68
2	0.19	0.19	5,332	0.19	-	40.14

Note: This figure depicts district-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 10 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Demographic Analysis: To further explore the impact of demographic factors, we extend the model for gender ($Pohl$) and education level ($ISCED$) as follows:

$$y_{i,d,t,p,e} = \alpha_{d,p,e} + \beta_{d,p,e} \cdot t + \sum_{q=1}^{4} \gamma_{d,q,p,e} \cdot \mathrm{I}(Q_t = q) + \epsilon_{i,d,t,p,e}, \tag{12}$$

where p and e index gender and education level, respectively, adding a further level of detail. Tables 22 to 25 report the generated categories, along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts categorised into the same category cell.

Table 22: District-, Gender-, Education-Specific Pre-Treatment Trends for Employment Rate

District-, gender-, and education-specific pre-treatment	Min	Max	Observ	Mean	Std. dev.	Average Employment
-16	-0.034	-0.034	777	-0.034	0.000	0.667
-15	-0.029	-0.029	429	-0.029	-	0.706
-14	-0.029	-0.028	795	-0.028	0.001	0.713
-13	-0.026	-0.025	3,561	-0.026	0.001	0.481
-12	-0.024	-0.024	422	-0.024	-	0.701
-11	-0.022	-0.021	9,320	-0.021	0.000	0.484
-10	-0.021	-0.019	7,397	-0.020	0.001	0.527
-9	-0.019	-0.017	14,672	-0.018	0.001	0.498
-8	-0.017	-0.015	10,986	-0.016	0.001	0.526
-7	-0.015	-0.013	19,259	-0.014	0.000	0.527
-6	-0.013	-0.011	23,396	-0.012	0.000	0.542
-5	-0.011	-0.009	53,673	-0.010	0.000	0.536
-4	-0.009	-0.007	53,468	-0.008	0.001	0.442
-3	-0.007	-0.005	43,695	-0.006	0.001	0.492
-2	-0.005	-0.003	69,136	-0.004	0.001	0.535
-1	-0.003	-0.001	92,044	-0.002	0.001	0.528
0	-0.001	0.001	71,557	0.000	0.001	0.520
1	0.001	0.003	61,797	0.002	0.001	0.540
2	0.003	0.005	53,273	0.004	0.001	0.518
3	0.005	0.007	24,168	0.006	0.001	0.536
4	0.007	0.009	17,277	0.008	0.001	0.513
5	0.009	0.011	15,754	0.010	0.000	0.478
6	0.011	0.013	12,099	0.012	0.001	0.531
7	0.013	0.015	9,068	0.014	0.000	0.477
8	0.015	0.016	1,884	0.016	0.000	0.578
9	0.017	0.019	4,721	0.018	0.000	0.511
10	0.019	0.020	1,818	0.020	0.000	0.542
11	0.021	0.023	1,444	0.022	0.001	0.483
12	0.023	0.025	878	0.024	0.001	0.654
13	0.025	0.027	998	0.026	0.001	0.390
14	0.028	0.028	1,315	0.028	-	0.531
15	0.036	0.036	416	0.036	0.000	0.454
16	0.037	0.037	266	0.037	-	0.827

Note: This figure depicts district-, gender-, and education-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 23: District-, Gender-, Education-Specific Pre-Treatment Trends for Unemployment Rate

District-, gender-, and education-specific pre-treatment	Min	Max	Observ	Mean	Std. dev.	Average Unemployment
-6	-0.018	-0.018	109	-0.018	-	0.037
-5	-0.010	-0.009	1,149	-0.010	0.000	0.040
-4	-0.007	-0.007	654	-0.007	-	0.035
-3	-0.007	-0.005	2,250	-0.006	0.001	0.025
-2	-0.005	-0.003	13,412	-0.004	0.001	0.018
-1	-0.003	-0.001	96,130	-0.002	0.001	0.015
0	-0.001	0.001	341,177	0.000	0.000	0.010
1	0.001	0.003	184,321	0.002	0.001	0.014
2	0.003	0.005	32,894	0.004	0.001	0.025
3	0.005	0.005	3,566	0.005	0.000	0.025
4	0.007	0.009	3,428	0.008	0.001	0.039
5	0.009	0.010	1,314	0.010	0.000	0.046
6	0.011	0.012	1,089	0.011	0.000	0.073
7	0.020	0.020	270	0.020	-	0.067

Note: This figure depicts district-, gender-, and education-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 24: District-, Gender-, Education-Specific Pre-Treatment Trends for Weekly Hours Worked

District-, gender-, and education-specific pre-treatment	Min	Max	Observ	Mean	Std. dev.	Average Weekly Hours Worked
-7	-2.45	-2.33	898	-2.42	0.05	33.67
-6	-1.27	-1.16	2,270	-1.20	0.04	38.15
-5	-1.06	-0.95	1,554	-1.03	0.05	36.54
-4	-0.90	-0.72	5,381	-0.79	0.07	38.01
-3	-0.68	-0.51	10,918	-0.54	0.04	40.98
-2	-0.49	-0.30	38,824	-0.37	0.05	40.75
-1	-0.30	-0.10	225,819	-0.18	0.05	39.90
0	-0.10	0.10	269,158	-0.02	0.06	39.19
1	0.10	0.30	90,120	0.18	0.06	38.77
2	0.31	0.47	19,561	0.37	0.05	38.81
3	0.51	0.70	5,829	0.64	0.07	37.84
4	0.71	0.90	3,567	0.80	0.07	38.02
5	0.90	0.99	4,257	0.95	0.03	37.90
6	1.13	1.16	880	1.14	0.02	38.75
7	1.44	1.44	448	1.44	-	36.74
8	1.56	1.70	1,240	1.62	0.07	33.64

Note: This figure depicts district-, gender-, and education-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 5 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Table 25: District-, Gender-, Education-Specific Pre-Treatment Trends for Inactivity Rate

District-, gender-, and education-specific pre-treatment	Min	Max	Observ	Mean	Std. dev.	Average Inactivity
-17	-0.041	-0.041	230	-0.041	-	0.678
-16	-0.037	-0.037	266	-0.037	-	0.173
-15	-0.036	-0.036	186	-0.036	-	0.349
-14	-0.028	-0.028	1,315	-0.028	-	0.463
-13	-0.027	-0.025	1,405	-0.026	0.001	0.621
-12	-0.025	-0.025	631	-0.025	0.000	0.464
-11	-0.023	-0.023	570	-0.023	-	0.395
-10	-0.021	-0.019	2,822	-0.020	0.000	0.521
-9	-0.019	-0.017	4,598	-0.018	0.001	0.475
-8	-0.015	-0.015	1,053	-0.015	0.000	0.406
-7	-0.015	-0.013	8,064	-0.014	0.001	0.465
-6	-0.013	-0.011	14,470	-0.012	0.001	0.441
-5	-0.011	-0.009	21,297	-0.010	0.000	0.514
-4	-0.009	-0.007	20,617	-0.008	0.001	0.460
-3	-0.007	-0.005	27,217	-0.006	0.001	0.472
-2	-0.005	-0.003	67,619	-0.004	0.001	0.451
-1	-0.003	-0.001	48,855	-0.002	0.001	0.478
0	-0.001	0.001	97,344	0.000	0.001	0.456
1	0.001	0.003	78,015	0.002	0.001	0.469
2	0.003	0.005	59,226	0.004	0.001	0.447
3	0.005	0.007	45,922	0.006	0.001	0.505
4	0.007	0.009	46,754	0.008	0.001	0.506
5	0.009	0.011	40,996	0.010	0.001	0.463
6	0.011	0.013	33,928	0.012	0.001	0.475
7	0.013	0.015	13,519	0.014	0.001	0.396
8	0.015	0.017	9,942	0.016	0.000	0.468
9	0.017	0.019	10,539	0.018	0.000	0.513
10	0.019	0.021	13,208	0.020	0.001	0.518
11	0.021	0.023	5,300	0.022	0.001	0.449
12	0.023	0.024	1,315	0.023	0.000	0.411
13	0.026	0.027	2,246	0.027	0.000	0.565
14	0.028	0.028	1,088	0.028	0.000	0.393
15	0.030	0.030	429	0.030	-	0.291
16	0.035	0.035	372	0.035	-	0.371
17	0.040	0.040	405	0.040	-	0.274

Note: This figure depicts district-, gender-, and education-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 500 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.

Sectoral Analysis: The model is further refined to examine sector-specific dynamics within each district, accounting for the main industry sector ($NACE$):

$$y_{i,d,t,n} = \alpha_{d,n} + \beta_{d,n} \cdot t + \sum_{q=1}^{4} \gamma_{d,q,n} \cdot \mathrm{I}(Q_t = q) + \epsilon_{i,d,t,n}, \tag{13}$$

with n indexing the NACE-level 1 industry sector (21 categories). Table 26 presents the generated categories, alongside the minimum and maximum for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts categorised into the same category cell.

Table 26: District- and Industry-Specific Pre-Treatment Trends for Weekly Hours Worked

District- and industry-specific pre-treatment	Min	Max	Observ	Mean	Std. dev.	Average Weekly Hours Worked
-5	-5.14	-5.00	40	-5.10	0.06	44.75
-4	-4.23	-3.69	78	-3.78	0.20	37.39
-3	-2.86	-2.79	67	-2.82	0.04	36.22
-2	-2.45	-1.54	803	-1.89	0.29	45.01
-1	-1.49	-0.50	19,341	-0.74	0.24	40.92
0	-0.50	0.50	319,602	-0.06	0.18	39.42
1	0.50	1.46	10,991	0.77	0.26	38.82
2	1.53	2.32	741	1.87	0.28	37.96
3	2.58	3.33	80	2.82	0.34	36.06
4	4.80	5.33	35	5.11	0.24	35.37
5	6.49	6.49	14	6.49	-	37.14

Note: This figure depicts district-, gender-, and education-specific pre-treatment trends for the employment rate. The continuous variable was transformed into categories using a process of 'scaled discretisation', where it was multiplied by a factor of 1 and then rounded to the nearest integer. The table reports the resulting categories along with the minimum and maximum values for the continuous variable, the number of observations, mean, standard deviation, and the average for the variable of interest in districts that were categorised into the same category cell.