

Appendix

The effect of Ukrainian refugees on the local labour markets: the case of Czechia The Effect of Ukrainian Refugees on Local Labour Markets in Czechia

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A Appendix: Overview of the Variables Used in the Analysis

Table A.1 provides an overview of the variables used in the analysis and their respective sources.

Table A.1: Description and Sources of the Variables Used in the Analysis

Variables	Description & Source
Variables of Interest (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_t 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_t 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_t 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_t 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 authors, defined as number of job openings divided by the number of job seekers. Sourced from the Czech Statistical Office (2023).
Unemployment Rate	Continuous: Sourced from the Czech Statistical Office (2023).

The Labour Force Sample Survey Coverage and Population Scope. The Labour Force Sample Survey (LFSS), according to its quality report (Czech Statistical Office, 2023a), covers individuals aged 15 and above living in private households across the country. Below are the key aspects of the survey’s coverage:

Who Is Included: The survey includes all individuals living in private households, whether they reside there permanently, temporarily, or even if they are not officially registered. Temporarily absent individuals, defined as those who plan to be away for no more than one year, are also included, as well as domestic servants residing in the household. The sample population is stratified by age, gender, and region using NUTS-3 classifications, ensuring a representative sample across geographic and demographic groups. In 2020, for example, the total sample size was 95,500 households annually, with 33,900 households sampled quarterly.

Who Is Excluded: The survey excludes people residing in institutional households, such as dormitories, hospitals, and prisons. Additionally, individuals living in collective accommodations, such as migrant workers in communal housing, are not covered. Those in military service or conscripts are also outside the scope of the survey.

Who Is More Likely to Be Sampled: The survey primarily targets individuals in standard private living situations. Workers employed under formal, regular contracts are more likely to be captured, as the survey draws from a continuously updated register of census areas. Stratification by the 77 districts (NUTS-3 level) ensures that labour market data are representative by region and sector.

Potential Underrepresentation: Informally employed workers, particularly those engaged in casual or undocumented work, risk underreporting or failing to report their employment status, leading to data gaps. This is especially true for workers in precarious conditions, such as those on short-term contracts, temporary assignments, or seasonal jobs, who may not be fully captured by the survey if their employment falls outside the reference week or if they do not consider their employment significant enough to report. Migrants, especially those living in collective accommodation or engaged in informal labour, face additional challenges in being accurately captured, as they may not be included in household-based surveys or may withhold employment details due to fear of legal repercussions or other barriers.

B Appendix: Auxiliary Figures and Tables

Table B.1: Educational Attainment of Ukrainian Refugees Compared to the Czech Population

	Refugees			Locals				
	MoLSA	IOM	UNHCR	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: the MoLSA survey conducted by the Czech Ministry of Labour and Social Affairs (2022) in July with 50,236 respondents, the IOM (2023) survey, conducted from June to December 2022 with 4,284 responses across all Czech regions, and 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 B.2: 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	III	T	I	T	III	T	I	T	III	T	I	T	III
Benešov	1	1	0	1	1	1	1	1	1	1	1	1	1	2	2	1
Beroun	1	2	1	1	1	2	1	2	2	2	3	3	3	3	3	2
Blansko	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Břeclav	1	1	1	1	1	2	1	1	2	1	1	2	1	1	2	1
Brno-město	1	1	1	2	2	2	3	3	2	3	3	3	3	3	3	3
Brno-venkov	1	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1
Brunál	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Česká Lipa	0	0	0	0	1	0	1	0	1	0	1	1	1	1	1	1
České Budějovice	1	1	0	1	1	1	1	1	1	1	2	2	1	2	2	1
Český Krumlov	3	3	2	2	1	2	1	2	2	1	2	3	2	4	3	2
Cheb	3	2	2	1	0	1	3	2	2	4	3	2	2	4	3	2
Chomutov	2	2	1	0	0	1	1	0	0	1	0	0	1	0	0	0
Chrudim	1	2	1	1	1	0	1	1	0	0	1	0	1	0	1	0
Dečín	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Domažlice	1	2	0	0	1	0	0	2	0	1	2	0	1	2	0	0
Frydek-Místek	0	0	0	0	0	0	1	1	0	1	1	0	1	1	1	0
Havlíčkův Brod	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Hlavní město Praha	2	1	1	3	2	2	3	2	2	3	2	2	3	2	2	2
Hodonín	0	1	0	1	1	1	1	1	0	1	1	0	1	1	0	0
Hradec Králové	0	0	0	1	1	1	2	2	1	2	2	2	2	2	2	2
Jablonec nad Nisou	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1
Jeseník	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Jičín	0	1	0	1	1	1	1	2	2	1	2	2	1	2	2	1
Jihlava	2	1	1	1	1	1	2	2	1	2	2	1	2	2	1	1
Jindřichův Hradec	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Karlovy Vary	1	1	1	2	2	1	2	2	2	3	3	2	3	2	2	1
Karviná	0	0	0	0	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	1	1	1	1
Klatovy	1	1	1	2	1	2	1	2	3	2	3	3	2	3	2	2
Kolín	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Kroměříž	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Kutná Hora	2	2	1	2	2	1	2	2	2	2	2	2	1	1	1	1
Liberec	0	1	0	2	3	1	2	3	1	2	3	2	3	2	2	2
Litoměřice	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Louny	0	1	0	0	1	0	1	2	1	1	1	1	2	1	1	1
Mělník	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Mladá Boleslav	2	3	2	3	4	2	5	5	3	6	6	4	4	4	4	4
Most	0	0	0	0	0	0	1	1	0	1	0	1	1	0	1	0
Náchod	0	0	0	1	1	1	2	2	1	2	1	2	1	2	2	1

 - 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 B.3: Summary of the Results: Positive Treatment Doses—Weekly Hours Worked by Gender

Female	(1)		(2)		(3)		(4)		(5)		(6)		(9)		(7)		(8)		(10)													
	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II												
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)	(0.05)	(0.06)	(0.12)	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)		
	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		
	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		
	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		
	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	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	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	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	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	Y	Y	Y	Y	
Treatment	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	16,800	
	32,843	35,071	514,659	26,961	28,891	514,772	20,073	20,387	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	9,869	
	-	-	-	-	-	-	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	0.35	0.59	0.11	0.11	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	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																																
Male	(1)		(2)		(3)		(4)		(5)		(6)		(9)		(7)		(8)		(10)													
	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II												
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***	0.23***	
	(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)	(0.09)	(0.11)	(0.07)	(0.08)	
	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	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	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	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	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	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	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	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	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Treatment	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	20,891	
	37,386	39,959	514,659	30,905	33,159	514,772	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	12,212	
	-	-	-	-	-	-	0.84	0.38	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	0.18	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	-	-	-	-	-	-	4	4	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 4.3 (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, 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.

Table B.4: Summary of the Results Positive Treatment Doses–Probability of Employment, Unemployment Inactivity for Females

Female	(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
Treatment	0.000 (0.000)	0.000* (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	0.002 (0.004)	0.000 (0.003)	-0.004* (0.002)	0.000 (0.003)	-0.005* (0.002)	-0.005** (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003** (0.002)	-0.001 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.002 (0.002)	-0.001 (0.002)	-0.003* (0.002)	0.001 (0.002)	0.000 (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
Individual 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	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District, gender and education	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	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 switches x periods	72,931	77,939	59,572	58,961	63,266	514,772	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
Treatment	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.003)	-0.001 (0.003)	0.002 (0.002)	-0.002 (0.002)	0.001 (0.002)	0.003 (0.002)	-0.001 (0.002)	0.001 (0.003)	-0.002 (0.002)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.001 (0.002)	-0.001 (0.002)	0.000 (0.001)	-0.002 (0.001)	-0.002 (0.002)	0.000 (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
Individual 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	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District, gender and education	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	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 switches x periods	72,931	77,939	59,572	58,961	63,266	514,772	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
Treatment	-0.000 (0.000)	-0.000* (0.000)	0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.001)	-0.001 (0.004)	0.001 (0.003)	0.003 (0.002)	0.001 (0.002)	-0.001 (0.003)	0.003 (0.002)	0.000 (0.002)	0.004 (0.002)	-0.001 (0.003)	0.000 (0.003)	0.002 (0.003)	0.003 (0.003)	0.001 (0.002)	0.002 (0.002)	-0.000 (0.003)	0.002 (0.002)	0.001 (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
Individual 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	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District, gender and education	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
pre-treatment trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	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 switches x periods	72,931	77,939	59,572	58,961	63,266	514,772	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

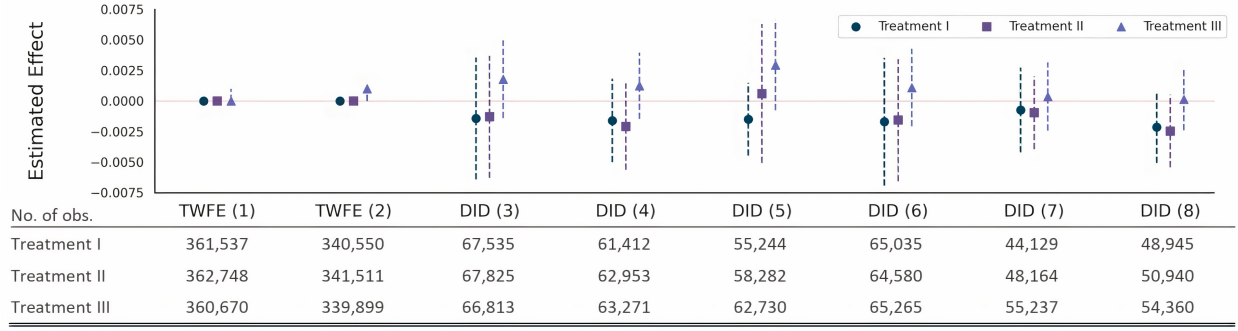
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table displays coefficient estimates, standard errors (in parentheses), observation counts, classifications of the extensions, and the p-values from placebo tests for the parallel trends assumption for ATT and nAVSQ across TWFE model in Section 4.3 (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.

Table B.5: Summary of the Results Positive Treatment Doses-Probability of Employment, Unemployment Inactivity for Males

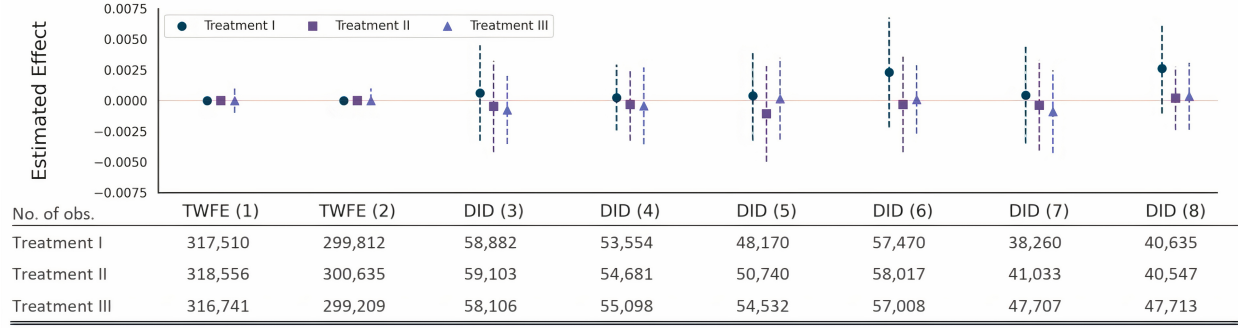
Male	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	I	II	I	II	I	II	I	II	I	II	I	II	I	II	I	II
Treatment	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.002 (0.002)	-0.000 (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.000 (0.002)	0.000 (0.002)	-0.002 (0.002)	-0.004 (0.003)	-0.001 (0.001)	-0.000 (0.001)	0.001 (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
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics																
District pre-treatment trends																
District, gender and education																
pre-treatment trends																
No. of observations	317,510	318,556	316,741	299,812	58,882	59,103	58,106	53,554	54,681	55,098	41,486	44,539	46,676	47,095	52,386	24,396
No. of switchers x periods	63,725	68,090	51,741	51,698	40,075	41,079	34,251	36,264	37,911	32,577	26,958	29,971	27,879	30,159	31,948	15,171
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	0.32	0.07
No. of effects estimated	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4
Unemployment probability																
Treatment	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.001 (0.002)	-0.000 (0.002)	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.002)	0.000 (0.002)	0.002 (0.002)	-0.000 (0.002)	0.000 (0.001)	-0.000 (0.002)	0.003 (0.002)	0.000 (0.001)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics																
District pre-treatment trends																
District, gender and education																
pre-treatment trends																
No. of observations	317,510	318,556	316,741	299,812	58,882	59,103	58,106	53,554	54,681	55,098	48,170	50,740	54,532	57,470	57,008	40,635
No. of switchers x periods	63,725	68,090	51,741	51,698	40,075	41,079	34,251	36,264	37,911	32,577	31,616	34,235	33,314	40,427	33,894	26,456
Parallel trends test p-value	-	-	-	-	0.85	0.75	0.07	0.05	0.98	0.99	0.77	0.78	0.39	0.60	0.37	0.98
No. of effects estimated	-	-	-	-	4	4	4	4	4	4	4	4	4	4	4	4
Inactivity probability																
Treatment	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.001 (0.002)	0.002* (0.001)	0.003* (0.002)	0.002* (0.001)	0.000 (0.001)	0.002 (0.002)	0.001 (0.001)	0.000 (0.002)	0.003 (0.002)	0.001 (0.001)	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
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics																
District pre-treatment trends																
District, gender and education																
pre-treatment trends																
No. of observations	317,510	318,556	316,741	299,812	58,882	59,103	58,106	53,554	54,681	55,098	44,446	41,721	48,862	43,498	50,523	24,331
No. of switchers x periods	63,725	68,090	51,741	51,698	40,075	41,079	34,251	36,264	37,911	32,577	29,748	27,769	29,274	27,137	30,207	14,688
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	0.02
No. of effects estimated	-	-	-	-	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 4.3 (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 B.1: Positive Treatment Doses—Probability of Unemployment by Gender



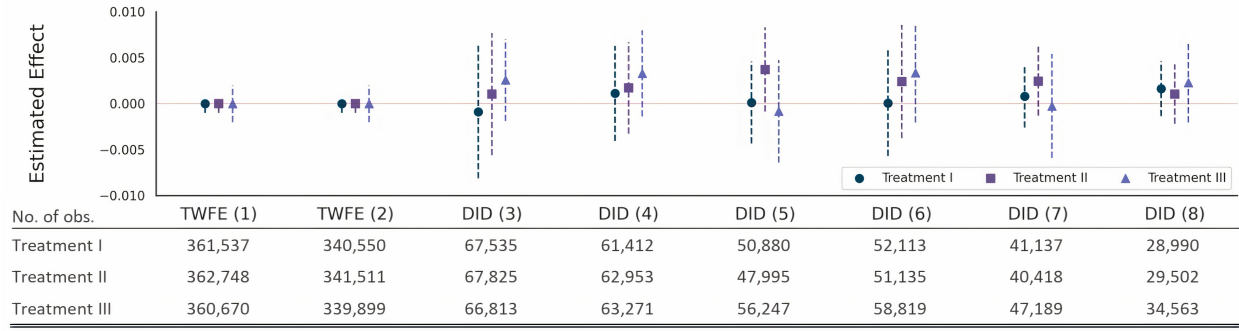
(a) Females



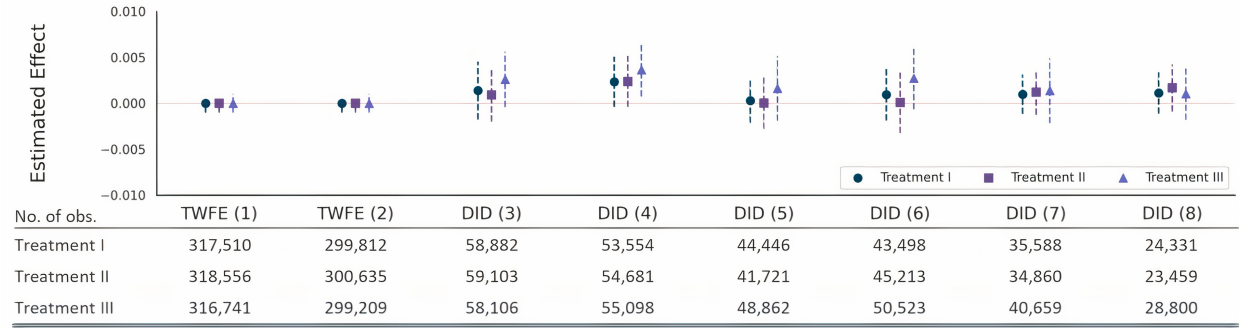
(b) Males

Note: The figure displays coefficient estimates, 95% level 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 4.3 (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 B.2: Positive Treatment Doses—Probability of Inactivity by Gender



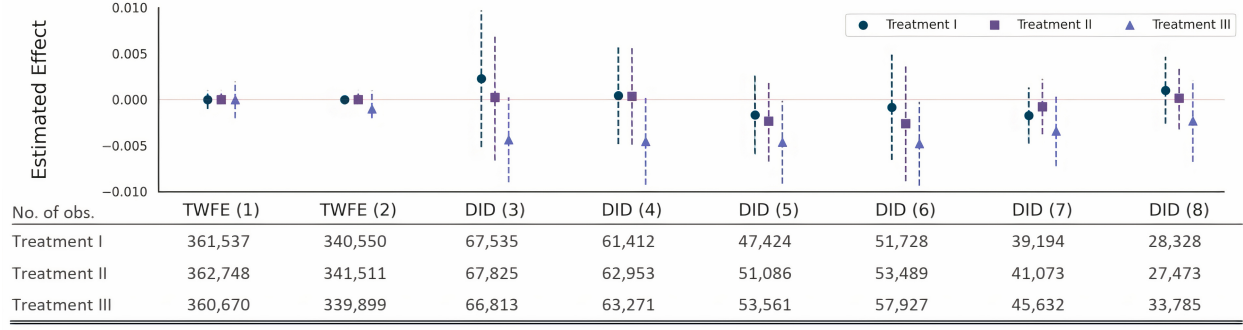
(a) Females



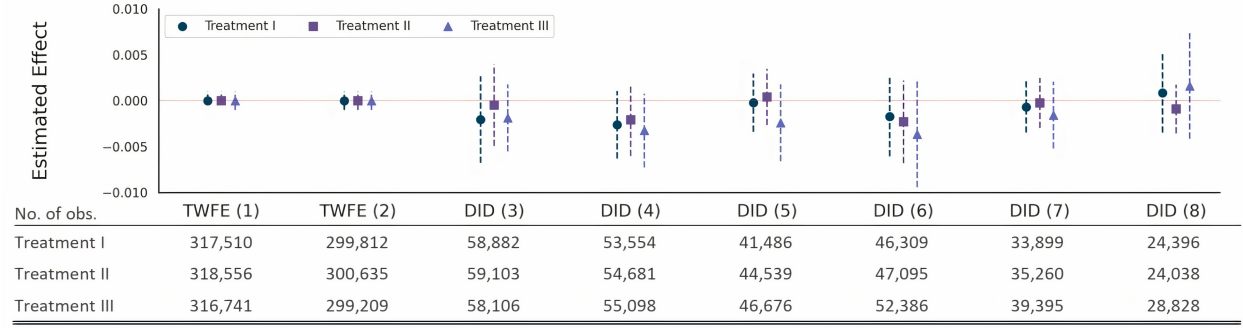
(b) Males

Note: The figure displays coefficient estimates, 95% level 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 4.3 (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 B.3: Positive Treatment Doses—Probability of Employment by Gender



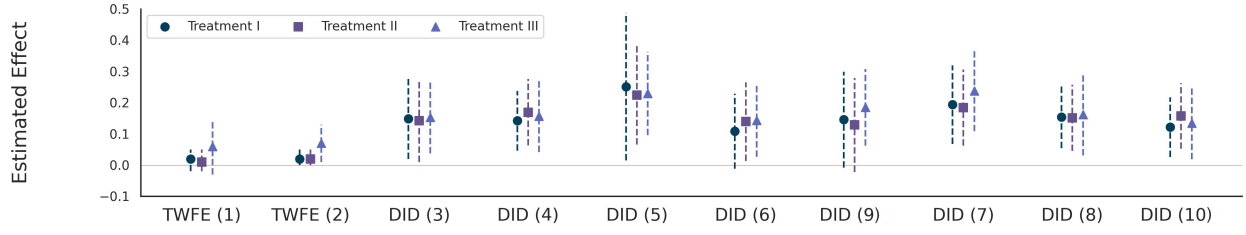
(a) Females



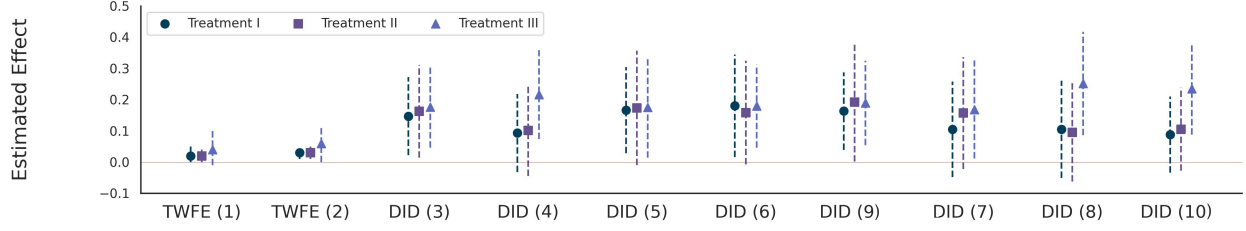
(b) Males

Note: The figure displays coefficient estimates, 95% level 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 4.3 (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 B.4: Positive Treatment Doses—Weekly Hours Worked by Gender



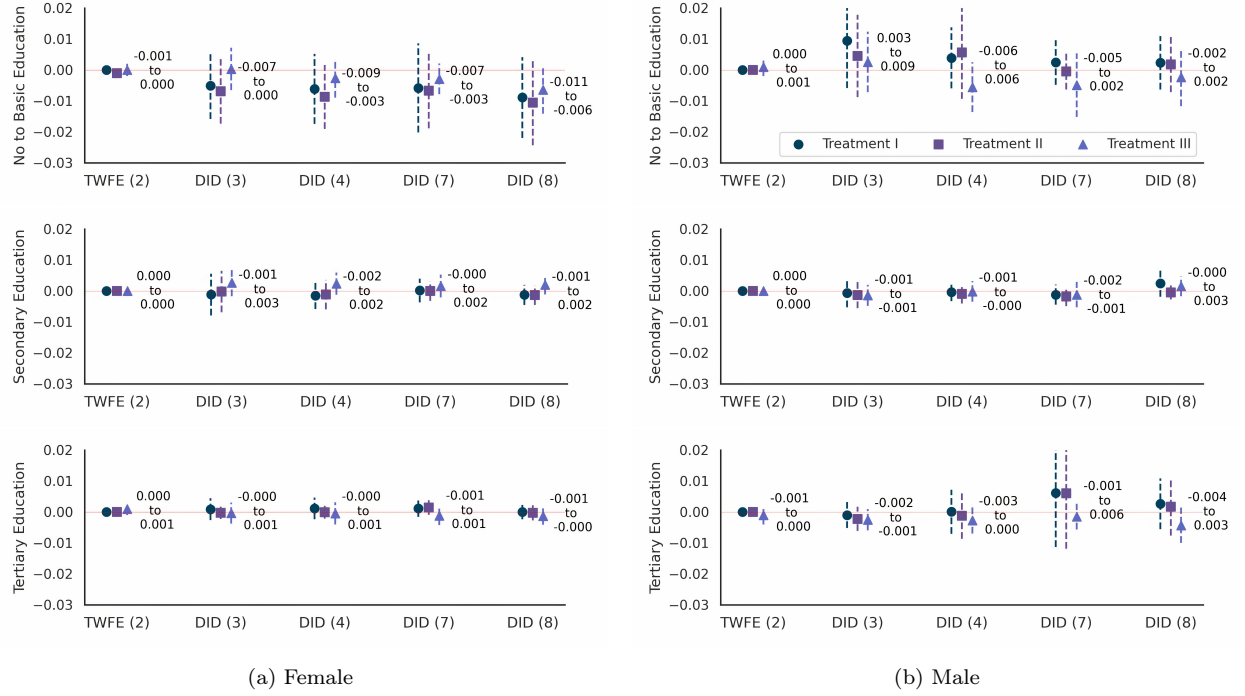
(a) Females



(b) Males

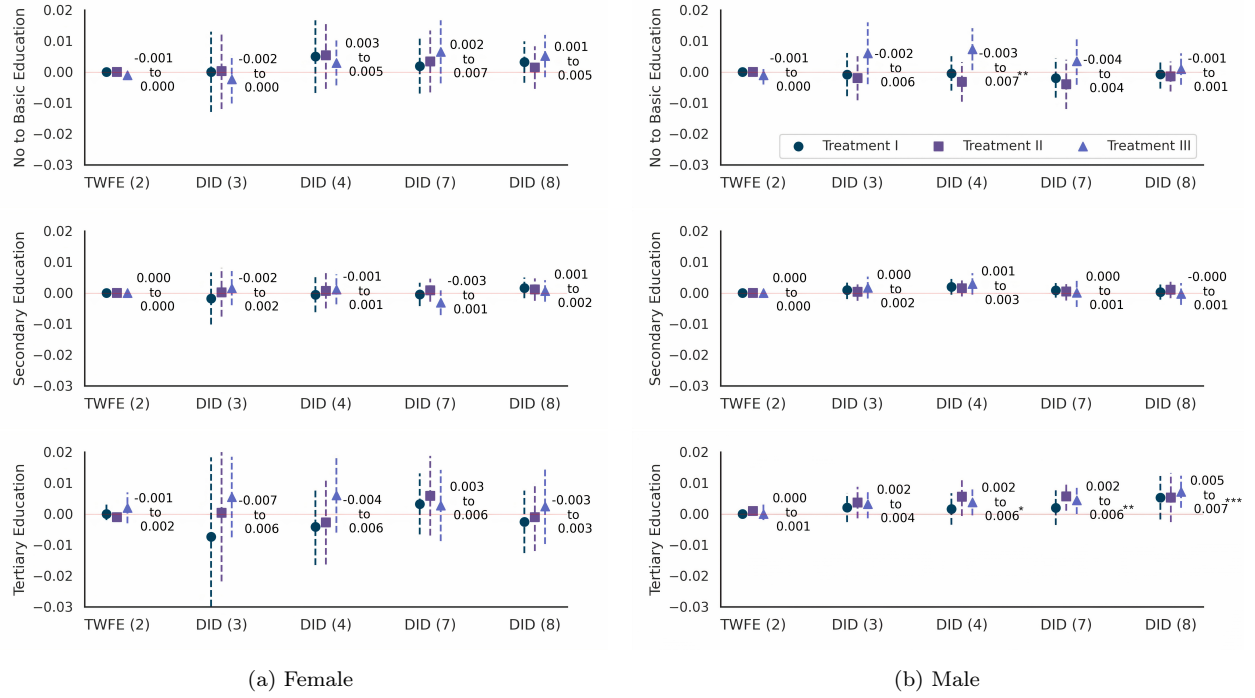
Note: The figure displays coefficient estimates, 95% level confidence intervals and observation counts for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.3 (columns 3-10) for Treatment I, II, and III. TWFE models control for: individual and time-fixed 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.

Figure B.5: Positive Treatment Doses—Probability of Unemployment by Gender & Education Level



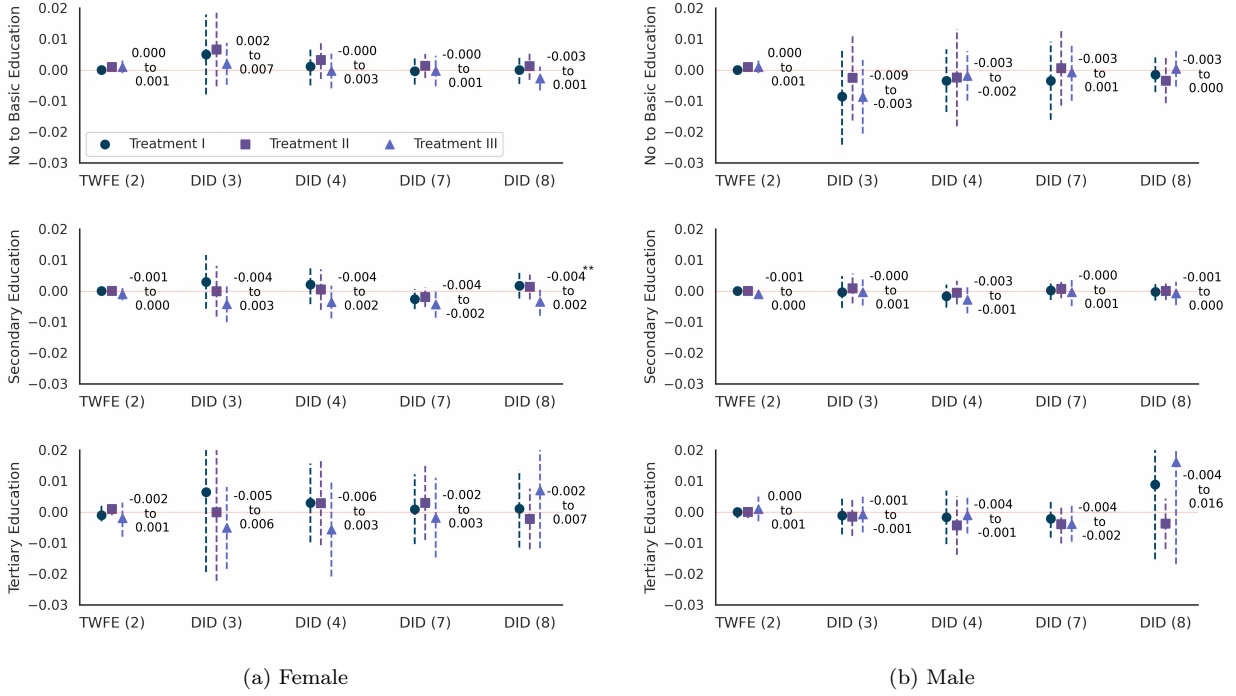
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (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 B.6: Positive Treatment Doses—Probability of Inactivity by Gender & Education Level



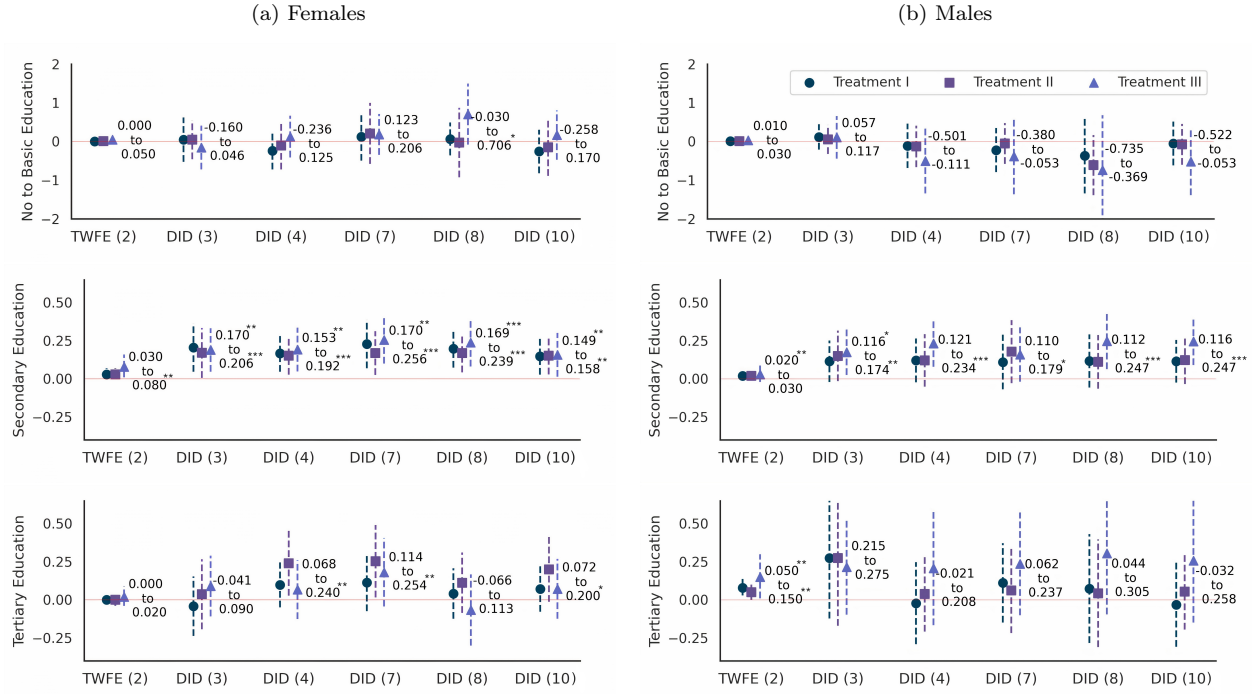
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (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 B.7: Positive Treatment Doses—Probability of Employment by Gender & Education Level



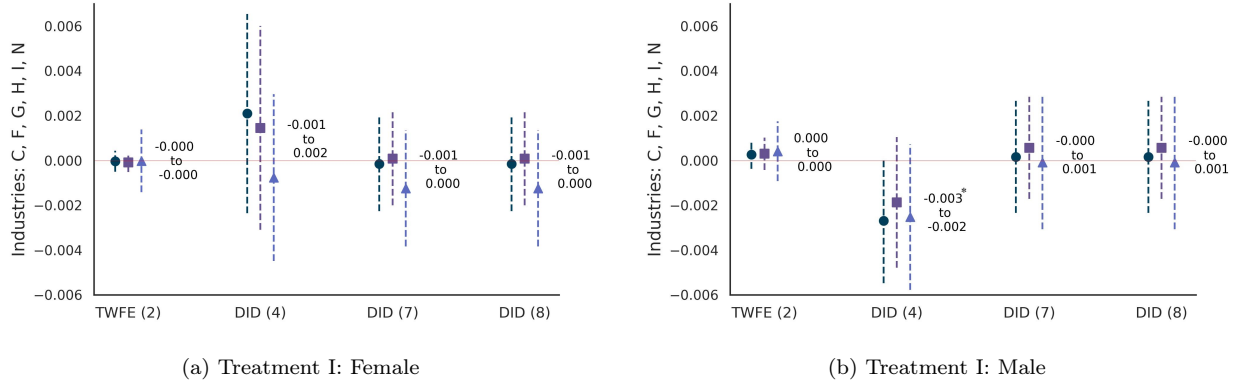
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (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 B.8: Positive Treatment Doses—Weekly Hours Worked by Gender & Education Level



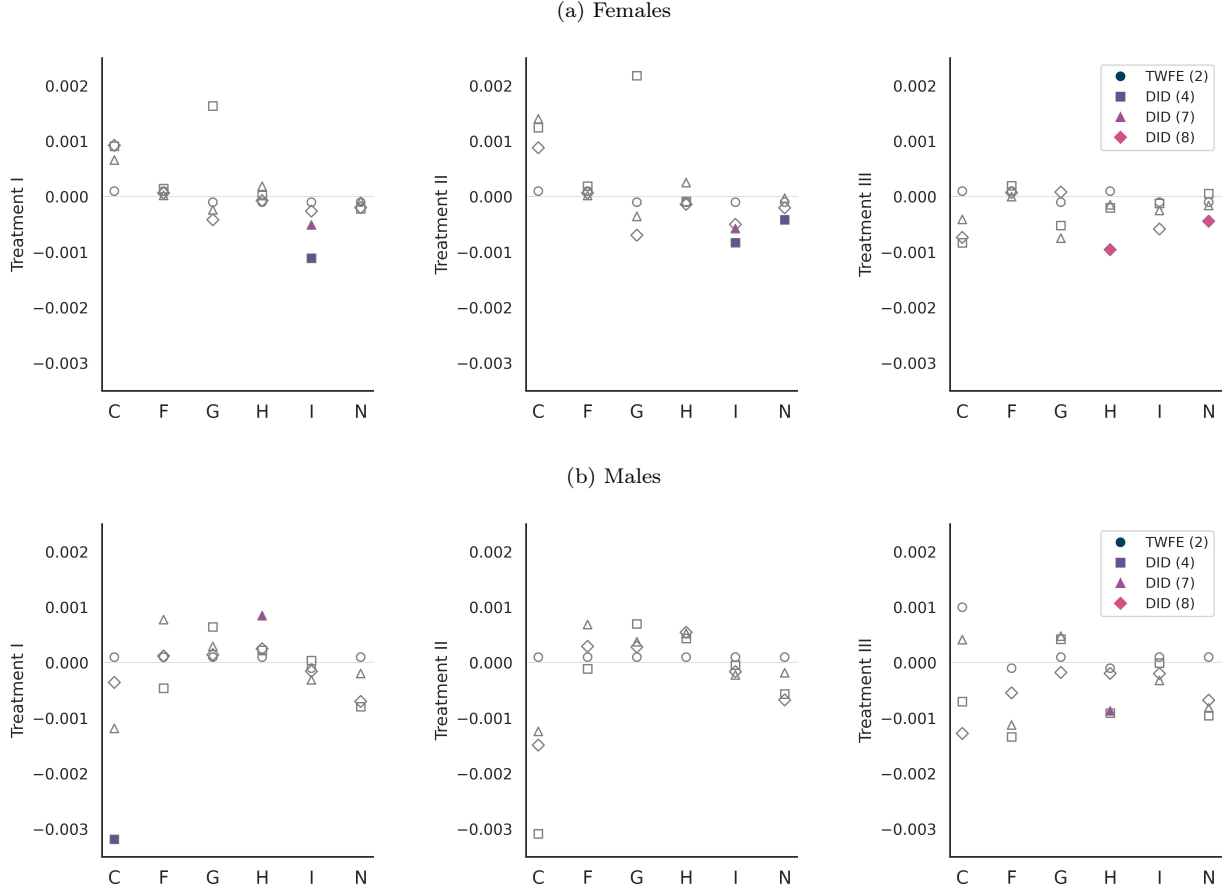
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (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 (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)), 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.

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



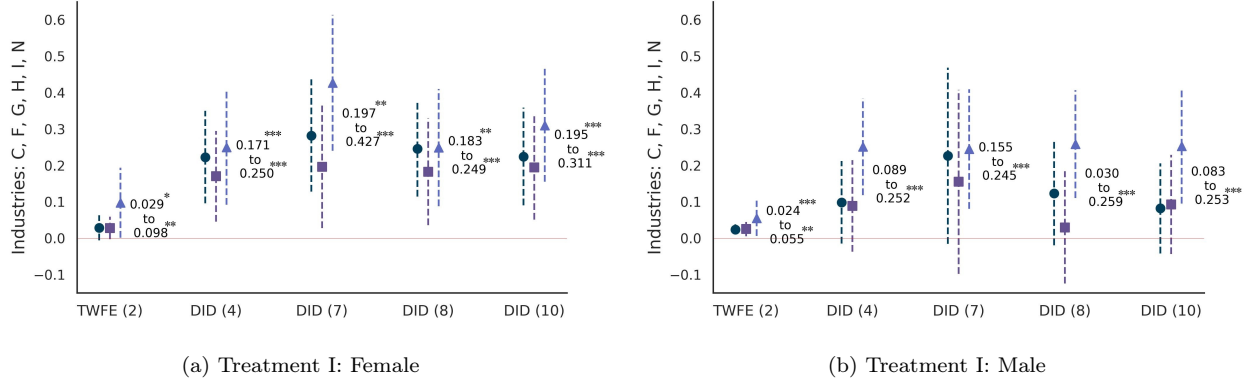
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. The sample is restricted to local individuals 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 who are 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.

Figure B.10: Positive Treatment Doses—Probability of Employment by Gender & Across Industries



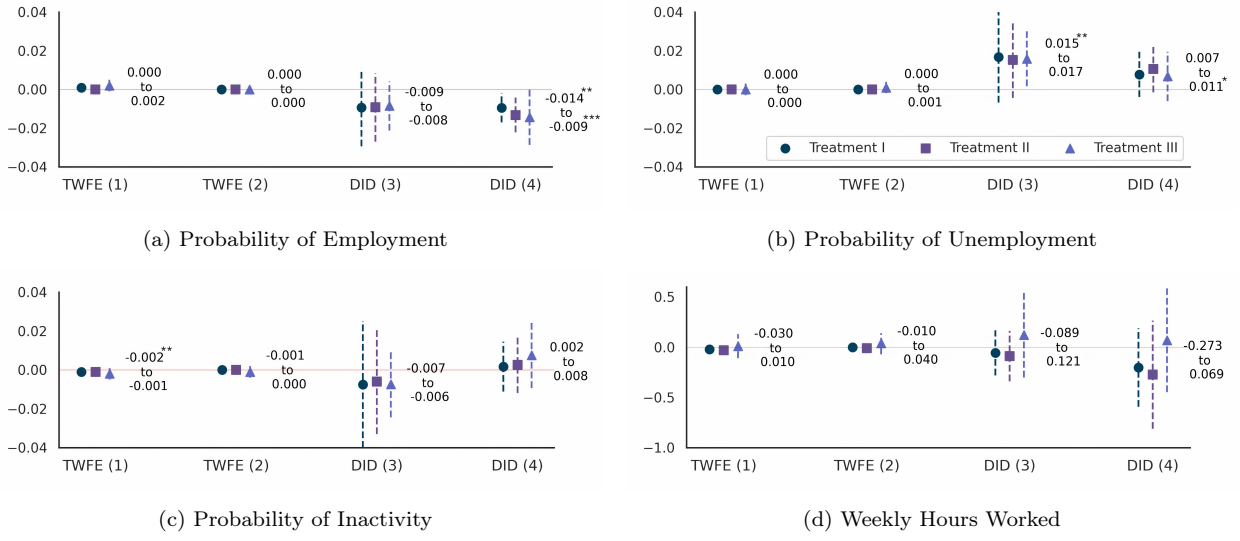
Note: Only coefficients significant at $p \leq 0.05$ are highlighted, while non-significant coefficients are represented by hollow symbols. The sample is restricted to local individuals employed in industries such as Manufacturing (C), Construction (F), Wholesale and Retail Trade (G), Transportation and Storage (H), Accommodation and Food Service Activities (I), and Administrative and Support Service Activities (N), or those who are not employed. The figure displays coefficient estimates for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.3 (columns 3-10) for Treatment I, II, and III. TWFE 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.

Figure B.11: Positive Treatment Doses—Weekly Hours Worked by Gender & Most Affected Industries



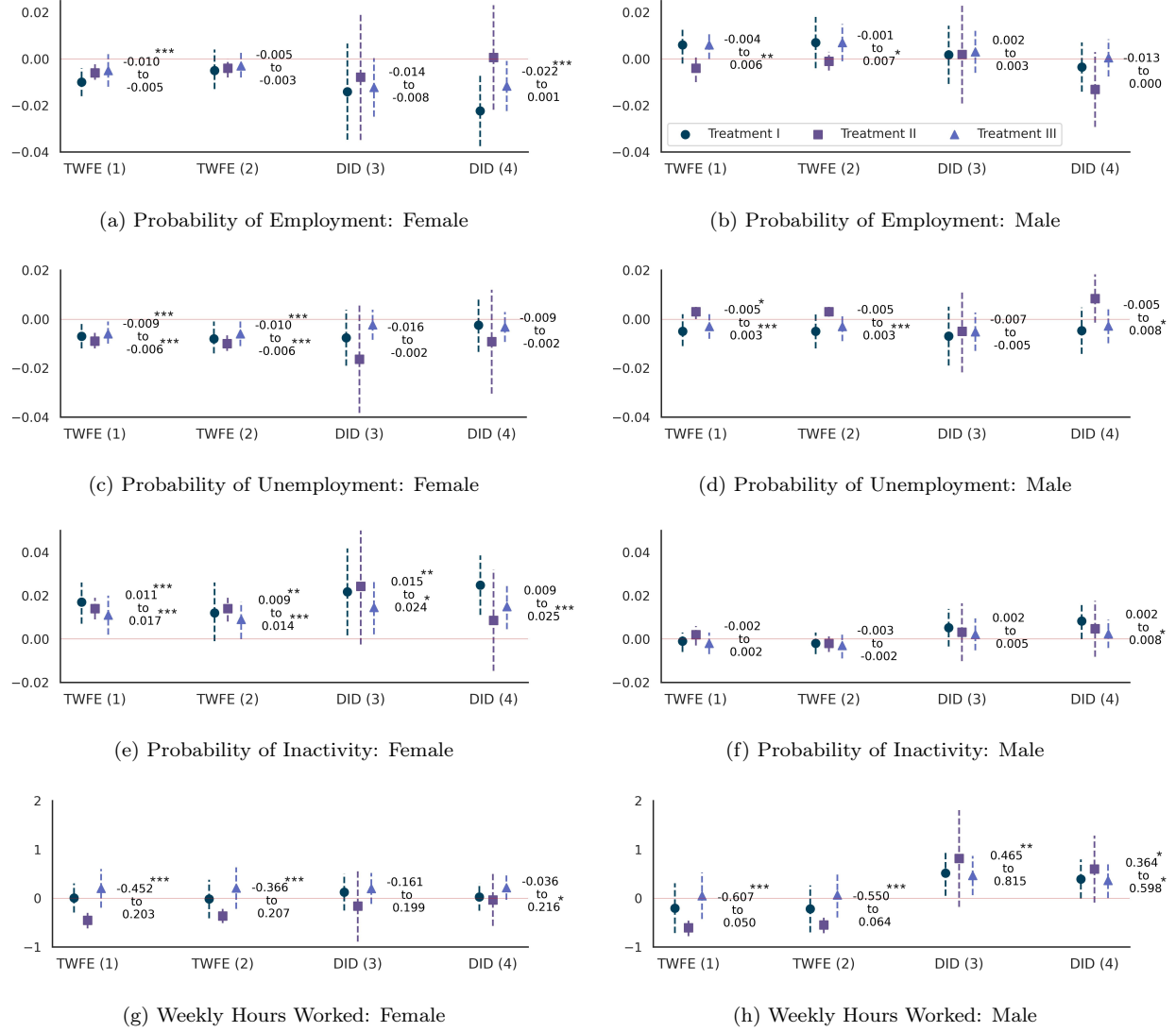
Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (columns 1-2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. The sample is restricted to local individuals 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 who are 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.

Figure B.12: Labour Market Outcomes: Positive Treatment Doses—Among Foreign Born Individuals Residing in Czechia



Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 1-2) and the expanded DiD model in Section 4.3 (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 (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 B.13: Summary of the Results: Negative Treatment Doses—Probability of Employment, Unemployment, Inactivity & Weekly Hours Worked by Gender



Note: Significance levels in the figure: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The figure displays coefficient estimates, the ‘minimum to maximum’ values for each model specification, and 95% level confidence intervals for ATT and nAVSQ across TWFE model in Section 4.2 (column 1-2) and the expanded DiD model in Section 4.3 (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 (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.

Table B.6: Alternative Treatment Variable—Local Females by Education Level

	Employment			Unemployment			Inactivity			Weekly Hours worked		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Females: All Education Levels												
Treatment	-0.001*	-0.000	-0.000	-0.000	-0.000	-0.000	0.001*	0.001	0.001	0.048**	0.041**	0.050**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.021)	(0.018)	(0.021)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	363,494	342,082	342,082	363,494	342,082	342,082	363,494	342,082	342,082	164,723	157,883	157,883
Females: Low Education												
Treatment	-0.000	0.001	0.001	-0.001	-0.001	-0.001	0.001	0.000	0.000	0.094	0.008	0.012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.078)	(0.070)	(0.079)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	62,749	58,882	58,882	62,749	58,882	58,882	62,749	58,882	58,882	8,098	7,763	7,763
Females: Middle Education												
Treatment	-0.000	0.000	-0.000	-0.001	-0.001	-0.001	0.001	0.000	0.001	0.066	0.061*	0.062*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.045)	(0.032)	(0.033)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	236,946	222,791	222,791	236,946	222,791	222,791	236,946	222,791	222,791	113,562	109,094	109,094
Females: High Education												
Treatment	-0.003*	-0.002	-0.002	0.001**	0.001**	0.001*	0.002	0.001	0.001	-0.007	-0.006	0.015
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.034)	(0.026)	(0.022)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	63,721	60,409	60,409	63,721	60,409	60,409	63,721	60,409	60,409	43,026	41,026	41,026

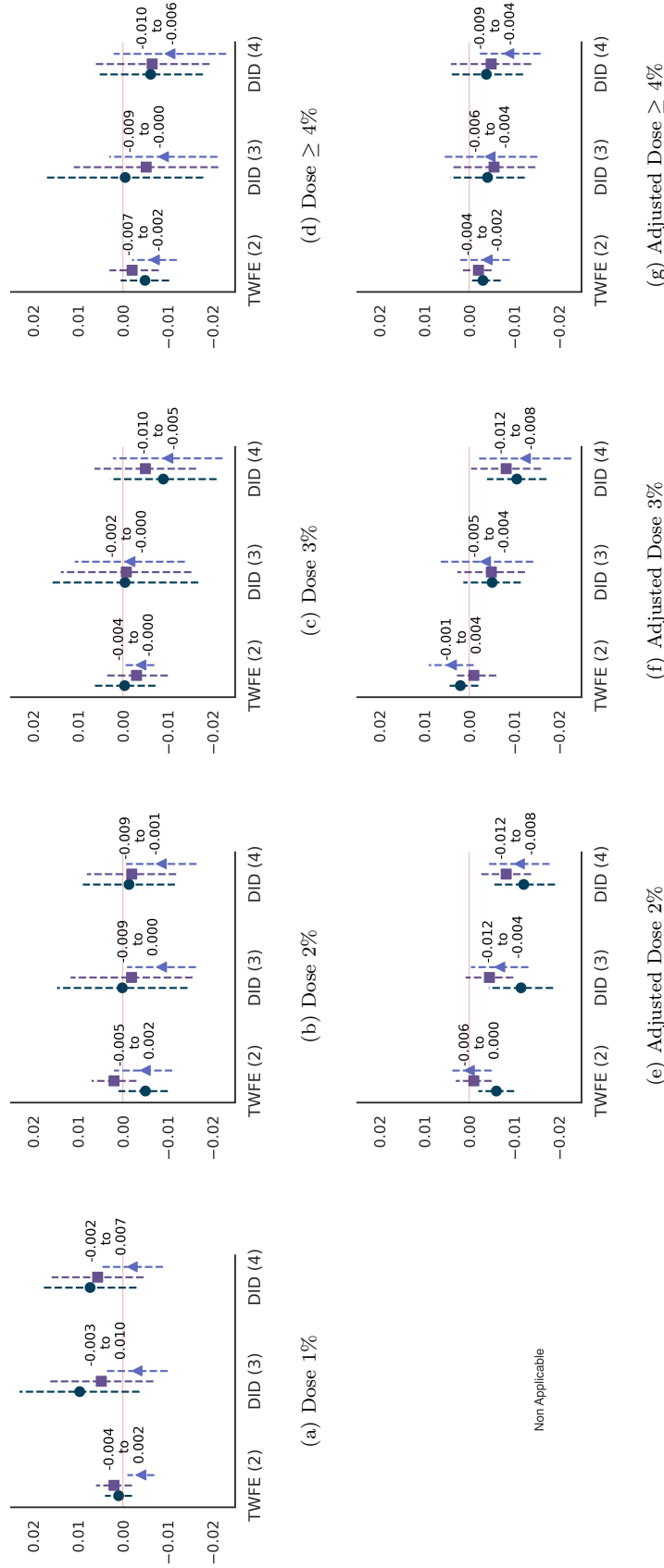
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table presents coefficient estimates of model 11. The table presents coefficient estimates of the alternative treatment models. Models (1, 4, 7, 10) are the most parsimonious, controlling for fixed effects at the individual and time levels. Models (2, 5, 8, 11) also control for individual characteristics. Models (3, 6, 9, 12) further include lagged-by-one-year variables for the unemployment rate and the rate of labour market tightness. Robust standard errors clustered at the district level are in parentheses.

Table B.7: Alternative Treatment Variable—Local Males by Education Level

	Employment			Unemployment			Inactivity			Weekly Hours worked		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Males: All Education Levels												
Treatment	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.093** (0.044)	0.064 (0.042)	0.052 (0.038)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	319,263	301,199	301,199	319,263	301,199	301,199	319,263	301,199	301,199	188,416	180,820	180,820
Males: Low Education												
Treatment	0.001 (0.004)	0.001 (0.002)	0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.000 (0.002)	-0.000 (0.001)	0.001 (0.002)	0.236** (0.116)	0.165*** (0.059)	0.146** (0.062)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	34,490	32,840	32,840	34,490	32,840	32,840	34,490	32,840	32,840	7,842	7,545	7,545
Males: Middle Education												
Treatment	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.061* (0.031)	0.028 (0.031)	0.020 (0.031)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	229,376	216,123	216,123	229,376	216,123	216,123	229,376	216,123	216,123	139,750	134,337	134,337
Males: High Education												
Treatment	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001* (0.001)	0.000 (0.001)	0.001 (0.001)	0.131* (0.073)	0.124* (0.071)	0.104 (0.064)
Time (Year: Quarter) FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual characteristics		Y	Y		Y	Y		Y	Y		Y	Y
Lagged Labour Conditions			Y			Y			Y			Y
No. of observations	55,331	52,236	52,236	55,331	52,236	52,236	55,331	52,236	52,236	40,789	38,938	38,938

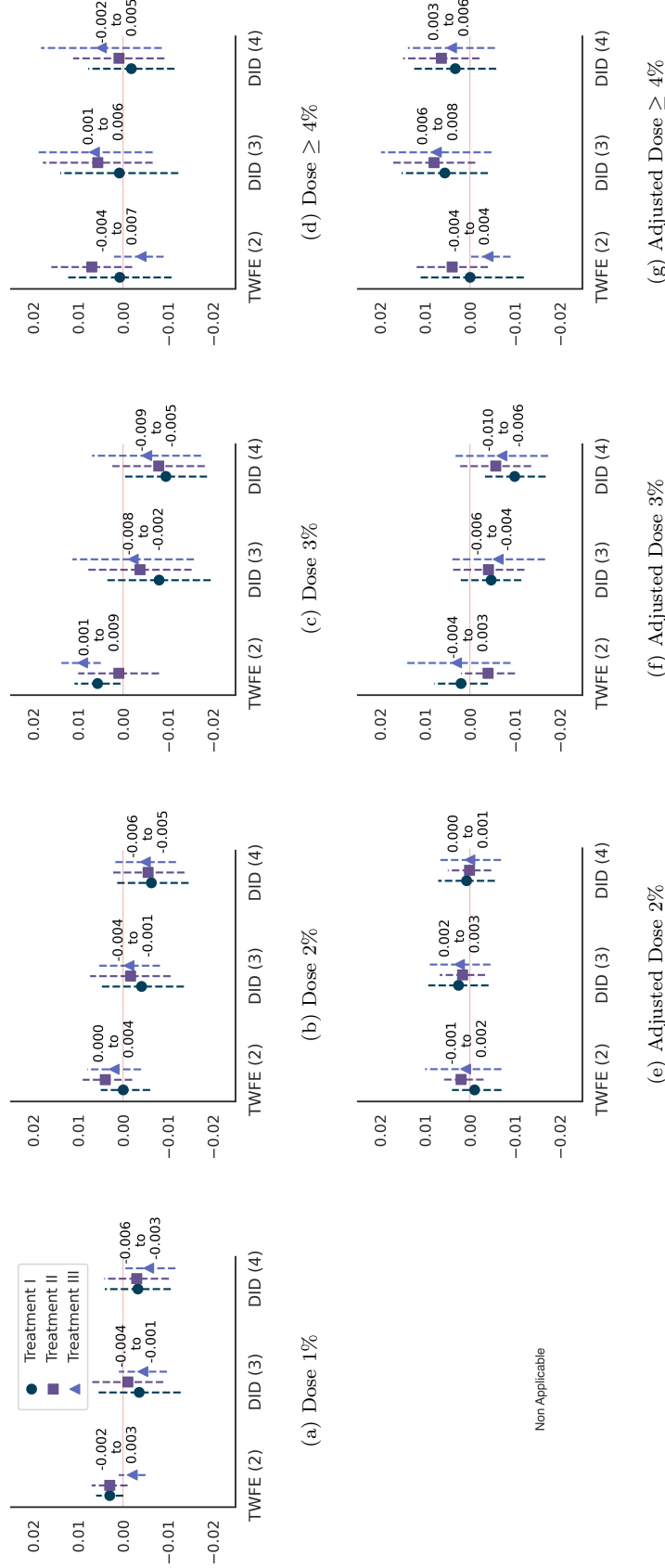
Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table presents coefficient estimates of model 11. The table presents coefficient estimates of the alternative treatment models. Models (1, 4, 7, 10) are the most parsimonious, controlling for fixed effects at the individual and time levels. Models (2, 5, 8, 11) also control for individual characteristics. Models (3, 6, 9, 12) further include lagged-by-one-year variables for the unemployment rate and the rate of labour market tightness. Robust standard errors clustered at the district level are in parentheses.

Figure B.14: Positive Treatment Doses—Probability of Employment for Females by Original & Adjusted Doses of Treatment



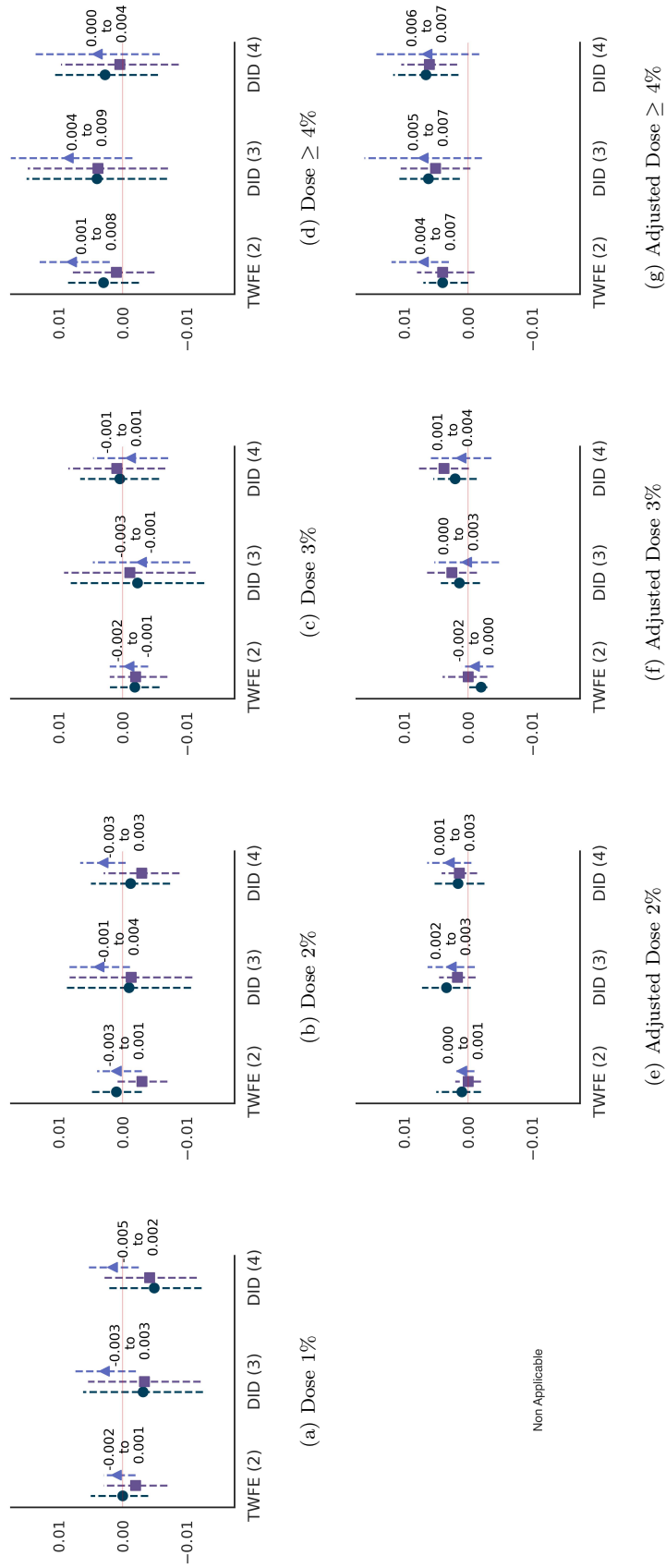
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.15: Positive Treatment Doses—Probability of Employment for Males by Original & Adjusted Doses of Treatment



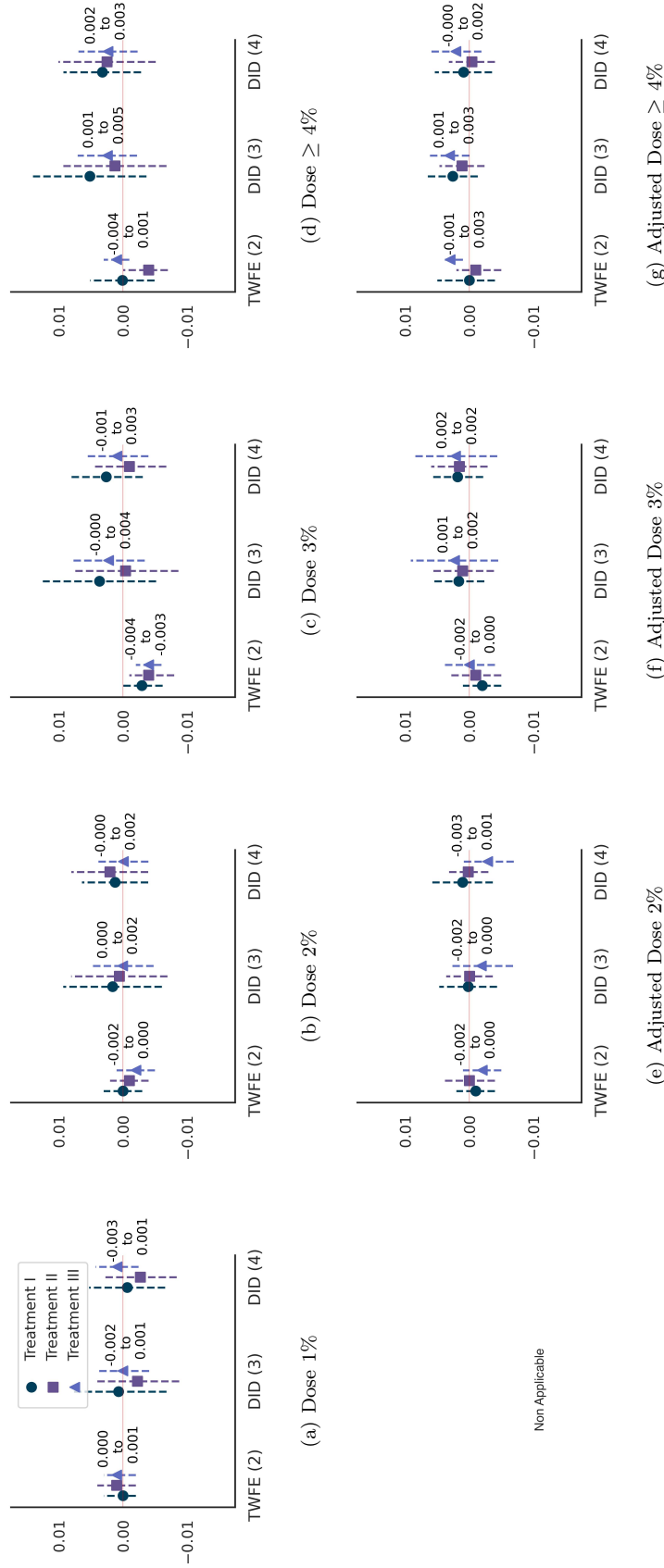
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.16: Positive Treatment Doses—Probability of Unemployment for Females by Original & Adjusted Doses of Treatment



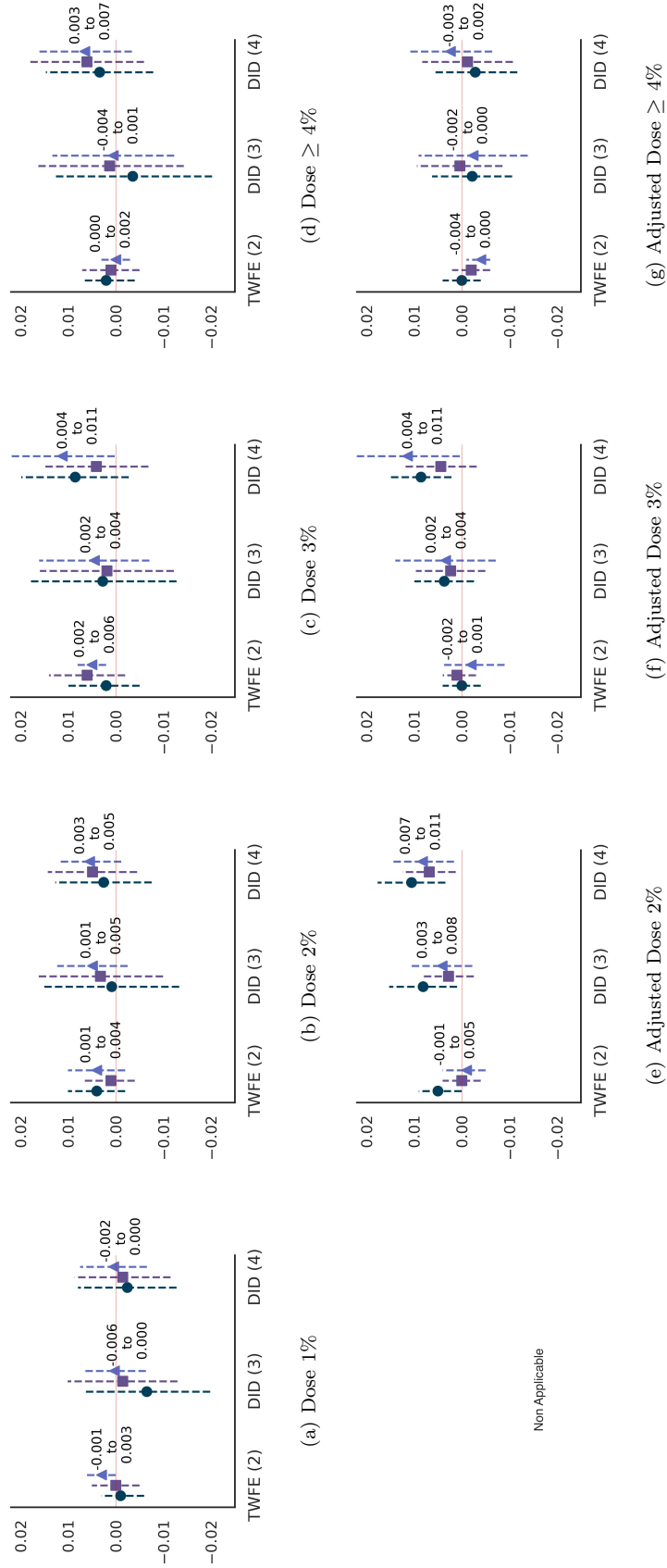
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.17: Positive Treatment Doses—Probability of Unemployment for Males by Original & Adjusted Doses of Treatment



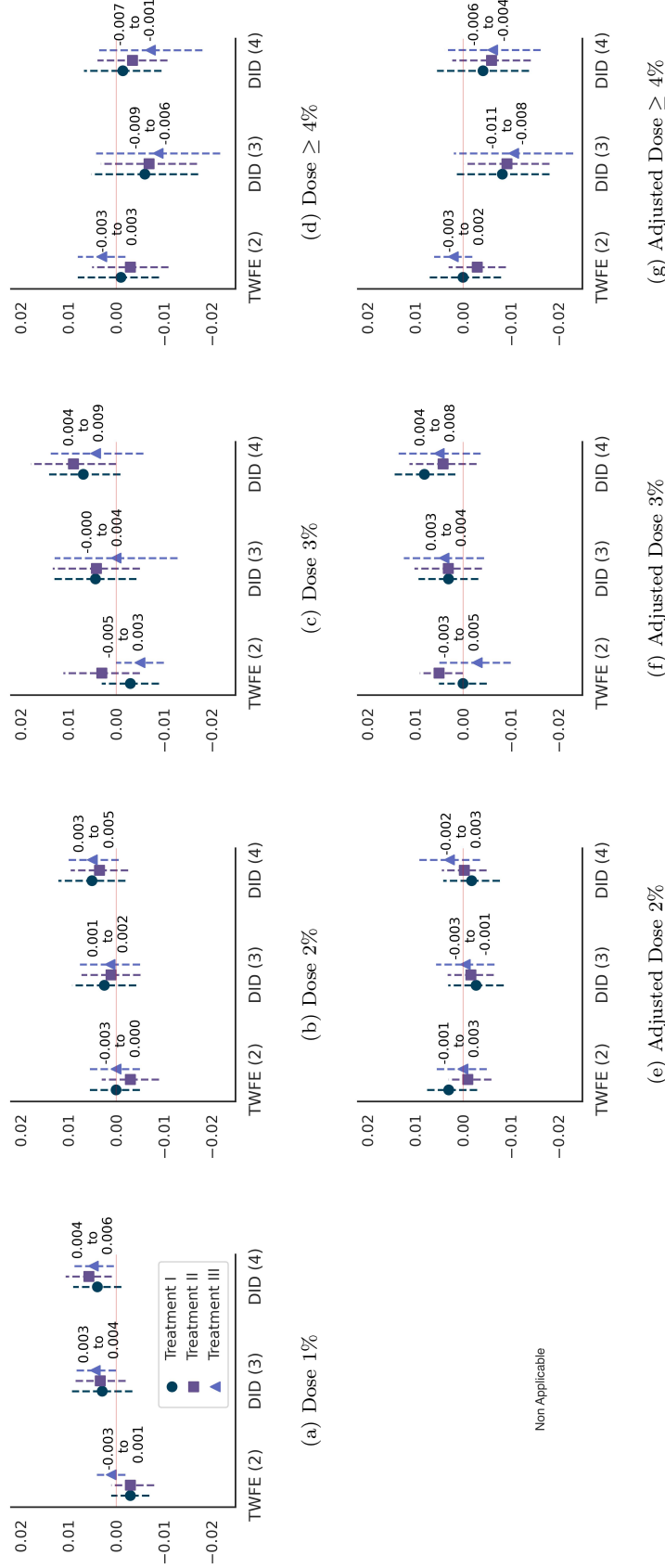
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.18: Positive Treatment Doses—Probability of Inactivity for Females by Original & Adjusted Doses of Treatment



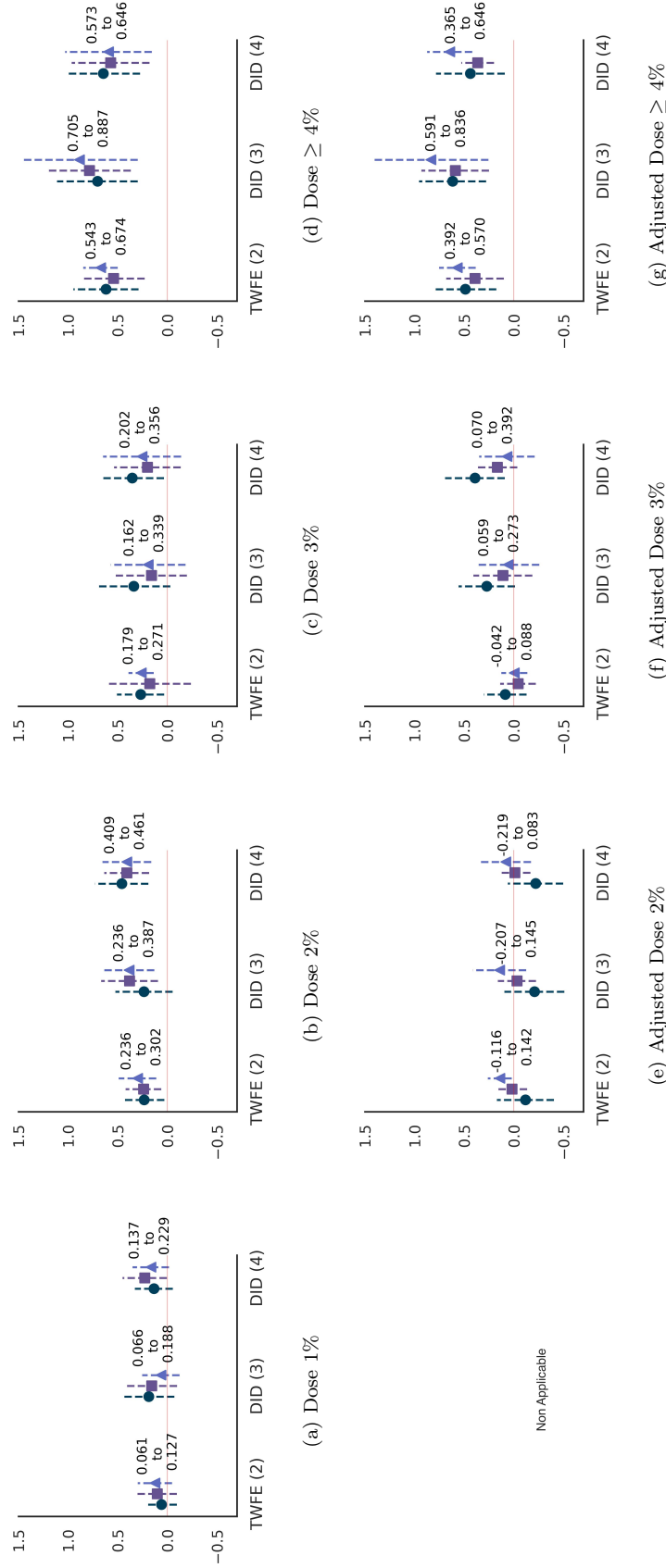
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVS across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.19: Positive Treatment Doses—Probability of Inactivity for Males by Original & Adjusted Doses of Treatment



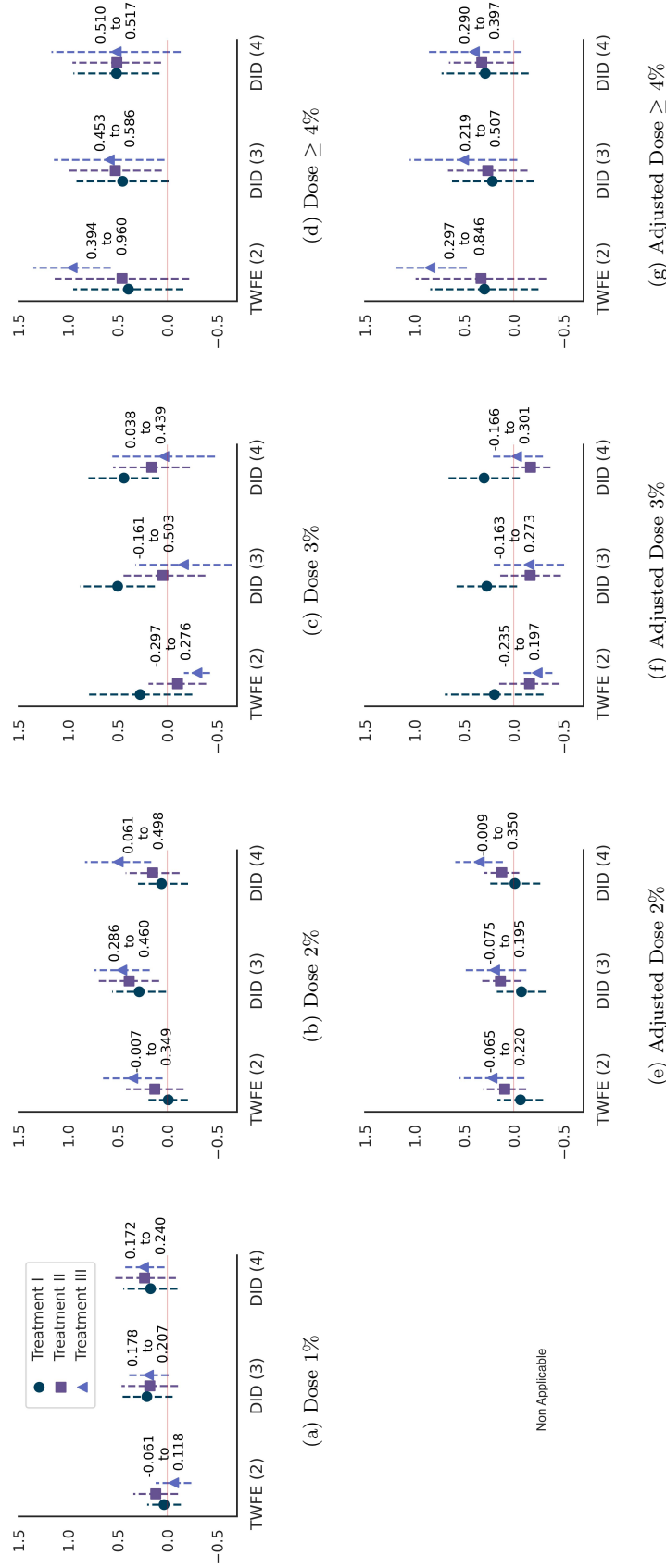
Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVS across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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 B.20: Positive Treatment Doses—Weekly Hours Worked for Females by Original & Adjusted Doses of Treatment



Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVSQ across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (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 B.21: Positive Treatment Doses—Weekly Hours Worked for Males by Original & Adjusted Doses of Treatment

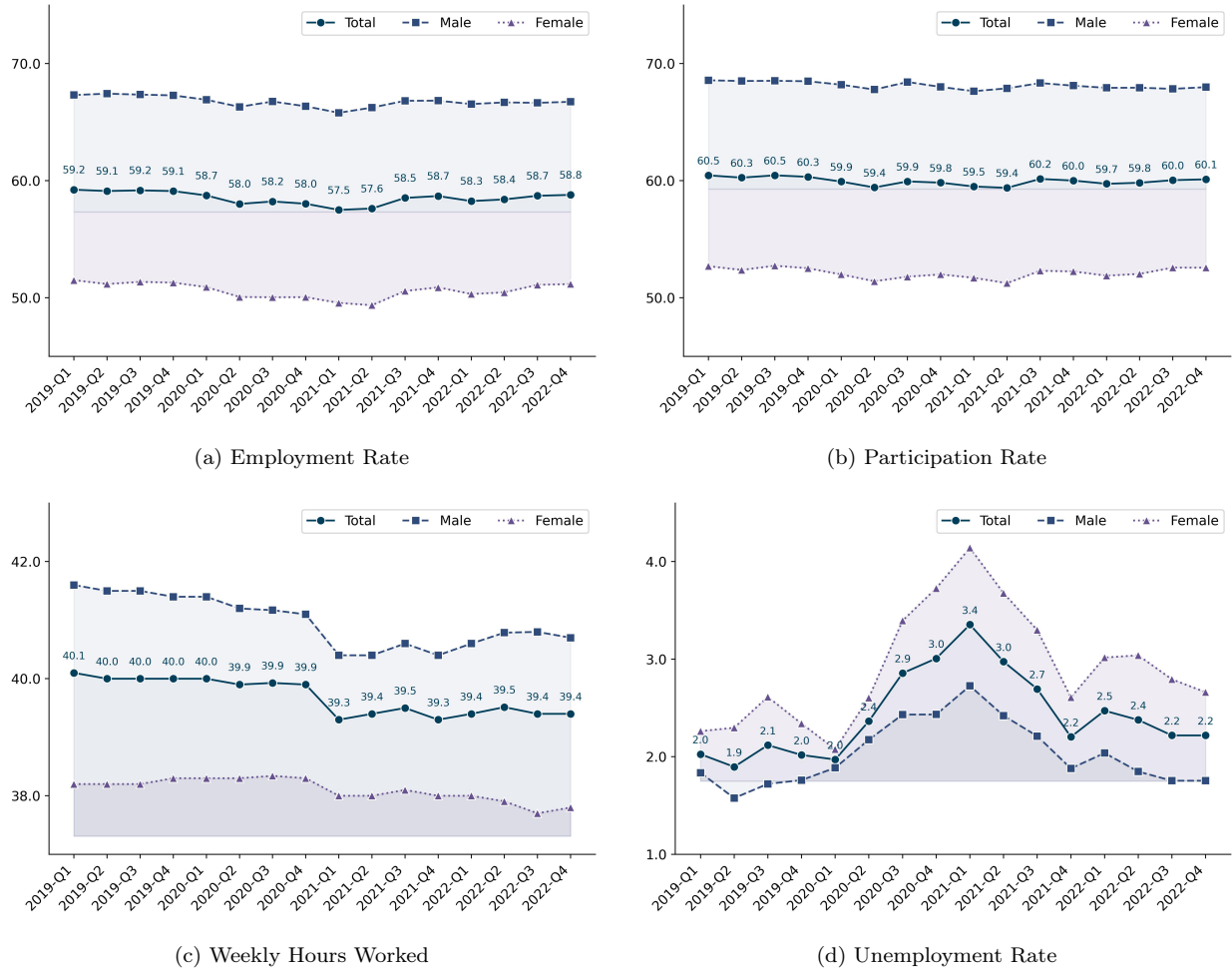


Note: The figure displays coefficient estimates, the 'minimum to maximum' values for each model specification, and 95% level confidence intervals for ATT and AVS across TWFE model in Section 4.2 (column 2) and the expanded DiD model in Section 4.3 (columns 3-4) for Treatment I, II, and III. Reported 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.

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, 2023; Eurostat, 2023). Refer to Figure C.1d. 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 C.1: Snapshot of Czechia's Labour Market Conditions



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

Despite global economic challenges, such as the COVID-19 pandemic, Czechia maintained relatively stable employment and participation rates throughout these years (Figures C.1a and C.1b). 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).

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 (1st, 2nd, 3rd, 4th or 5th 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 thousand 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 D.1.

Table D.1: 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	[sqrt, ‘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.

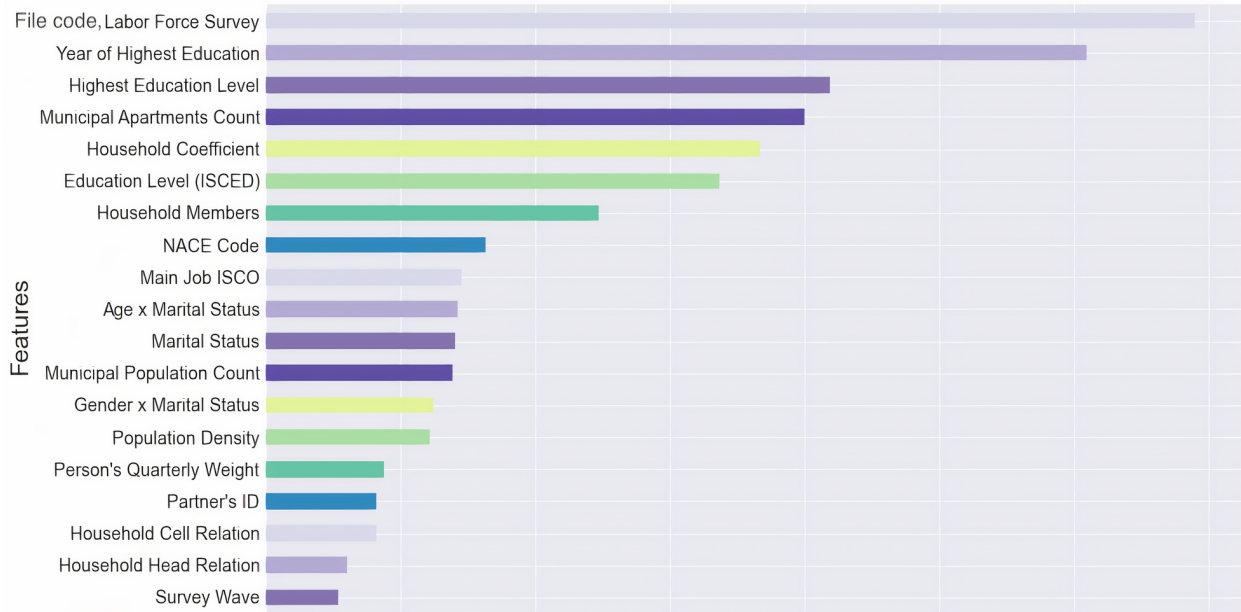
Evaluating the model on the test set involved metrics such as accuracy, ROC AUC score, F1 score, precision, and recall. These metrics collectively provided a succinct overview of the model’s robustness and predictive precision, detailed in Table D.2. The model achieved high performance across all metrics, 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 D.2: 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 D.1, 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 D.1: Top 20 Feature Importances in the Random Forest Model

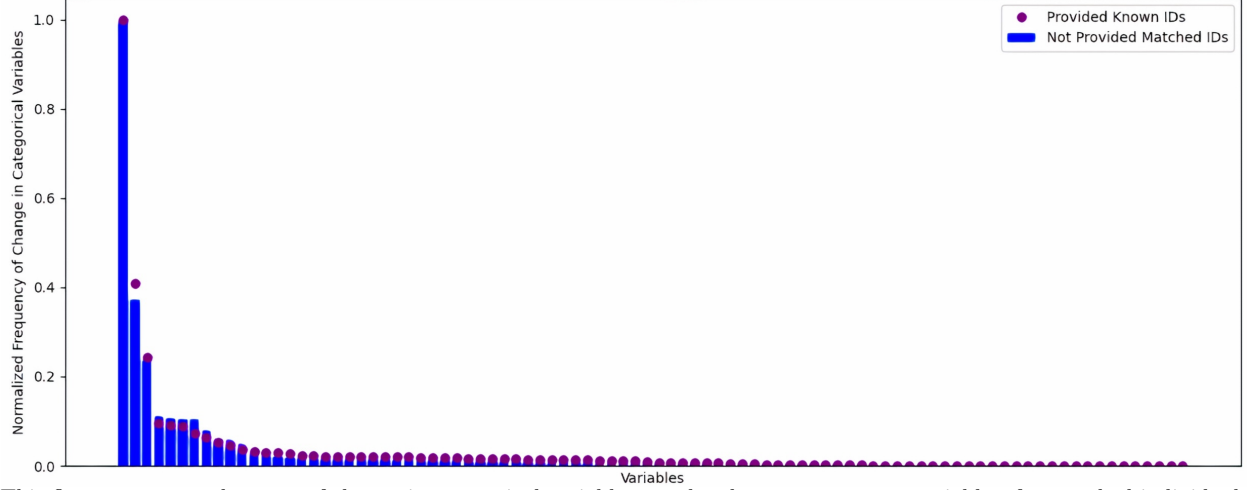


Note: This figure visualizes the relative importance of the top 20 features used by the Random Forest model. Features are ranked based on their impact on model performance, offering insights into the variables most predictive of match accuracy.

The best parameters from the grid search were then applied to predict the likelihood of ‘correct’

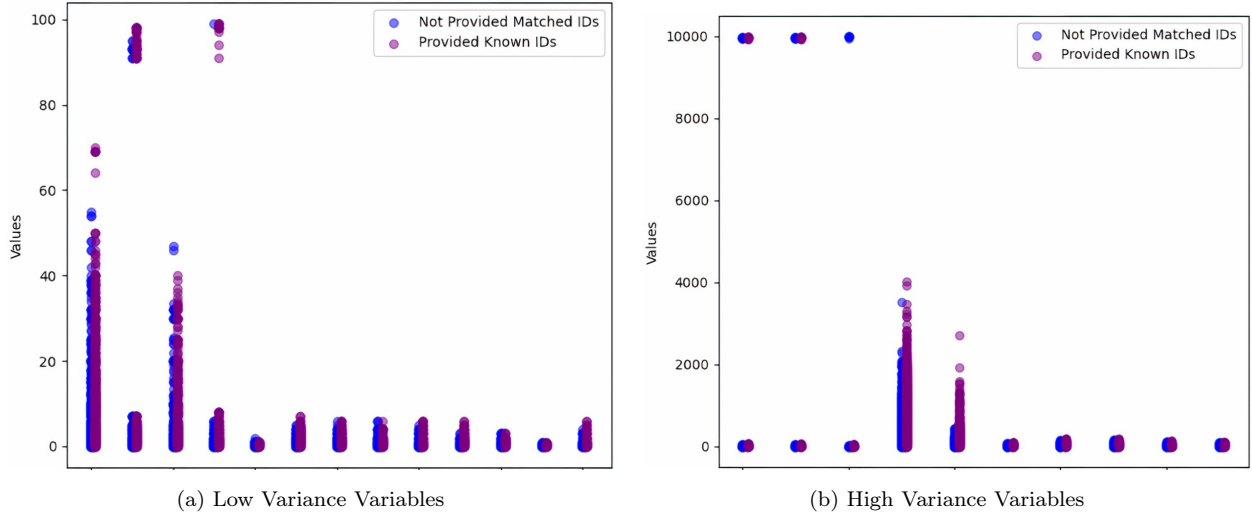
matches for individuals without an ID. Consequently, we successfully matched the remaining observations from the deterministic matching step, with only 0.8% of observations unmatched in Q3 and 2.2% in Q4 2022.

Figure D.2: 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 D.3: Rate of Change in Continuous 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 D.3 and D.2 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 E.1 to E.3 list the districts categorised by their average treatment doses for Average Treatment $_{d}^{I,II, \text{ or } III}$, respectively.

Table E.1: Districts by Average Treatment Doses^I

Average Treatment I			
Dose 1%	Dose 2%	Dose 3%	Dose $\geq$ 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 E.2: Districts by Average Treatment Doses^{II}

Average Treatment II			
Dose 1%	Dose 2%	Dose 3%	Dose $\geq$ 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 E.3: Districts by Average Treatment Doses^{III}

Average Treatment III			
Dose 1%	Dose 2%	Dose 3%	Dose $\geq$ 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-Differences 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.¹ 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

¹Implemented with the Stata command ‘`twowayfeweights`’. For details, see de Chaisemartin et al. (2023).

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-Differences Estimators (DiD) in our Setting. The notation used below aligns with that of de Chaisemartin and D’Haultfœuille (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 1st quarter of 2021 to the 4th 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 1st quarter of 2022; therefore, data on individuals recorded before the 1st quarter of 2021 are disregarded as their observations would not coincide with the treatment period. Consequently, we utilise data from the 1st quarter of 2021 to the 4th 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:

$$\text{DiD}_{i,\ell} = Y_{i,F_i-1+\ell} - Y_{i,F_i-1} - \frac{1}{N_{F_i-1+\ell}^i} \sum_{i': D_{i',1}=D_{i,1}, F_{i'} > F_i-1+\ell} (Y_{i',F_i-1+\ell} - Y_{i',F_i-1}), \quad (1)$$

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_t^i 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. To compare the estimated average AVSQ effects for each location with results from the TWFE regression, we follow a suggestion by de Chaisemartin and D’Haultfoeulle (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:

$$y_{i,d,t} = \alpha_d + \beta_d \cdot t + \sum_{q=1}^4 \gamma_{d,q} \cdot I(Q_t = q) + \epsilon_{i,d,t}, \quad t \in \{1Q\ 2019, \dots, 4Q\ 2021\}, \quad (2)$$

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 G.1 to G.4 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 G.1: 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 G.2: 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 G.3: 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 G.4: 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:

$$y_{i,d,t,p,e} = \alpha_{d,p,e} + \beta_{d,p,e} \cdot t + \sum_{q=1}^4 \gamma_{d,q,p,e} \cdot I(Q_t = q) + \epsilon_{i,d,t,p,e}, \quad (3)$$

where p and e index gender and education level, respectively, adding a further level of detail. Tables G.5 to G.8 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 G.5: 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 G.6: 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 G.7: 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 G.8: 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 ($NACE$):

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

with n indexing the NACE-level 1 industry sector (21 categories). Table G.9 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 G.9: 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.

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