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Zuzana Košťálová - Lukáš Lafférs - Miroslav Štefánik

Afraid of Automation?
Choose your training carefully

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AUTHORS

Zuzana Košťálová, Institute of Economic Research SAS, Bratislava, Slovakia, kostalova.zuzana@savba.sk
Lukáš Lafférs, Faculty of Natural Sciences at the Matej Bel University, Banská Bystrica, Slovakia; Department of Economics, Norwegian School of Economics, Bergen, Norway, lukas.laffers@umb.sk
Miroslav Štefánik, Institute of Economic Research SAS, Bratislava, Slovakia, miroslav.stefanik@savba.sk

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ABSTRACT

Due to automation's impact on the labour market, publicly funded training programs have gained increased attention. This paper explores a training program provided to job seekers in Slovakia, the OECD country with the highest average automation risk. The scheme allows job seekers to choose their training specialisation. We evaluate the most popular training specializations chosen by job seekers, which were gender-divided, with healthcare workers, beauticians and accountants dominated by females and welders, drivers, and security guards dominated by males. Our findings suggest that job seekers, when allowed to select their specialization, use training to reduce their risk of automation. Female participants showed a preference for specializations targeting occupa-tions with a lower risk of automation. Training participation also reduced the automation risk of male participants, but mainly because they suffered a higher automation risk in their previous oc-cupations. We apply double machine learning to estimate the average treatment effect of training participation under the unconfoundedness assumption. In line with existing empirical studies, our results indicate a negative lock-in effect in the short run and a positive employment effect in the long run. Furthermore, our data allowed us to observe different stories related to particular train-ing specializations. Some training specializations are used as a means to find employment abroad or enter the informal sector. Other training specializations provide opportunities for low-skilled job seekers to obtain within-country employment in occupations with a lower risk of automation.

KEYWORDS: active labour market policy; automation risk; double machine learning

JEL CLASSIFICATION: J08, D04, C21

Bojíte sa automatizácie? Starostlivo si vyberte školenie

ABSTRAKT

Vzhľadom na vplyv automatizácie na trh práce sa zvýšila pozornosť venovaná programom odbornej prípravy financovaným z verejných zdrojov. Tento článok skúma program odbornej prípravy poskytovanej uchádzačom o zamestnanie na Slovensku, v krajine OECD s najvyšším priemerným rizikom automatizácie. Program umožňuje uchádzačom o zamestnanie vybrať si špecializáciu odbornej prípravy. Hodnotíme najobľúbenejšie špecializácie odbornej prípravy, ktoré si uchádzači o zamestnanie vybrali a ktoré boli rozdelené podľa pohlavia, pričom medzi zdravotníckymi pracovníkmi, kozmetičkami a účtovníkmi dominovali ženy a medzi zváračmi, vodičmi a strážnikmi muži. Naše zistenia naznačujú, že uchádzači o zamestnanie, ak si môžu vybrať špecializáciu, využívajú odbornú prípravu na zníženie rizika automatizácie. Účastníčky uprednostňovali špecializácie zamerané na povolania s nižším rizikom automatizácie. Účasť na odbornej príprave znížila riziko automatizácie aj u mužských účastníkov, ale najmä preto, že vo svojich predchádzajúcich povolaniach trpeli vyšším rizikom automatizácie. Na odhad priemerného účinku účasti na školení za predpokladu nenarušenosti uplatňujeme tzv. double machine learning. V súlade s existujúcimi empirickými štúdiami naše výsledky naznačujú negatívny lock-in efekt v krátkodobom horizonte a pozitívny efekt na zamestnanosť v dlhodobom horizonte. Okrem toho nám naše údaje umožnili pozorovať rôzne príbehy súvisiace s jednotlivými špecializáciami odbornej prípravy. Niektoré špecializácie odbornej prípravy sa využívajú ako prostriedok na hľadanie zamestnania v zahraničí alebo na vstup do neformálneho sektora. Iné špecializácie odbornej prípravy poskytujú uchádzačom o zamestnanie s nízkou kvalifikáciou príležitosť získať zamestnanie v rámci krajiny v povolaniach s nižším rizikom automatizácie.

KĽÚČOVÉ SLOVÁ: aktívne opatrenia politiky práce; riziko automatizácie; double machine learning

JEL KLASIFIKÁCIA: J08, D04, C21

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LAYOUT BY: Zuzana Košťálová

Institute of Economic Research SAS
Ekonomický ústav SAV, v.v.i.
Šancová 56, 811 05 Bratislava
www.ekonom.sav.sk

CONTACT / KONTAKT: ekonedra@savba.sk

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Introduction

The impact of new technologies on labour market is expected to accelerate due to recent technological advancements. A panel of managers surveyed by the World Economic Forum expects that approximately one out of four employees will be changing jobs, and six out of ten will require training due to introducing new technologies during 2023-2027 (WEF, 2023). Upskilling becomes eventually a necessary strategy for individuals to overcome challenges imposed by technological changes, while inequality in the access to training has moved to the focus of public policies[2](Ernst et al., 2018).

Active labour market policies (ALMPs) present a crucial set of policy tools for supporting individuals through labour market transitions, potentially smoothing the impact of automation on the labour market (Grigoli et al., 2020; Schmidpeter and Winter-Ebmer, 2021; Hötte et al., 2023; Heß et al., 2023). Training facilitating ALMPs and particularly jobseeker-selected training schemes address this policy challenge. In this study, we examine one particular training scheme implemented within the portfolio of ALMP programmes in Slovakia, an OECD country that is facing the highest average risk of automation (Nedelkoska and Quintini, 2018). The studied scheme allows registered job seekers to select both their training specialisation and a provider. In its goals and design, this scheme is comparable to numerous other programmes implemented across the EU. The aim of this study is to inspect whether publicly funded training provided within this scheme improves the re-employment prospects of registered jobseekers and supports them in their career transition. To achieve this, we explore the portfolio of client-chosen training specialisations and estimate the specialisation-specific treatment effects of training participation using a causal machine learning estimator under the unconfoundedness assumption. While doing so, we address a hypothesis as to whether training specialisation targeting occupations with reduced automation risks improves the employment probability of the unemployed.

Our study contributes to the literature in three areas. First, we contribute to the literature on the role of ALMP training in tackling the challenges and risks imposed by automation (Tamm, 2018; Grigoli et al., 2020; Schmidpeter and Winter-Ebmer, 2021; Heß et al., 2023). Compared to existing studies, we explore whether the training selected by job seekers themselves helps them upgrade their skills affected by new technologies and increase their re-employment probability. Second, our work also extends the literature on gender differences in the effectiveness of publicly provided training (Lechner et al., 2007; Osikominu, 2013; Biewen et al., 2014; Kruppe and Lang, 2018; Schmidpeter and Winter-Ebmer, 2021). The client's choice of training specialisations resulted in a gender-split portfolio, with specialisations mostly chosen by either women or men. Female participants tend to choose specialisations with a lower risk of automation. We estimate gender-specific treatment effects of participation in the most frequently chosen training specialisations. Third, our study also contributes to a new literature stream that uses machine learning techniques in programme evaluation (Athey and Imbens, 2017; Cockx et al., 2019; Goller et al., 2020; Knaus et al., 2022).

Our findings reveal substantial differences in the impact of participation in different training specialisations. Although some training can improve job seekers' re-employment possibilities, observed differences in their impact cannot be explained by the differences in the risk of automation.

While publicly funded, client-chosen training provided to unemployed job seekers could serve as a measure to overcome challenges or the risks imposed by automation, attention should be paid to the composition of training specialisations.

The structure of the rest of the paper is as follows. Section 1 discusses the automation risk in

[2]Policy strategies address this challenge through initiatives such as the Upskilling Pathways of the European Commission (`https://ec.europa.eu/social/main.jsp?catId=1224`). Supporting individuals through labour market transitions presents one of the crucial pillars of the Human-Centred Agenda designed to adapt to changes in the future of work (International Labour Organization, 2019).

labour market. Section 2 reviews the impact evaluation literature on training for the unemployed. Section 3 provides an institutional background of studied ALPM in Slovakia. Section 4 describes our data and defines our evaluation samples and outcomes of interest. Section 5 outlines the econometric framework. Section 6 presents our findings and Section 7 concludes.

1 Automation and the change of the occupational structure

It has been well-documented that technological change is altering the occupational structure of labour markets (Acemoglu and Loebbing, 2022; Graetz et al., 2022), as automation leads to a decline in routine-intensive jobs and thus decreases job opportunities for workers with routine tasks (Autor et al., 2003; Autor and Salomons, 2018; Biagi et al., 2018). The pace of this change is expected to increase in the near future (European Commission, 2023; WEF, 2023), increasing the importance of skills upgrading. Although the overall number of jobs is expected to decline only marginally, an occupational churn of approximately 23 percent is expected during 2023-2027 (WEF, 2023). With approximately 42 percent of tasks being automated, six out of ten employees will need some training.

1.1 Occupation-specific risk of automation

A study of Frey and Osborne (2017) enlivened the discussion on the labour market impact of new technologies by considering the contemporary advancements in machine learning (ML) and mobile robotics in their estimations of the occupation-specific probability of computerisation. Based on their extended quantification, approximately 47 percent of the US jobs were at high risk of computerisation. Consequential studies calmed the public debate (Arntz et al., 2016; Nedelkoska and Quintini, 2018; Mihaylov and Tijdens, 2019), claiming that although a substantial share of tasks is routine-intensive and easily replaceable, even a minor share of non-routine and hard-to-automated tasks might present a barrier for automating the whole job.

In estimating the occupation-specific index of the risk of computerisation, Frey and Osborne (2017) adopted a task-based model, which was inspirational to a stream of subsequent studies (Arntz et al., 2016; Nedelkoska and Quintini, 2018; Mihaylov and Tijdens, 2019). Webb (2019) introduced a methodological approach based on a content analysis of patent applications. The study provides three indices of occupational tasks exposure to automation due to new software, robotisation, and artificial intelligence. The methodology was adopted and validated by multiple later studies (Acemoglu et al., 2022; Heß et al., 2023). In measuring the risk of automation, we decided to use the average of the three indices introduced by Webb (2019). We refer to them as the occupation-specific risk of automation. Additionally, in the Appendix we are also reporting results for the risk of computerisation published by Frey and Osborne (2017), as well as other occupation-specific measures capturing the risk of automation introduced by: Dengler et al. (2014) and Mihaylov and Tijdens (2019). We take advantage of the alignment of the indices produced by (Webb, 2019) and the risk of computerisation reported by (Frey and Osborne, 2017), as well as their ability to consider advances in ML and robotics. Moreover, the extent of their estimated total automation risk aligns surprisingly well with more recent estimates acquired by expert panels (WEF, 2023).

1.2 Precariousness of the risk of automation

Occupations with a higher average risk of being automated are associated with lower wages and a higher risk of unemployment (Nedelkoska and Quintini, 2018). Additionally, working experience gained from routine intensive occupations more often precedes a longer unemployment spell (Blien et al., 2021; Schmidpeter and Winter-Ebmer, 2021), with poorer employment dynamics observable, especially for the middle-wage routine occupations (Cortes et al., 2020). Adult education and training provide a channel for switching from routine career paths. Unfortunately, firm-sponsored training appears to deepen the precariousness of routine occupations (Mohr et al., 2016). The routine versus non-routine occupations training gap, or the automation training gap (Görlitz and Tamm, 2016), is particularly pronounced for medium-skilled and male workers and is largely driven by the lack of ICT training and training for soft skills (Heß et al., 2023; Tamm, 2018).

Based on the data from the Eurobarometer, European workers are greatly concerned with the labour-substituting effects of new technologies, and this subjective insecurity, to a great extent, reflects their exposure to objective automation risk (Kozak et al., 2020). Additionally, workers who fear automation have lower job satisfaction (Schwabe and Castellacci, 2020) and a greater intention to participate in training (Innocenti and Golin, 2022). They also declare higher support of public workfare policies, such as publicly financed training programmes for unemployed job seekers (Im and Komp-Leukkunen, 2021). In contrast, workers in occupations with a higher risk of automation seem to participate less in continuing non-formal training (Koster and Brunori, 2021), or adult training in general (Cabus et al., 2020). Additionally, Heß et al. (2023) demonstrates that transitioning to an occupation with a lower risk of automation increases the likelihood of training participation. Therefore, addressing the automation training gap might need publicly funded training programmes that support career transitions.

2 Role of client choice of ALMPs in labour market transitions

Existing evidence on the impact of training provided to the unemployed within a portfolio of ALMP programmes remains ambivalent. However, existing meta-analyses indicate that if there is some impact of training on labour market outcomes: i) it can be observable after a longer period and ii) female participants seem to profit more from provided training (Card et al., 2010, 2018; Vooren et al., 2019).

We focus our interest on ALMP training programmes that allow job seekers to choose the training specialisation or provider. The possibility to select training specialisation and the provider by the job seekers themselves is becoming more frequent in ALMP training programmes (e.g. in Austria, Croatia, Slovakia) or implemented through training vouchers schemes (as the one implemented under the HARTZ II reform in Germany which inspired ALMP training voucher schemes in Estonia and Lithuania)[3].

The well-documented German training voucher scheme is associated with a positive impact on employment (Kruppe and Lang, 2018; Doerr et al., 2017) as well as income (Stephan and Pahnke, 2011; Biewen et al., 2014). Moreover, empirical studies identify a positive gain from introducing the voucher model of provision in comparison to the original provision model where training assignment was dominantly determined by the caseworker (Rinne et al., 2013). On the other hand, switching to client-driven training provision might result in a fundamentally different composition of training specialisation, thus clouding pre-reform versus post-reform comparisons (Doerr and Strittmatter, 2021).

A US-based randomised controlled trial compared three models of ALMP training provision (Perez et al., 2011). In the first model, clients followed an exact structure in deciding on their training specialisation; the second model balanced client choice and counselor guidance; the third model maximised client choice. The study reported the most favourable results for the third model, maximising client choice. The positive impact is identified on participants' satisfaction, dropouts as well as post-participation employment. Their evidence draws a favourable picture of the client-driven provision of publicly funded training and suggests the mechanism driving the favourable impact. In choosing the specialisation, participants account for their training-related costs. Therefore, allowing the liberty to choose should result in shared responsibility for the training outcomes, reduce

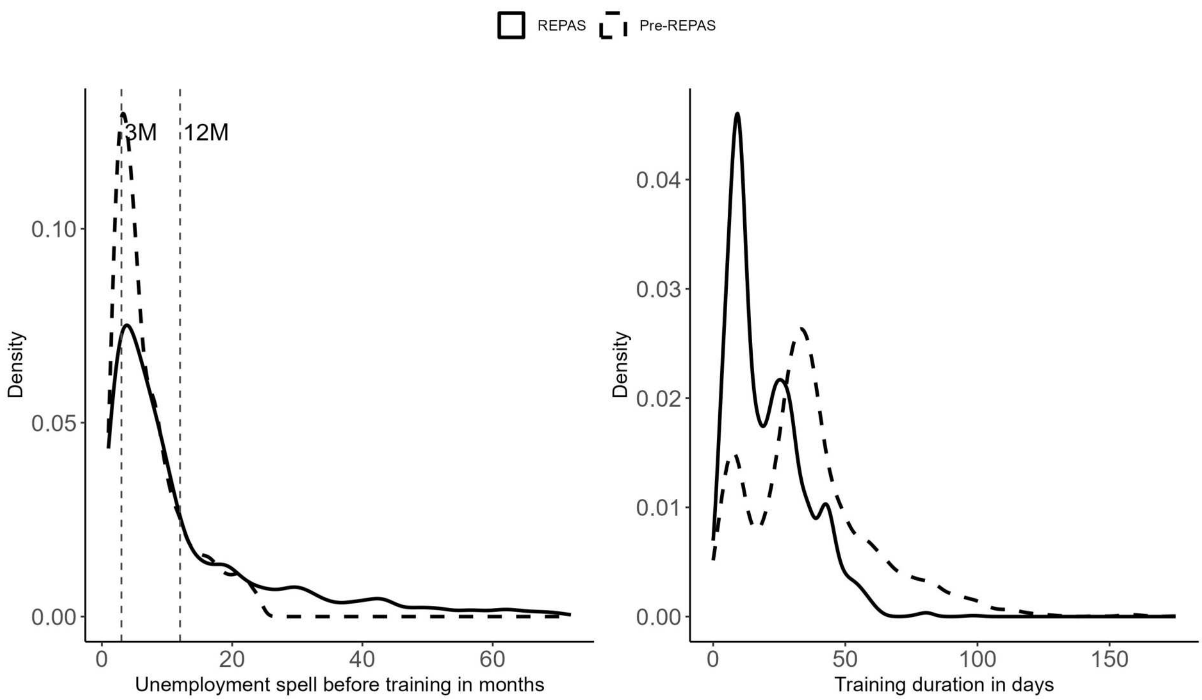
[3] For more details on the design of ALMP programmes implemented across the EU, see the Labour Market Policy Qualitative Reports at: https://ec.europa.eu/social/main.jsp?pager.offset=0&advSearchKey=LMP+Qualitative+report&mode=advancedSubmit&catId=1307&doc_submit=&policyArea=0&policyAreaSub=0&country=0&year=0#navItem-latestDocuments

dropout, and increase the completion rate.

3 Institutional context of the REPAS programme

Slovakia is a small, open, and manufacturing-oriented economy, which is manifested by its world leadership in the number of cars produced per capita.[4] Due to its occupational structure, it is exposed to the highest average risk of automation Nedelkoska and Quintini (2018). Challenges imposed by this situation led the public employment policy provider COLSAF (Central Office of Labour, Social Affairs and Family of the Slovak Republic) to introduce a so-called REPAS reform, which enlivened the publicly funded training provided to registered job seekers. Training provided under the portfolio of Slovak ALMPs was highly undernourished during the pre-REPAS period and struggling in a complicated process of centralised procuring of the training provider (Institute of Fiscal Policy, 2016)[5].

Figure 1: Distribution of training participation



Notes: Distribution of training participation by unemployment spell until the training participation in months (left plot) and length of programme in days (right plot).
Source: COLSAF

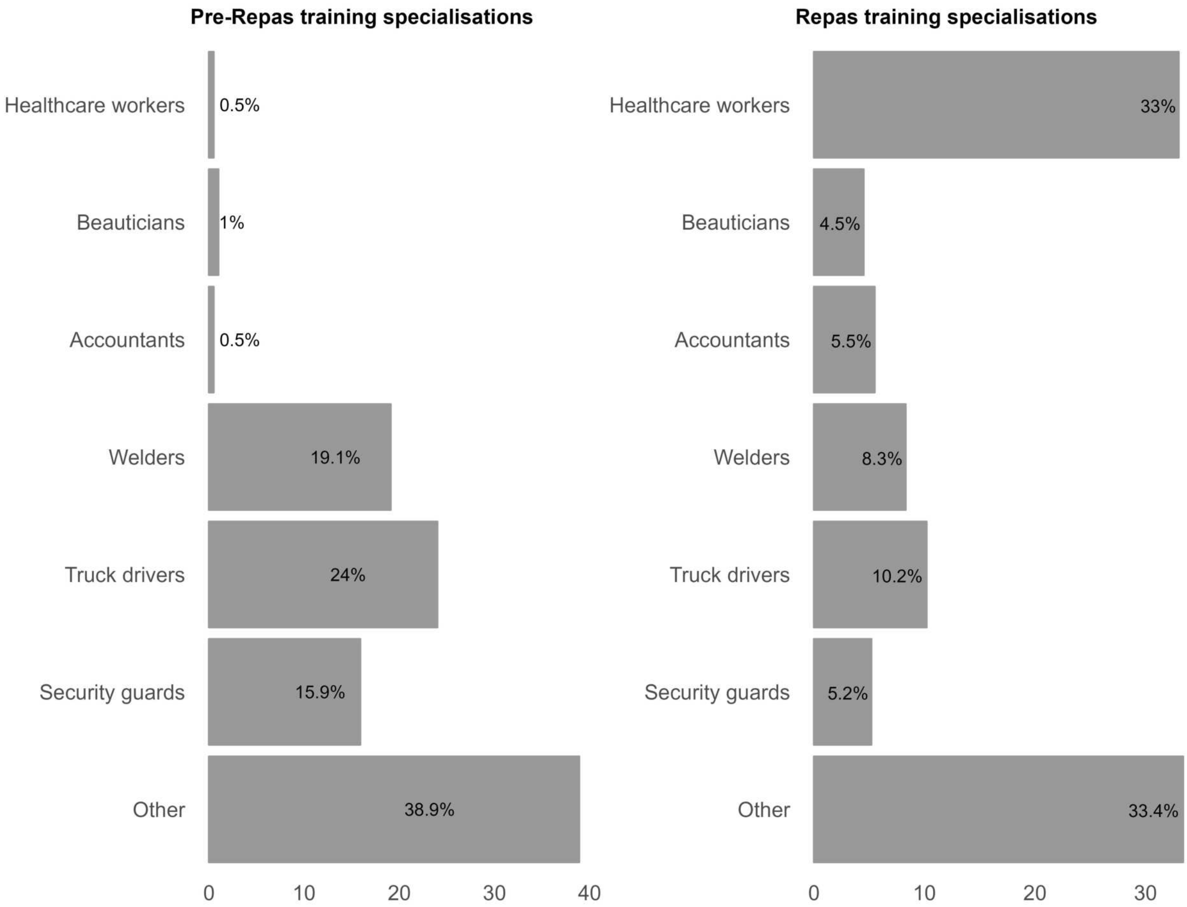
After the REPAS reform in 2014, the training specialisation and the provider can be chosen by the jobseeker from a list of accredited commercial training providers. The REPAS reform led to an increase in a sharp rise in number of participants in ALMP training. Delegating the choice of the training provider and specialisation to the job seeker, not only led to an increase in the number of participants but also made the impact on post-participation employment and income from negative

[4] https://www.oica.net/category/production-statistics/

[5] Before the REPAS reform, Slovakia ranked as the last among the EU countries based on the Labour Market Policy Database indicator: Activation-Support - LMP (training) participants per 100 persons wanting to work with a figure close to zero. After the REPAS reform, Slovakia took over Poland and the Czech Republic with a figure of approximately one training participant per 100 persons wanting to work. (Source: The Labour Market Policy Database, European Commission - Directorate-General for Employment, Social Affairs and Inclusion (DG EMPL), accessed 01.08.2023)).

to positive figures (Stefanik, 2021). The REPAS reform also made access to training much easier in the later stages of the unemployment spell, after 24 months (see the left plot in Figure 1). In terms of training duration, the REPAS reform increased the proportion of shorter, four-week training (see the right plot in Figure 1).

Figure 2: Training specialisation split in pre-REPAS and REPAS framework



Note: The bar charts are constructed based on the total number of training participants: 2860 participants in the first six months in 2015 of the REPAS period and 2974 participants in the last six months of the pre-REPAS period.
Source: COLSAF

Naturally, the REPAS reform also altered the composition of training specialisations. We can observe different splits of completed training specialisation before and after the REPAS reform in Figure 2. Interestingly, the six most numerous training specialisations were common in the pre-REPAS and REPAS periods and are much similar to training programmes provided within the German training voucher system (Kruppe and Lang, 2018). The six most numerous specialisations also covered a comparable share of training participation before (61 percent) and after the REPAS reform (67 percent). On the other hand, the composition of training specialisations altered as training programmes targeting female-dominated occupations increased their share in the portfolio: healthcare workers, beauticians and accountants.

All registered job seekers are eligible for REPAS training since their very first day of unemployment. Participants should apply before they start the training. The applications are assessed by the regional employment committees comprising COLSAF management and representatives of local social partners. The assessment considers the contribution of training in improving the reemployment chances of participants. As there are considerable inter-regional differences in the composition of participants, the assessment policies differ substantially between regional COLSAF offices.

If the application is successful, COLSAF covers the full training costs, including per diems of participants during the training. In situations where accessibility is low, job seekers' initiatives to submit applications are limited to cases where the caseworker provides information about the possibility of participation and draws attention to the allocated resources. Although rare, job seekers may also participate based on general information available on the COLSAF website or based on informal recommendations.

4 Data and the sample selection

We combine individual administrative data from COLSAF and information on employment status and earnings from the Social Insurance Agency (SIA). The data covers individuals who registered as unemployed at COLSAF between 1.1.2007 - 31.12.2017 and aged 20–55 at the time of registration. Job seekers with more than five re-entries into the registry and those with disabilities were excluded. In total 892,753 registrations of 538,249 jobseekers. From this database, we select job seekers who participated in a REPAS programme starting from 1.1.2015 until 30.6.2015. We further removed participants in multiple ALMP and with unemployment spells longer than two years before starting their REPAS participation. We keep a sample of 2,860 participants out of all 4,141 REPAS participants.

The control group consists of job seekers who were eligible during the reference period but did not participate in any ALMP programme between 1.1.2014 - 31.12.2017.[6] We kept individuals who were in the unemployment register during the first 6 months of 2015 and with unemployment spells shorter than two years before the start of the reference period (January the 1st, 2015). In total, the control group has 243,836 eligible non-participants.

For both groups, participants and the control group, we observe their:

- Individual characteristics (incl. gender, education level)
- Socio-economic characteristics (incl. skills, household composition, social benefit eligibility)
- Labour market history (incl. past income and employment status, past unemployment registrations)
- Rich set of high-granularity regional characteristics (incl. average wage, unemployment rate, commuting time, municipality-level statistics)

All in all, we control for 123 variables capturing different characteristics of both job seekers and their places of residence. A complete list of variables used in the model can be found in the Appendix (Table A.1).

Within this sample, we further restrict our attention to the six most numerous training specialisations provided after the REPAS reform, covering two out of three REPAS participants during the evaluation period[7]:

- Health Care Assistant (ISCO-08 code: 5321)
- Welder (ISCO-08 code: 7212)
- Truck Driver (ISCO-08 codes: 8332 and 8344)
- Security Guard (ISCO-08 code: 5414)
- Accountant (ISCO-08 code: 2411)

[6] Accessibility of ALMP programmes was low (less than ten percent) during the reference period, allowing us to cut this share of the sample without a considerable bias.

[7] The number of treated job seekers in selected program specializations after the cleaning was $1,732$ out of the total participants of $2,831$ (around 66.6 percent).

- Beautician (ISCO-08 codes: 5141 and 5142)

Similarly, as in the German training voucher system (Kruppe and Lang, 2018), the REPAS training specialisations are strongly gender-imbalanced. Women dominate in healthcare assistance, accounting, and beauty training, while men in welding, truck driving, and security. We take advantage of this concentration, and for the sake of limiting heterogeneity, we focus on gender-specific samples, meaning that we keep only women (resp. men) in both the treatment and control groups of each of the training specialisations.[8] The size of the final evaluation sample for each training specialisation is reported in Table 1. In contrast to other gender-specific studies (Lechner et al., 2007; Kruppe and Lang, 2018; Schmidpeter and Winter-Ebmer, 2021), the training specialisations did not target only low-educated job seekers. Interestingly, there is a considerable number of female participants with university diplomas, particularly in accounting training. A more detailed overview of selected characteristics of the treatment and control groups is reported in Table 2.

Table 1: Evaluation sample per training specialization

Training specialization	**Sample**	**Dropped job seekers**
Female-specific group	Women	Men
Healthcare workers	841	91
Beauticians	124	2
Accountants	131	24
Control group	114,434	
Male-specific group	Men	Women
Welders	235	1
Truck drivers	123	12
Security guards	278	23
Control group	129,402	

Additionally, we linked these specialisations with target occupations at the level of a four-digit ISCO code. This link enables us to assign the occupation-specific risk of automation of Webb (2019) to each of the considered training specialisation[9].

To investigate the effectiveness of self-chosen REPAS programmes, we use various labour market outcomes. More specifically, the outcomes of interest are:

i) The absence from the register of unemployed administered by COLSAF (proxy for employment status).

ii) Employment status based on mandatory registration of employed persons at the Social Insurance Agency (SIA)[10].

(Un)employment status may differ between the data sources (COLSAF and SIA). This can happen in cases when an ex-COLSAF client leaves registered unemployment but finds a job abroad or enters into the informal economy. To reduce their social contributions, a self-employed person often intentionally reports less income in the SIA system than was actually received, significantly

[8]We further apply data cleaning techniques since we are dealing with high-dimensional data. Datasets can have predictors with distribution (predictors with only a single unique value or with a very low frequency of unique values), which can cause errors when fitting a model or report unstable results. To clean data, we follow these steps: : i) we remove all covariates with 0 variance since most of our variables are dummy variables, ii) we remove dummy variables that do not have at least 0.001% of 1s or 0s, iii) we remove dummy variables that do not have at least 0.005% of 1s or 0s in the sub-group of participants and iv) we only keep dummy variables that have a minimal number of 5 observations in the sub-group of participants.

[9]Using the average of the three indices of automation exposure introduced by Webb (2019) and linked to the ISCO-08 classification wising the bridge between the SOC and ISCO classification available, published by the US Bureau of Labour Statistics, at `https://www.bls.gov/soc/isco_soc_crosswalk_process.pdf`. In the Appendix, we also report results for alternative occupation-specific measures of the risks of computerisation, reported in Appendix A of Frey and Osborne (2017)

[10]A jobseeker is considered unemployed if his/her monthly earnings do not exceed 148.57 EUR.

Table 2: Descriptive statistics of participants for each training specialization and non-participants

	Female-specific groups				Male-specific groups			
	Healthcare workers	**Beauticians**	**Accountants**	**Control group**	**Welders**	**Truck drivers**	**Security guards**	**Control group**
Individual characteristics								
Number of observations	841	124	131	114434	235	123	278	129402
Age (years)	41	33.5	36.2	34.5	31	38.6	32.8	33.7
Married (%)	28.1	50.8	51.9	41.7	26.4	39	28.1	41.7
Kids in the household	17.7	18.5	16	16.2	8.1	7.3	6.5	6.2
Foreign language (%)	78.4	89.5	90.1	79.1	83.8	76.4	84.9	79.5
PC skills (%)	62.1	81.5	87	66.7	68.1	60.2	67.3	60.3
Driving licence (%)	49.3	66.1	71.8	50.9	77.9	73.2	78.8	67.8
Education level (%)								
No education	0.5	0	0	1.2	0.4	0	0.4	1.4
Primary	7.7	4.8	3.8	11.7	8.5	8.9	7.9	12.8
Lower secondary	35.7	12.9	7.6	22.7	36.2	39.8	26.6	34.2
Upper secondary	47.3	65.3	47.3	41.6	48.9	43.1	54	38.8
Tertiary	8.8	16.9	41.2	22.7	6	8.1	11.2	12.8
Nationality (%)								
Slovak (%)	81.8	90.3	96.9	90.1	91.5	85.4	92.1	90.9
Hungarian (%)	17.6	8.1	2.3	8.7	8.1	13	6.8	8.1
Roma (%)	0	0	0	0.1	0	0.8	0.4	0.1
Other (%)	0.6	1.6	0.8	1.1	0.4	0.8	0.7	0.9
Region (%)								
Bratislavsky	3.1	17.7	10.7	11.1	0.9	9.8	8.3	9.2
Banskobystricky	14.1	5.6	17.6	11.8	17	23.6	18	12.3
Kosicky	16.2	16.1	20.6	13.3	14	13	11.5	14.5
Nitriansky	18.4	11.3	6.9	14.1	9.8	8.1	7.9	12.9
Presovsky	18.3	12.1	12.2	15.1	24.3	13	20.1	17.6
Trenciansky	8.1	13.7	9.2	11.1	15.3	10.6	8.6	10.9
Trnavsky	10.8	12.9	15.3	10.7	7.2	16.3	14.7	9.4
Zilinsky	10.9	10.5	7.6	12.8	11.5	5.7	10.8	13.3
Individual labor market history								
Unemployment spell length (months)	20	19	19	24	18	22	21	25
Previous employment (%)	61.8	58.1	64.1	34.5	56.6	69.9	61.9	33.7
Economic field of previous employment (%)								
Accommodation & food service	2	6.5	1.5	2.4	0.9	1.6	1.1	1
Agriculture, forestry & fishing	1	1.6	1.5	0.7	1.3	0	1.8	1.2
Arts, entertainment & recreation	0.5	2.4	0.8	0.6	0.4	0.8	0.4	0.3
Construction	2.1	2.4	2.3	0.9	7.7	8.1	4.3	5.8
Education	1.9	4.8	2.3	1.4	0	0.8	0	0.3
Financial & insurance	0.6	1.6	2.3	1.2	0.4	0.8	0	0.4
Human health & social work	2	0.8	3.1	1.4	0.4	1.6	1.4	0.3
Information & communication	0.5	0	1.5	0.7	0.4	0.8	0.7	0.7
Manufacturing	17.2	8.9	9.9	8.1	16.6	12.2	9.7	8.1
Other services activities	0.7	3.2	1.5	0.9	0.9	0	0.4	0.4
Professional, scientific & technical act.	1.5	4	6.1	2.1	0.9	2.4	0.7	1.4
Public administration & defence	2.3	2.4	6.9	1.6	1.3	1.6	1.1	1.3
Real estate	1.2	1.6	0	0.5	0	0.8	0.7	0.3
Transporting & storage	1.8	0.8	2.3	0.9	1.3	1.6	3.6	1.8
Wholesale & retail trade	12.5	16.1	16.8	9.5	3.8	9.8	10.1	5.4

harming the information collected about this group of employed[11]. We explore the average treatment effects on the treated on these outcomes of interest during 36 months after the start of the first cohort[12].

[11]A self-employed person might decide to pay social contributions only based on the minimum income (148.57 EUR)

[12]The evaluation period is restricted by the available data from the SIA.

5 Empirical strategy

5.1 Measuring the risk of automation

Using the occupation-specific risk of automation estimated by Frey and Osborne (2017), we assign a risk of automation to the position performed before the start of the unemployment spell and the position targeted by the chosen training specialisation. Our data do not allow us to follow the exact occupation in the employment after the registered unemployment. Therefore, we presume that training participation leads to finding a job in a sector related to the self-chosen training specialisation.

Potential observable positive effects of training participation could support such a presumption. The additional employed participants on top of the group of eligible non-participants could be attributed to skills enhanced by the training. At the same time, existing empirical studies report relatively longer negative lock-in effects after ALMP training programmes that could be driven by the motivation of participants to take up a job in an area in which their newly acquired skills can be better utilised (Lechner et al., 2011; Schochet et al., 2008; Rinne et al., 2013).

5.2 Identifying the impact on labour market outcomes

To investigate the effectiveness of self-chosen REPAS programmes, we use various labour market outcomes. More specifically, the outcomes of interest are:

i) The absence from the register of unemployed administered by COLSAF (proxy for employment status).

ii) Employment status based on mandatory registration of employed persons at the Social Insurance Agency (SIA)[13].

(Un)employment status may differ between the data sources (COLSAF and SIA). This can happen in cases when an ex-COLSAF client leaves registered unemployment but finds a job abroad or enters into the informal economy. To reduce their social contributions, a self-employed person often intentionally reports less income in the SIA system than was received, significantly harming the information collected about this group of employed[14]. We explore the average treatment effects of the treated on their presence in formal employment during 36 months[15] and on the absence from unemployment during 95 months after the start of the first cohort.

We estimate the average treatment effect on the treated (ATET) to address the research question regarding the impact of REPAS training on job seekers' probability of finding a job. This means that we compare the outcomes of REPAS participants with those of non-participants if they had not participated. Following the potential outcome framework described by Rubin (1974), each job seeker has two potential outcomes: Y^1 denotes the outcome if a job seeker took part in the REPAS programme and Y^0 if not. The ATET is the difference between the mean outcomes of participants and non-participants within a treated group:

$$ATET = E[Y^1|D = 1] - E[Y^0|D = 1] \quad (1)$$

where D if the treatment was received (equal 1 if a job seeker participated in the REPAS programme).

We identify the ATET under the conditional independence assumption (CIA). In other words, we assume that after conditioning on a set of confounding variables, the potential outcomes are independent of treatment assignment (Rosenbaum and Rubin, 1983). We follow Lechner and Wunsch (2013) and Biewen et al. (2014) who highlight the importance of including not only the individual

[13] A job seeker is considered unemployed if his/her monthly earnings do not exceed 148.57 EUR.

[14] A self-employed person might decide to pay social contributions only based on the minimum income (148.57 EUR)

[15] The evaluation period is restricted by the available data from the SIA.

socio-demographic characteristics but also information related to personal labour market history and regional labour characteristics. Accordingly, to justify the assumption, we control for individual and socio-economic characteristics but also control for individual labour market history, including long-term unemployment, the unemployment spell, unemployment status, and earnings up to three months before the start of the first cohort, which seems to be relevant for employment prospects. Lastly, we include variables to capture regional peculiarities, e.g. regional dummies, the population at the place of residence, the share of Roma in the city of residence, travelling time to Bratislava in minutes and to the nearest PES in minutes, and regional unemployment rate. Because of the richness of our database of detailed administrative records, we see the advantages of identifying the impact of training participation under CIA over the alternatives.

In addition to the CIA, we assume that the stable unit treatment value assumption (SUTVA) holds, that is to say, non-participants are not affected by the participation in the REPAS programmes of the treated group.

5.3 Estimation procedure

In this study, we use causal machine learning which adapts machine learning methods in causal analysis. The advantage of machine learning estimators is that they are flexible, allow to capture nonlinear relationships, and can deal with high-dimensional data (Lechner, 2023). However, the issue is that these estimators are usually biased, leading to bias in the estimation of the main effect, and their convergence rate tends to be slow. Thus, we follow an approach proposed by Chernozhukov et al. (2018) that applies double/debiased machine learning (DML) approach to estimate the treatment effect. This method was developed to overcome the problem of bias resulting from the trade-off between bias and variance, the so-called regularization bias, and overfitting. DML combines doubly robust score functions and cross-fitting which helps to remove regularization bias and from overfitting.

The main idea is to construct a following moment function ψ (with property $E[\psi] = 0$) for estimating our target parameter $\theta = ATET$:

$$\psi(W;\theta,\eta) = \frac{D(Y-\mu(X))}{p} - \frac{m(X)(1-D)(Y-\mu(X))}{p(1-m(X))} - \frac{D}{p}\theta, \tag{2}$$

where $W = (Y, D, X)$ is our data sample, and $\eta = (\mu, m, p)$ denotes nuisance parameters, that are estimated using machine learning algorithms. The nuisance parameters i) $\mu(X) = E[Y|D = 0, X]$, ii) $m(X) = Pr(D = 1|X)$ and iii) $p = Pr(D = 1)$ are not of our direct interest. The first parameter $\mu(X)$ is the outcome model for the control group. The function $m(X)$ corresponds to the propensity score function capturing the probability that an individual will participate in a given programme based on observable characteristics X. Lastly, p is the unconditional probability of being treated and can be estimated as a simple proportion of the treated. The observed confounders X affect the treatment D via the propensity score $m(X)$ and the outcome via the function $\mu(X)$. We made use of `causalweight` package (Bodory and Huber, 2019) that implements 3-fold cross-fitting and random forest algorithms (`SuperLearner` package of Polley et al. (2019)) for our nuisance parameter estimation of μ and m.[16] To account for a common support issue,[17] We rely on trimming and discarding observations with extreme propensity scores.[18]

In the sensitivity analysis, we apply inverse probability weighting (IPW) to test the robustness of estimated causal treatment effects. Results acquired following the routine of Austin and Stuart (2015) can be found in the Appendix (Figures A.4 and A.5).

[16]We modified `treatDML()` function to estimate ATET using moment function from `https://docs.doubleml.org/stable/guide/scores.html` subsection (5.2.3).

[17]However, the question remains whether a DML setup is sensitive to a lack of common support and what degree of covariate overlap is sufficient (Lechner, 2023).

[18]We drop observations with treatment propensity score values smaller than 0.01.

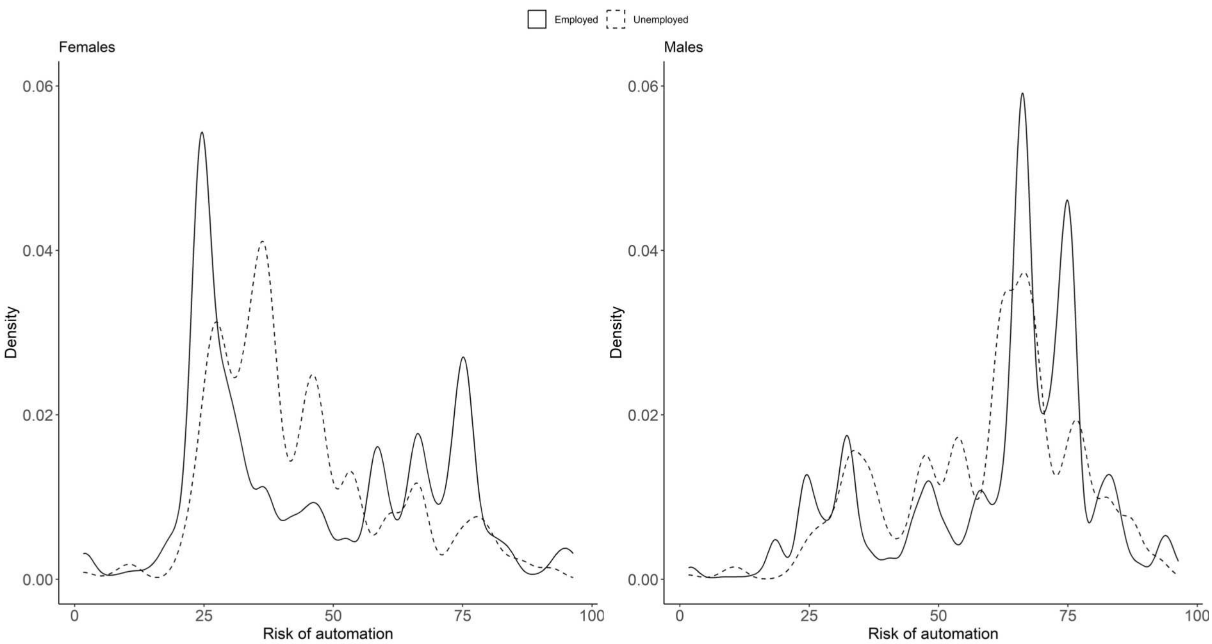
6 Findings

In this section, we first investigate whether registered job seekers, when they are allowed to choose their training, tend to reduce their risk of automation. In the second part, we explore the impact of participating in the chosen training specialisation on selected labour market outcomes.

6.1 Change in automation risk

Training provided during transitions between jobs could compensate for the automation training gap. Here, we examine a publicly funded programme where the choice of training provider and specialisation is left to the participating jobseeker. In particular, we examine whether jobseekers prefer specialisations that prepare them for occupations with a lower risk of automation. Aware of the gender differences in the chosen training specialisations, we first plot the distribution of the automation risk for the employed and unemployed population of women and men (see Figure 3). In line with the literature (Heß et al., 2023; Nedelkoska and Quintini, 2018), we observe that, on average, males are exposed to a higher risk of automation. More surprisingly, the distribution of the occupation-specific automation risk of the unemployed does not significantly differ from the distribution of the employed.

Figure 3: The distribution of the risk of automation of employed and unemployed

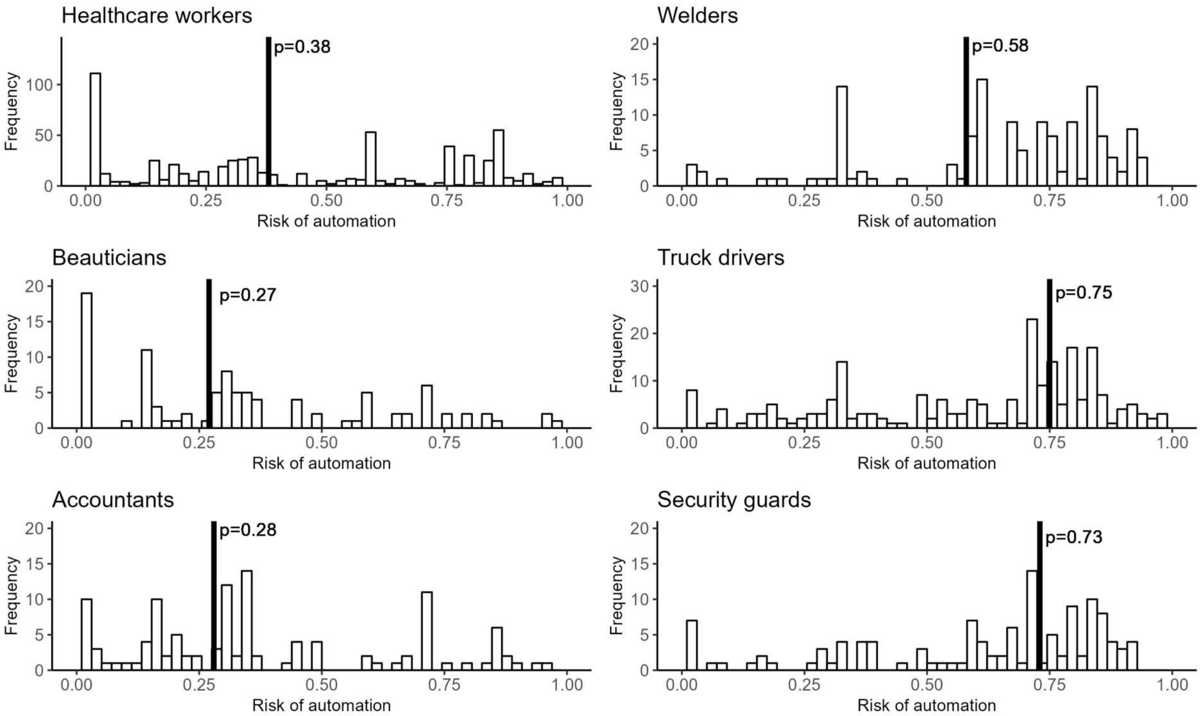


Note: The risk of automation in the occupation preceding the start of unemployment (dashed line) and the risk of automation in the current occupation of employed (solid line).
Source: COLSAF Database based on Webb (2019).

Further, we examine the risk of automation of participants by training specialisations (Figure 4). We compare the automation risk in the occupation preceding the unemployment during which participants received the training with the risk associated with the occupation targeted by the training specialisation. Figure 4 illustrates the distribution of the automation risk that participants faced before becoming unemployed. The bar charts show the estimated risk of automation for the occupation associated with the training specialisation. The left column displays female training specialisations, while the right column shows the three male specialisations. The actual occupation of employment after training participation is not observed.

The three most popular specialisations for women are in occupations with a lower risk of automation (between 0.27 and 0.38). On the other hand, the three most popular specialisations for men all target occupations with a higher risk of automation (between 0.58 and 0.75). Despite these differences, both genders tend to choose a training specialisation that is less threatened by automation compared to the pre-unemployment occupation.

Figure 4: Change in the risk of automation of participants implied by training



Note: The risk of automation of participants in the occupation preceding registration and the risk of automation in the target occupation (probability in parentheses displayed by the solid vertical line). The risk of automation stands for the average of the three measures of exposure to automation reported by Webb (2019).
Source: COLSAF Database.

Looking at training programmes attended predominantly by women, it can be seen that training as an accountant leads to a career in an occupation with a 28% chance of automation. By comparison, retrained beauticians would face a much lower chance of automation (27%) in the occupation to which their training is directed. Although healthcare training presents the most popular specialisation, it faces a relatively higher (38%) risk of automation. However, this reduction in automation risk is offset by the high automation risk that participants faced in their pre-training occupation. The same is true for male-dominated occupations such as welders, security guards and drivers. Although their automation risk is relatively high, their previous occupation was associated with an even higher automation risk. It seems that participation in the selected training specialisations may result in a reduction in their automation risk.

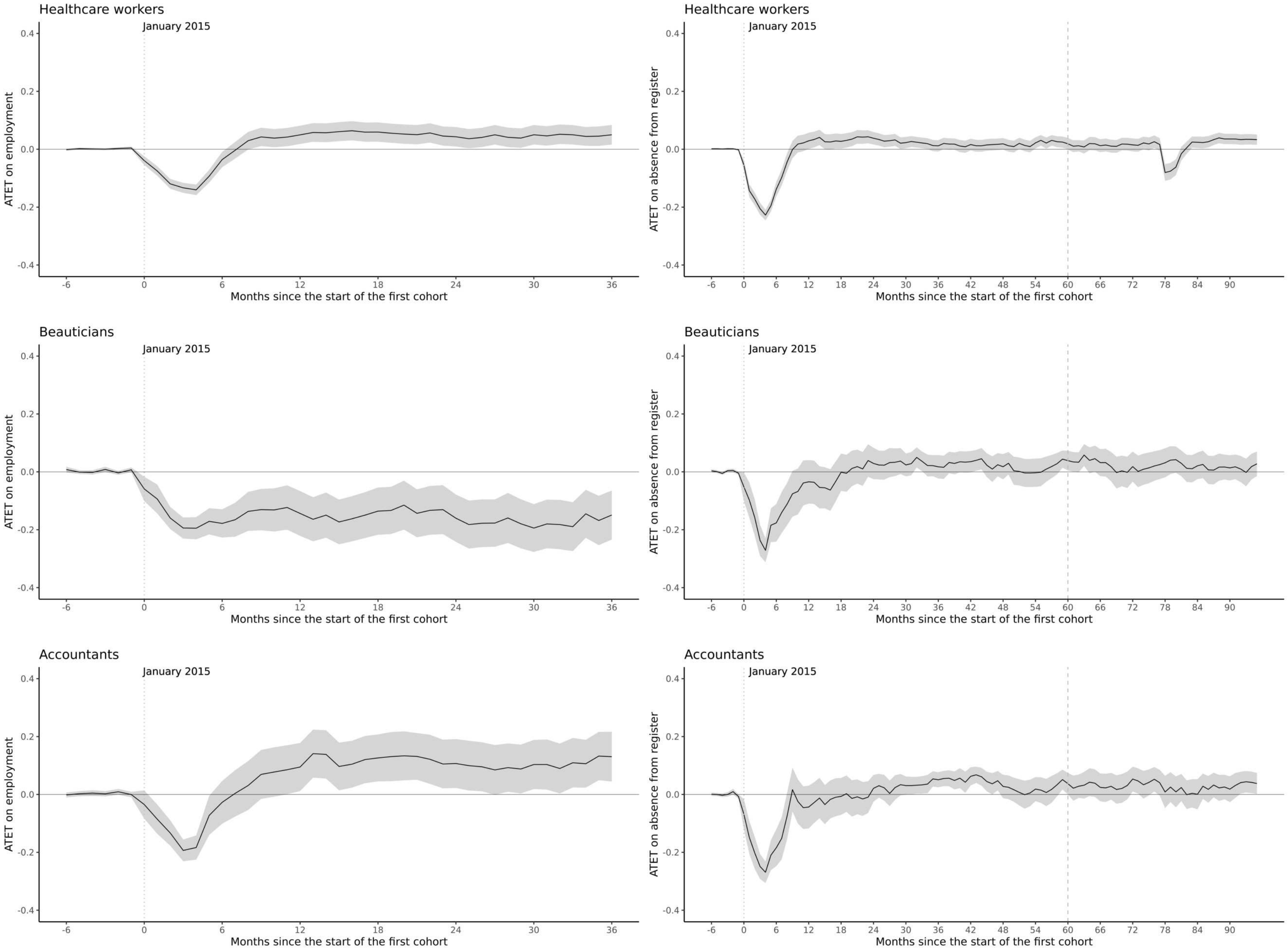
6.2 Impact on labour market outcomes

This section presents the estimation of the average treatment effect on the treated (ATET) for outcomes described in the Empirical strategy section. Figure 5 shows the estimated ATETs on employment probabilities of women who completed training in healthcare assistance, beauty, and accounting. Figure 6 displays the ATETs on employment probabilities of men who completed training in welding, truck driving, and security [19]. The plots on the right capture the estimated probability of not being registered in the COLSAF unemployment register, while the plots on the left capture the probability of being registered in formal employment by the SIA.

We observe both similarities and differences in outcomes across training specialisations. In general, our results imply a positive employment effect of training programmes in the long run and a negative lock-in effect in the short run, which is in line with earlier empirical studies ((Lechner et al., 2011; Doerr et al., 2017; Doerr and Strittmatter, 2021). Second, after the lock-in period, the probability of employment rises from negative to insignificant or positive and statistically significant values. The only exception is the beautician specialisation, whose participants more often find jobs in the informal economy. This is evidenced by the combination of negative ATETs for employment registered by the SIA and predominantly no or occasionally positive ATETs estimated for absence from registered unemployment. After the training, participants less often left the unemployment register and also remained out of registered employment for longer than the quasi-control group.

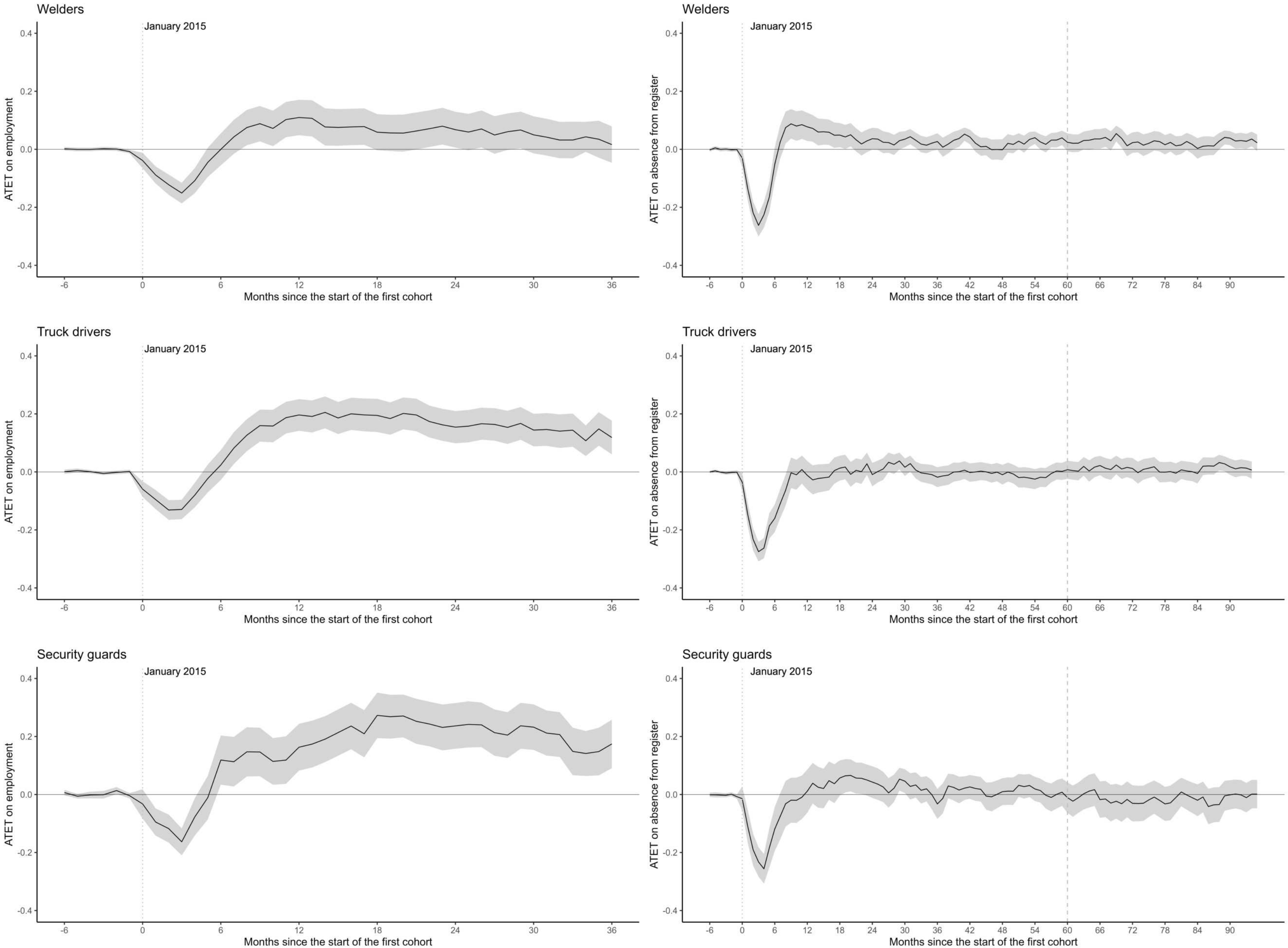
[19] The raw proportions of participants and controls who were employed or absent from the unemployment register can be found in the Annexe (Figures A.2 and A.3).

Figure 5: Average treatment effect of participation in training for healthcare workers, beauticians and accountants



Note: The shaded region provides the 95% confidence intervals of ATET. The dashed line on the 60th month indicates the start of measures against Covid-19.
Source: COLSAF, SIA

Figure 6: Average treatment effect of participation in training for welders, drivers and security guards



Note: The shaded region provides the 95% confidence intervals of ATET. The dashed line on the 60th month indicates the start of measures against Covid-19.
Source: COLSAF, SIA

The ATETs reported in Figures 5 and 6 are calculated based on the difference between the potential outcomes of participating and not participating in any training programme. These outcomes present the shares of participants in and out of the two registers (SIA and COLSAF) and can be found in the Appendix (see the orange dotted line in Figure A.2 and A.3 of the Appendix). Our data allow us to trace participants in the SIA register for 36 months (presence in formal employment) and for 95 months in the COLSAF register (absence from unemployment). The proportion of presence in registered employment differs from the absence from the unemployment register. Observing this discrepancy[20] across genders and training specialisation reveals some interesting findings. Several possible explanations can be identified for the different employment outcomes observed by COLSAF and SIA; mainly:

- Leaving the COLSAF unemployment register for reasons other than employment typically involves carrying out duties, and taking maternity or parental leave.
- Alternatively, it could be explained by emigration to find employment outside Slovakia. Studies suggest that this is particularly common among healthcare professionals who frequently work as care workers abroad, especially in Austria (Bahna et al., 2019).
- Undeclared employment in Slovakia, which refers to work that is not declared to the authorities (SIA), may affect the discrepancy in both directions (undeclared workers may not be unregistered from the COLSAF register[21].

When exploring the discrepancy across genders, it becomes apparent that it is more pronounced for female training specialisations. However, the differences between particular specialisations overshadow those driven by gender. For training specialisations preparing for occupations within the country, potentially linked to a certificate only valid in Slovakia (accountants or security guards), there is basically no discrepancy between the absence of unemployment and the presence of formal employment at the beginning of the post-participation period (up to 12 or 18 months). In contrast, the discrepancy is most pronounced when it comes to training specialisations for occupations that are mobile across borders, such as healthcare workers, welders, and partially, truck drivers. It begins right after the lock-in effect fades out, six months after participation.

Leaving the unemployment register to carry out duties or employment abroad should result in a combination of positive ATET on the absence from the unemployment register (COLSAF) combined with no ATET observable on the employment register (SIA). In the case of beauty training, there is an increased likelihood of participating in undeclared work projects, which results in negative effects on the absence from the unemployment register (COLSAF) as well as negative effects observable in the employment register (SIA).

Comparing the ATETs of female specialisations on formal employment (left column of Figure 5), the highest positive impact is observed for accountants, followed by healthcare workers, the female specialisations with the highest exposure to automation, based on Webb (2019), but also Frey and Osborne (2017) (see Figure A.1a). The positive effect is also observed in the absence of the unemployment register[22]. Doerr et al. (2017) and Schmidpeter and Winter-Ebmer (2021) point out that unemployed workers with higher levels of education have better re-employment prospects. For female participants, our evidence aligns with their findings, as participants in accounting training are the most educated in our sample and show the ATETs of the highest magnitude among female training specialisations.

The male-dominated training specialisations tend to attract participants with a lower level of education than the female-dominated training specialisations. However, in contrast to the female-

[20]The reader is invited to examine the difference between the green and orange lines shown in Figures A.2 and A.3.

[21]In the European comparison, COLSAF is classified as a rather strict PES, with random call-ups and close cooperation with Labour Inspections.

[22]The drop in healthcare training ATETs after the 78th month is due to the lockdown measures during the COVID-19 pandemic.

dominated specialisations, all three male-specific specialisations show positive and statistically significant ATETs. For all three male-dominated training specialisations, the observed impact on registered employment (SIA) is more pronounced than the observed impact on not being registered as unemployed (COLSAF). For the two specialisations associated with higher exposure to automation (Truck drivers and Security guards), participation in training is associated with a higher impact on registered employment after participation. In the case of welding training, the occupation with the lowest risk of automation (based on Webb (2019)), the impact is positive but less intense. Lower ATETs for formal employment among welders may be due to a higher proportion of participants seeking employment outside of Slovakia. This is because welders have the highest ATETs for absence from the unemployment register among male-dominated specialisations. Training of security guards is associated with the highest gains from the perspective of the public budget. Participation in security guards' training has positive effects on registered employment with magnitudes of more than 20 percentage points. However, its impact on the absence of registered unemployment is less favourable than for welders, especially in the long term. Although all the male-dominated training specialisations are associated with a higher risk of automation, welders are relatively less exposed (Frey and Osborne, 2017; Webb, 2019), which may explain the more favourable long-term effects.

To check the robustness of our findings, we also report ATETs estimated by an inverse probability weighting estimator (IPW) in Figures A.4 and A.5 in Appendix. Overall, the IPW models produced results comparable to those of the DML, but the magnitude of the ATETs is higher. We interpret the reduction in the magnitude of the estimated ATETs (in comparison to the IPW estimators) to be driven by the improved ability of DML to account for confounding factors. These factors may be driving part of the larger estimated effect when using the IPW estimators."

7 Discussion and conclusion

Labour market changes resulting from automation and technological advancements are frequently discussed in policy circles. The role of ALMP training programmes in mitigating the adverse impact of the increasing risk of automation is essential. These programmes support individuals in their career transitions, which is an objective in itself. We provide a case study of one particular ALMP training program comparable to numerous others across European countries. While the dominant stream of impact evaluations considers ALMP training programmes as one type of intervention ,we focus on specific training specialisations that yield results comparable to a German training voucher scheme (Kruppe and Lang, 2018). In addition to previous studies (Schmidpeter and Winter-Ebmer, 2021; Blien et al., 2021), we raise the question of the contribution of ALMP training to reducing the automation risk of individuals, taking into account the structure of the programme specialisations chosen by the unemployed participants.

We use high-dimensional administrative data to explore the training choices of unemployed job seekers and investigate the effect of participation in a publicly funded training programme available to registered jobseekers in Slovakia. After controlling for potentially relevant confounding variables capturing the observable characteristics, we apply a double machine learning estimator to remove a potential regularisation and overfitting bias.

We document that by being allowed to select the provider and training specialisation, job seekers tend to choose the training that is less likely to be automated than their previous occupation. While men tend to re-skill into occupations with a higher risk of automation, their pre-unemployment occupations are associated with an even higher risk of automation. Although women target occupations with a lower automation risk, their pre-unemployment automation risk is also much lower.

Finally, allowing job seekers to choose their training specialisation and provider improved equality of access to publicly funded training. The move to a client-choice model led to an increase in female-dominated training specialisations to a proportion more in line with the structure of the eligible population, ultimately allowing a rise in the share of female participants. On the other hand, a client-choice model of training provision may not result in the most effective allocation of public funds, with individuals being trained for employment abroad (healthcare workers, welders) or in the informal sector (beauticians).

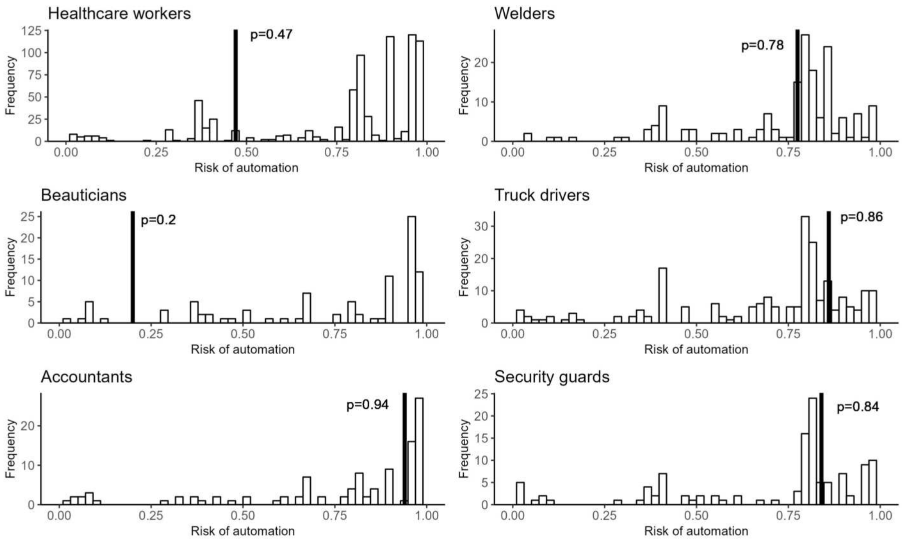
Our results suggest that unemployment training can improve job seekers' existing skills, potentially leading to better re-employment prospects. However, the most effective training specialisations do not overlap with those that are most effective in reducing the risk of automation. As supported by several empirical studies, we estimate a positive employment effect observable in the long run and a negative lock-in effect in the short run. In addition, there may be unobserved patterns that help explain the differences in labour market outcomes across specialisations. Thanks to a wider list of observed outcomes, our results show that certain training specialisations, such as healthcare assistant and welding training, are used as channels to find employment abroad. On the other hand, beauty training seems to provide an opportunity to set up a beauty business in the informal sector. In contrast, other training specialisations, such as truck driving or security guards, provide a path for low-skilled male job seekers to find employment in Slovakia in occupations with a relatively higher risk of automation, which still might present an improvement compared to the risk of automation experience in the preceding occupation.

Given the impact of new technologies and automation on the occupational structure and the likelihood of finding a job, there are expectations of an increase in demand for career-track changes following unemployment. Publicly funded training offered to the unemployed can help job seekers enhance their skills, which are ever more exposed to automation. However, we document that the potential benefit of reducing the risk of automation does not always overlap with the benefit of increasing job seekers' chances of re-employment. Each training specialisation tells a different story, with different aspects playing a role in determining post-participation employment chances. It is important to examine the effectiveness of AMLPs in the light of reducing the risk of automation while also maintaining a comprehensive perspective, assessing their impact on labour market outcomes against their costs to the public budget. Examples of client-chosen, publicly sponsored ALMP training show that the individual and public gains do not always overlap. Moreover, also the reduction of the participants' automation risk does not always overlap with their gains in post-participation labour market prospects.

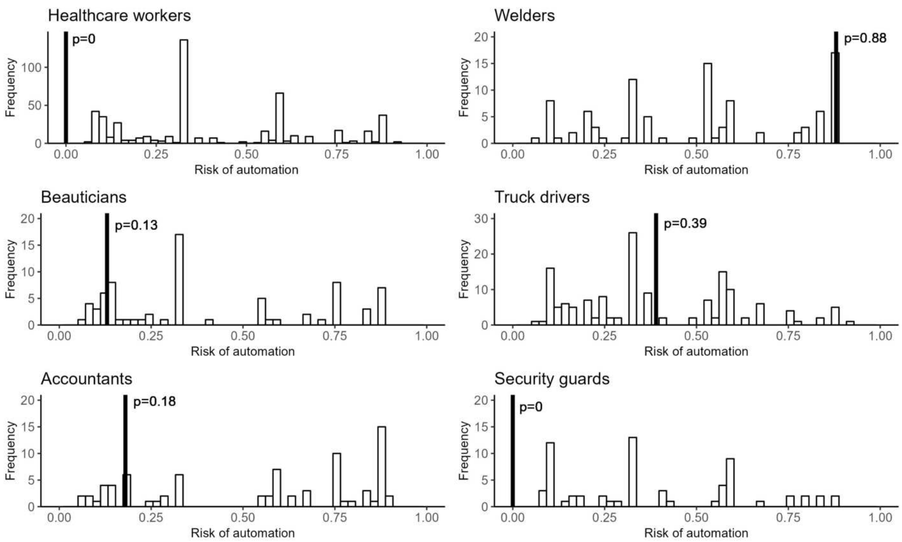
Appendix

Figure A.1: Change in the risk of automation implied by training

(a) Frey and Osborne (2017)

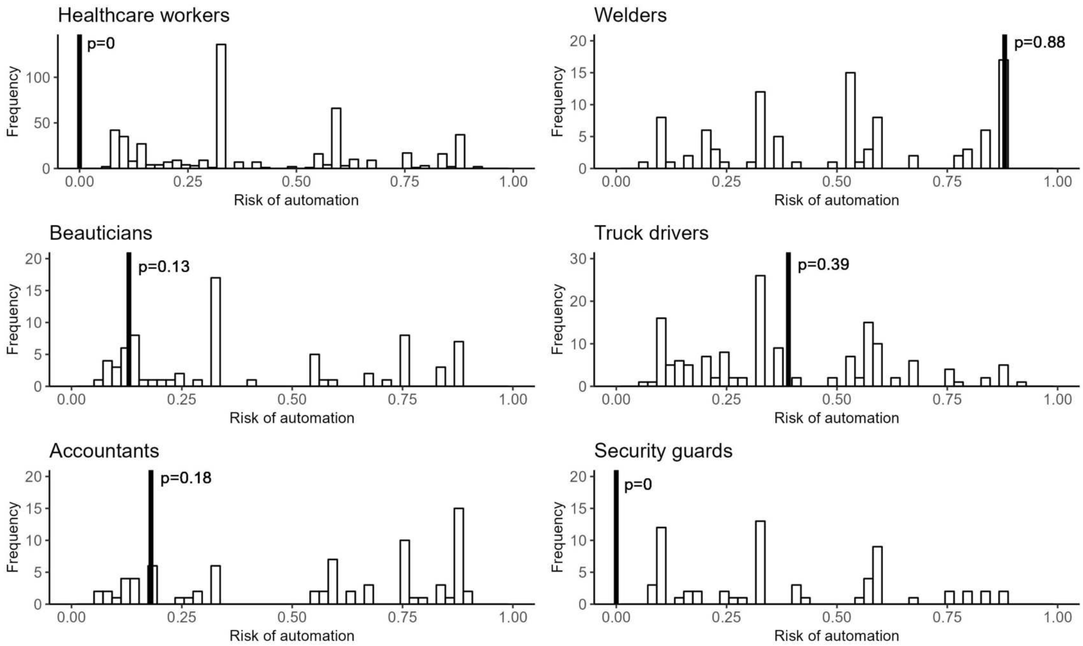


(b) Mihaylov and Tijdens (2019)



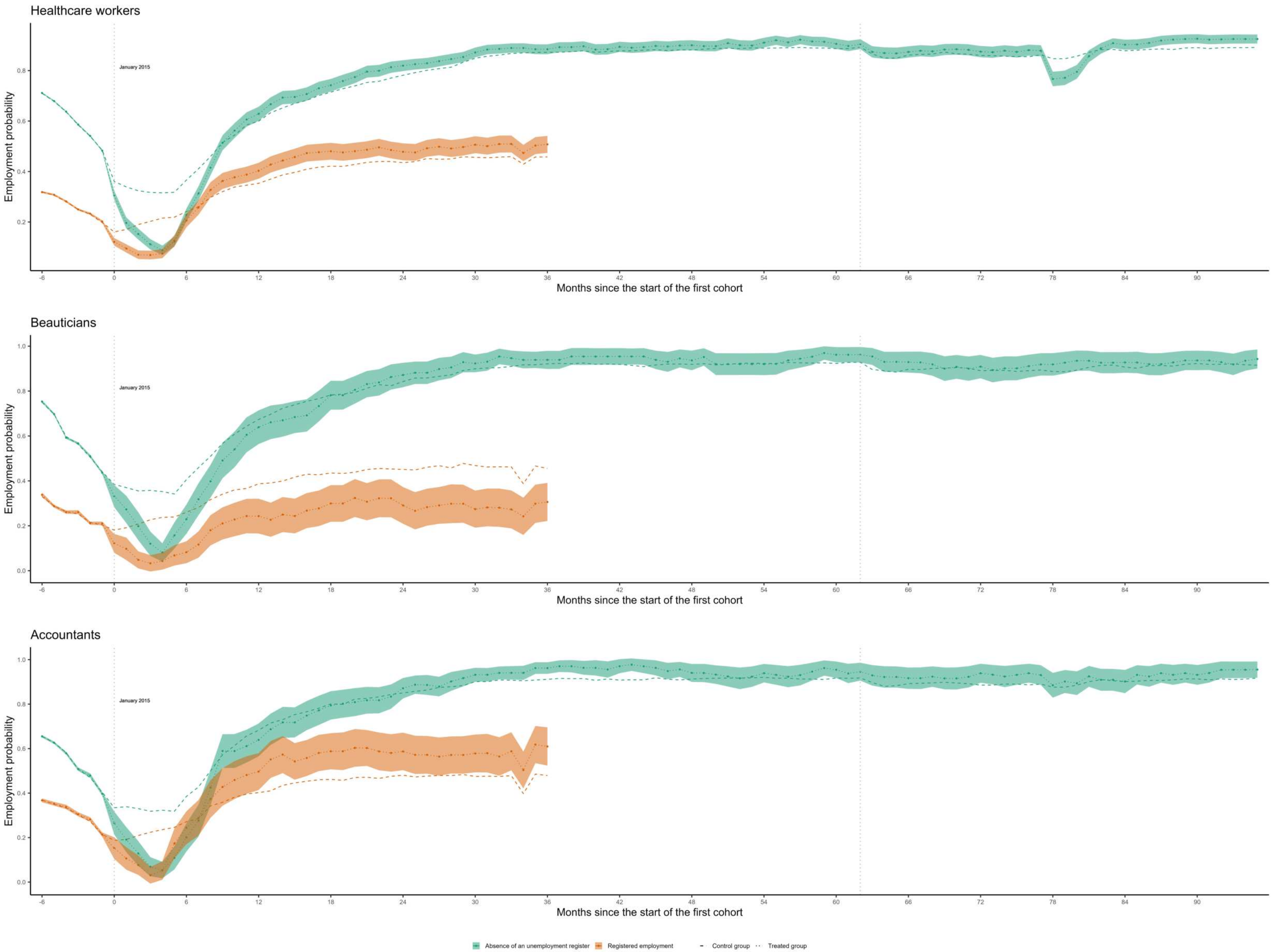
Change in the risk of automation implied by training (continued)

(c) Dengler et al. (2014)



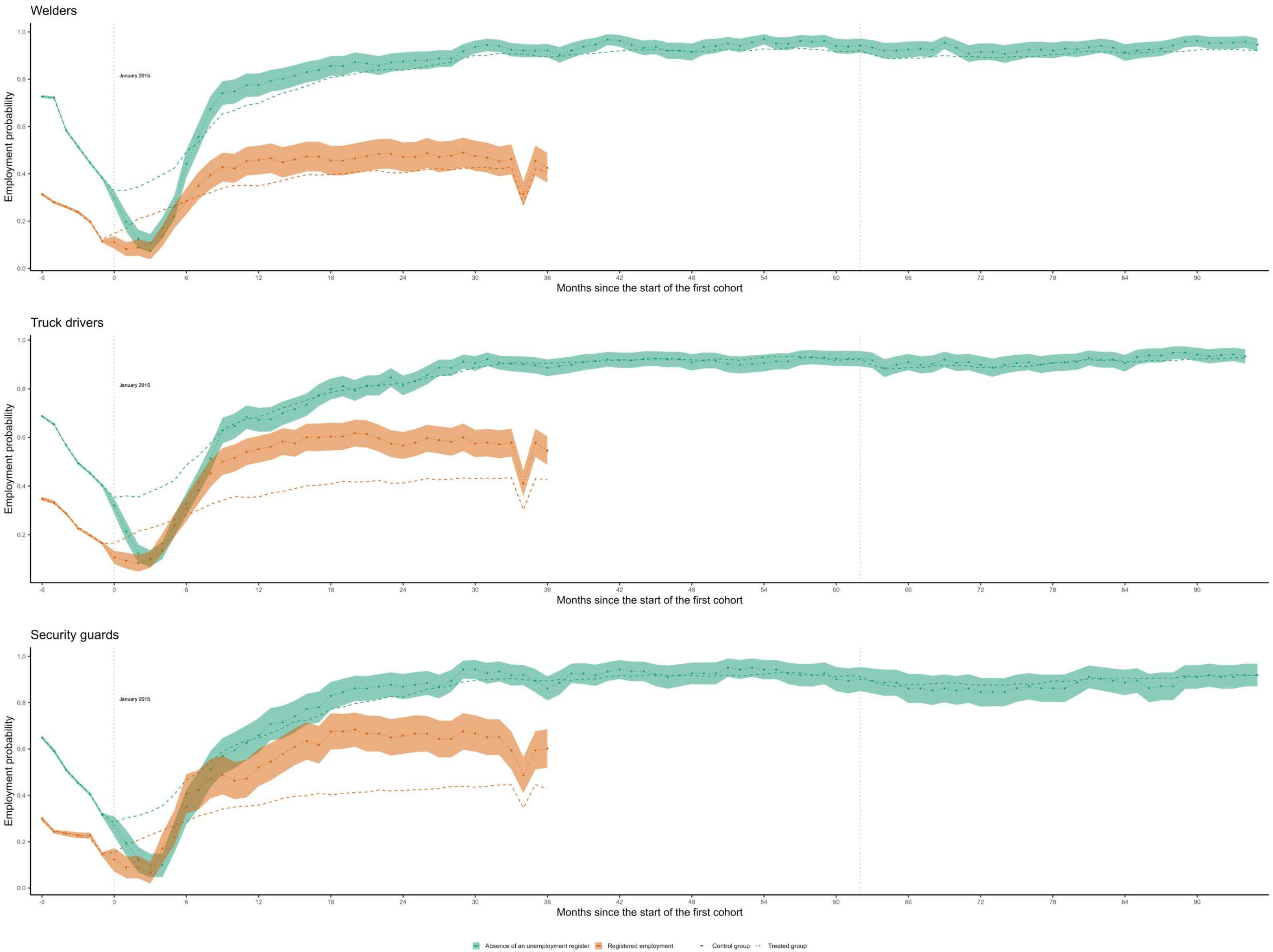
Note: The risk of automation in the occupation preceding registration and the risk of automation in the target occupation (probability in parentheses displayed by the solid vertical line).
Source: COLSAF Database.

Figure A.2: Casual effect of participation in training for healthcare workers, beauticians and accountants based on DML



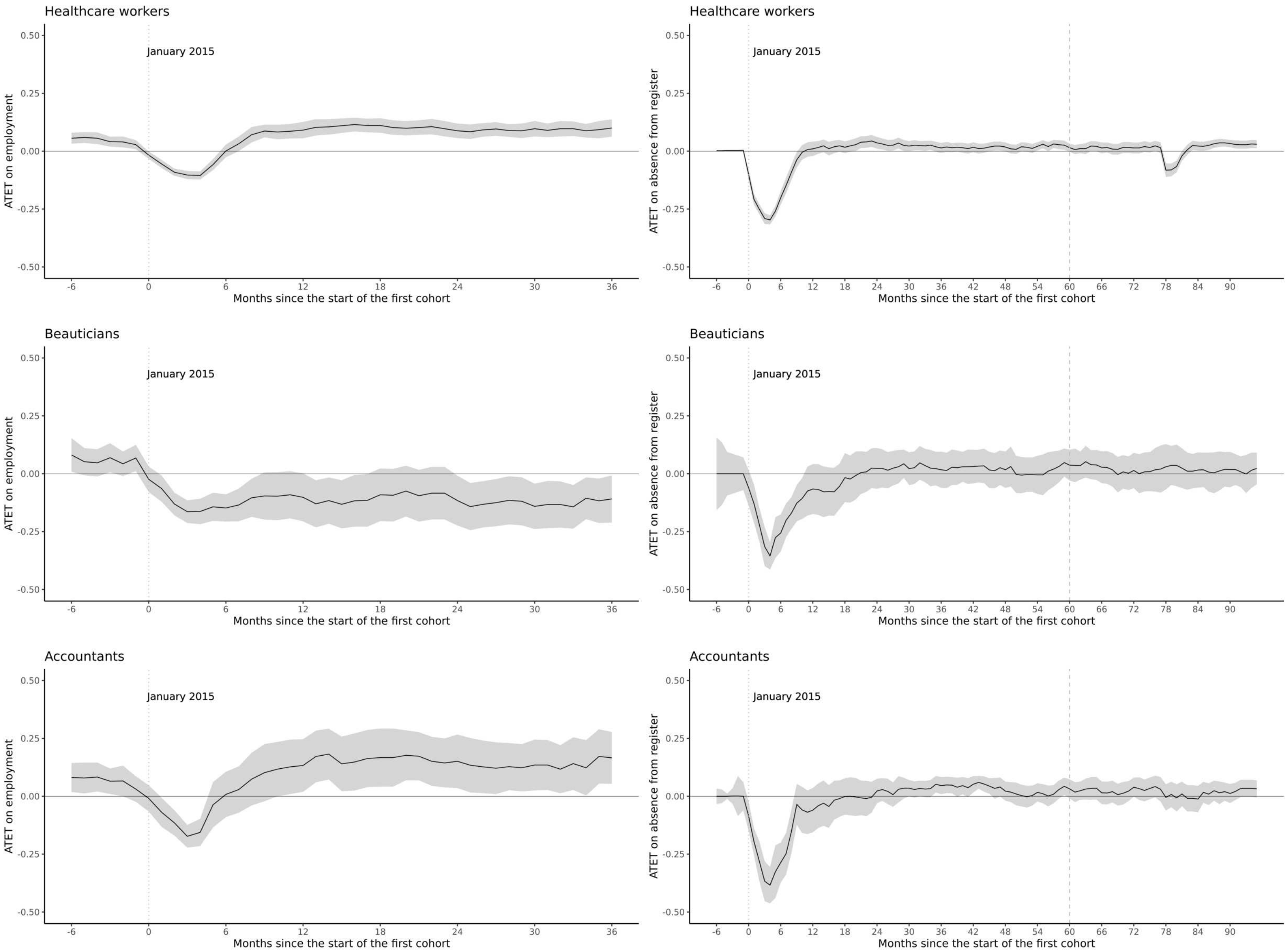
Note: The employment probability is captured as the absence of an unemployment register of COLSAF (in green) and registered employment from the Social Insurance Agency (in orange). The dashed line shows the employment probability for the control group, the dotted line shows the employment probability for the treated. The shaded region provides the 95% confidence intervals of ATET.
Source: COLSAF, Social Insurance Agency.

Figure A.3: Casual effect of participation in training for welders, truck drivers and security guards based on DML



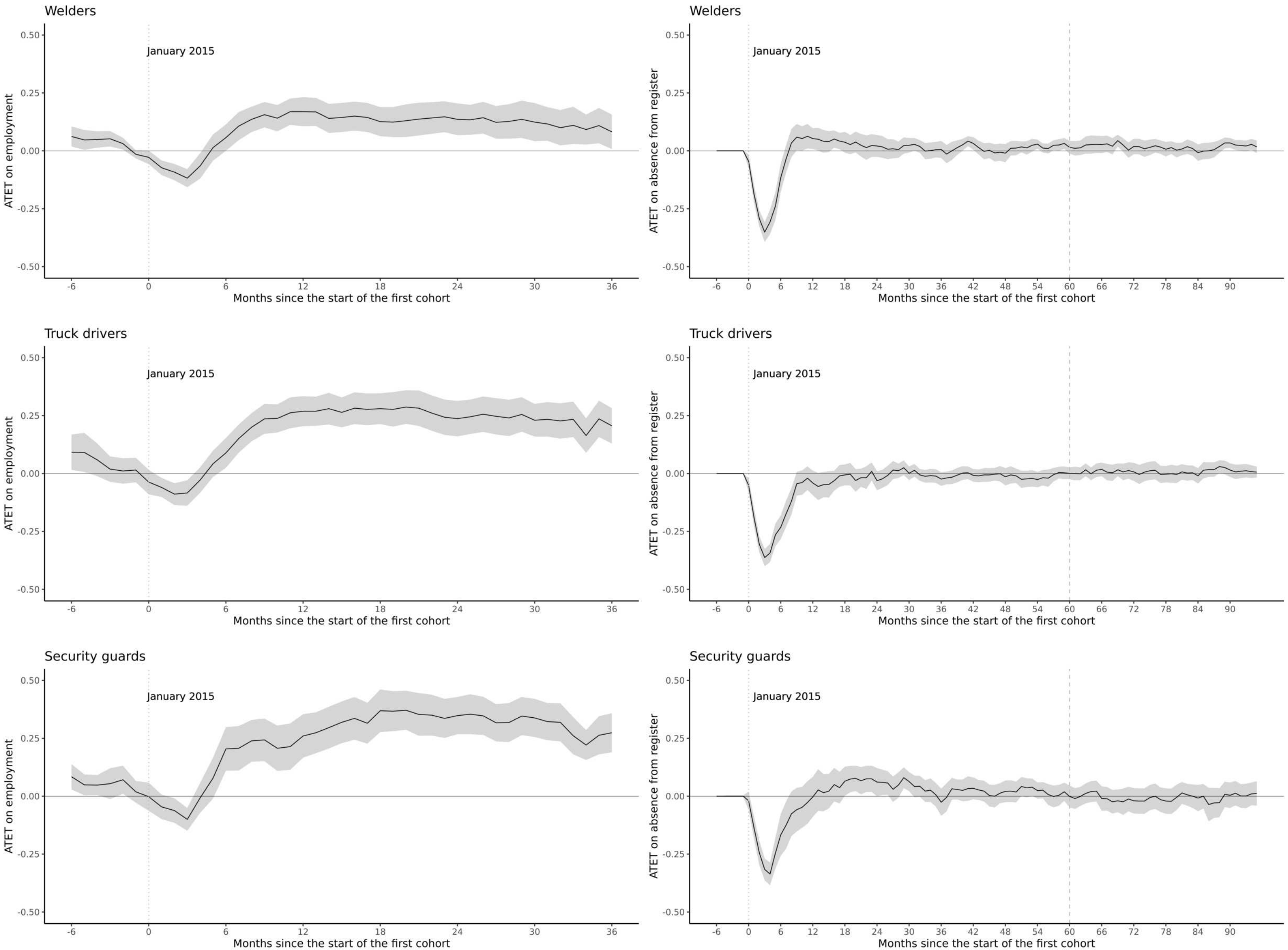
Note: The employment probability is captured as the absence of an unemployment register of COLSAF (in green) and registered employment from the Social Insurance Agency (in orange). The dashed line shows the employment probability for the control group, the dotted line shows the employment probability for the treated. The shaded region provides the 95% confidence intervals of ATET.
Source: COLSAF, Social Insurance Agency.

Figure A.4: Average treatment effect of participation in training for healthcare workers, beauticians and accountants based on inverse probability weighting



Note: The shaded region provides the 95% confidence intervals of ATET. The dashed line on the 60th month indicates the start of measures against Covid-19.
Source: COLSAF, SIA

Figure A.5: Average treatment effect of participation in training for welders, drivers and security guards based on inverse probability weighting



Note: The shaded region provides the 95% confidence intervals of ATET. The dashed line on the 60th month indicates the start of measures against Covid-19.
Source: COLSAF, SIA

Figure A.6: Absolute standardized mean differences in unweighted and weighted samples for healthcare workers based on inverse probability weighting

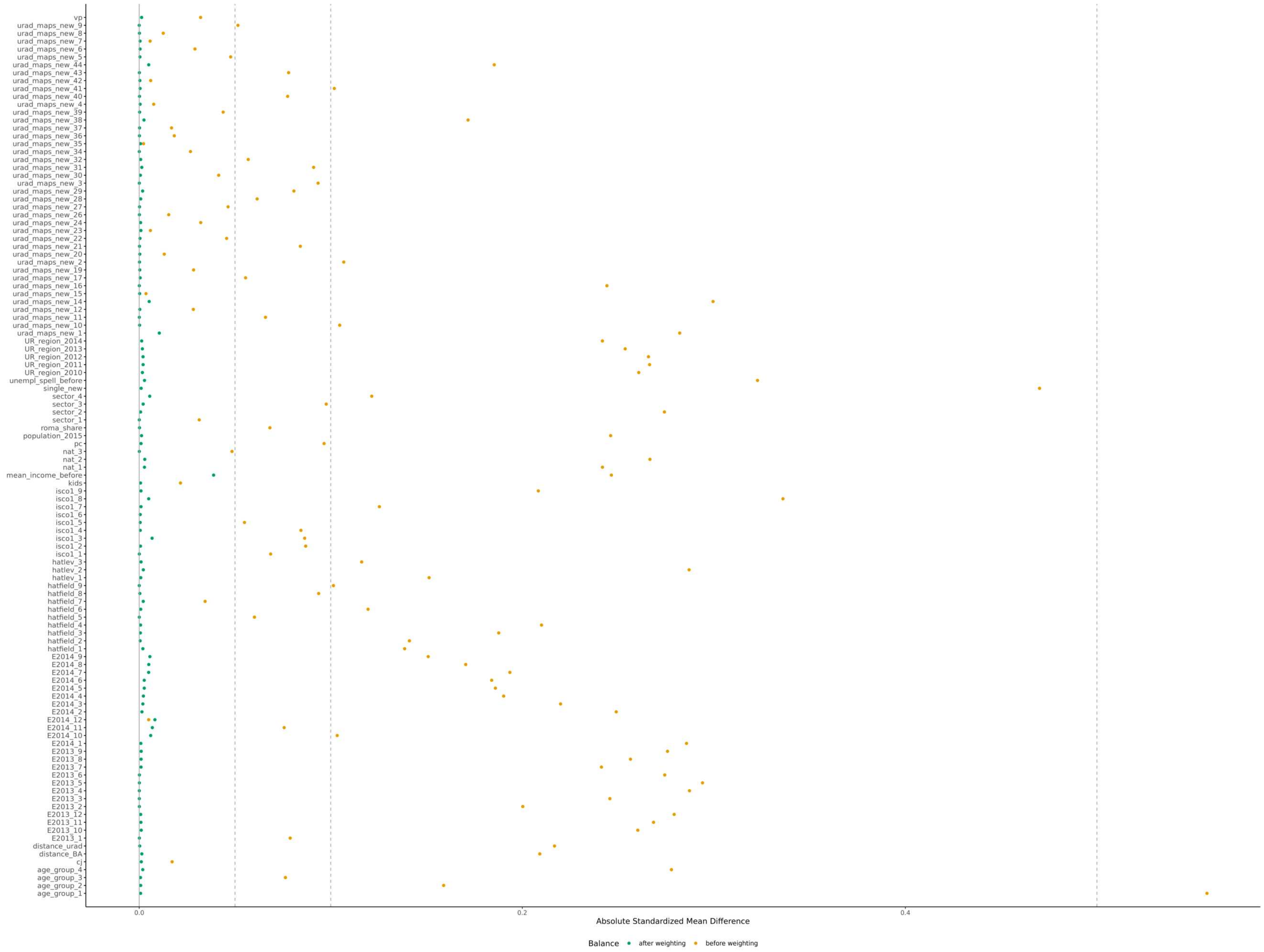


Figure A.7: Absolute standardized mean differences in unweighted and weighted samples for beauticians based on inverse probability weighting

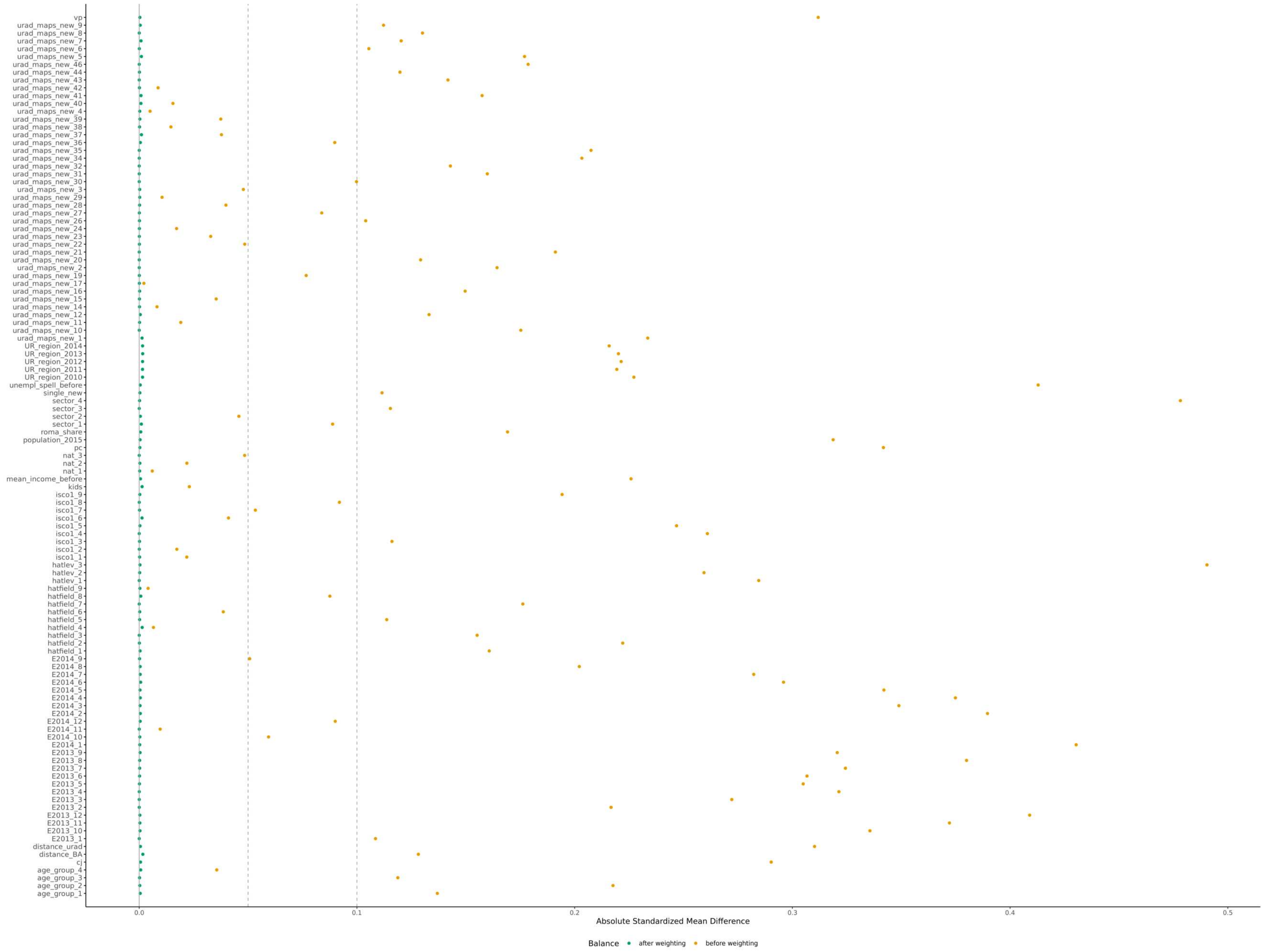


Figure A.8: Absolute standardized mean differences in unweighted and weighted samples for accountants based on inverse probability weighting

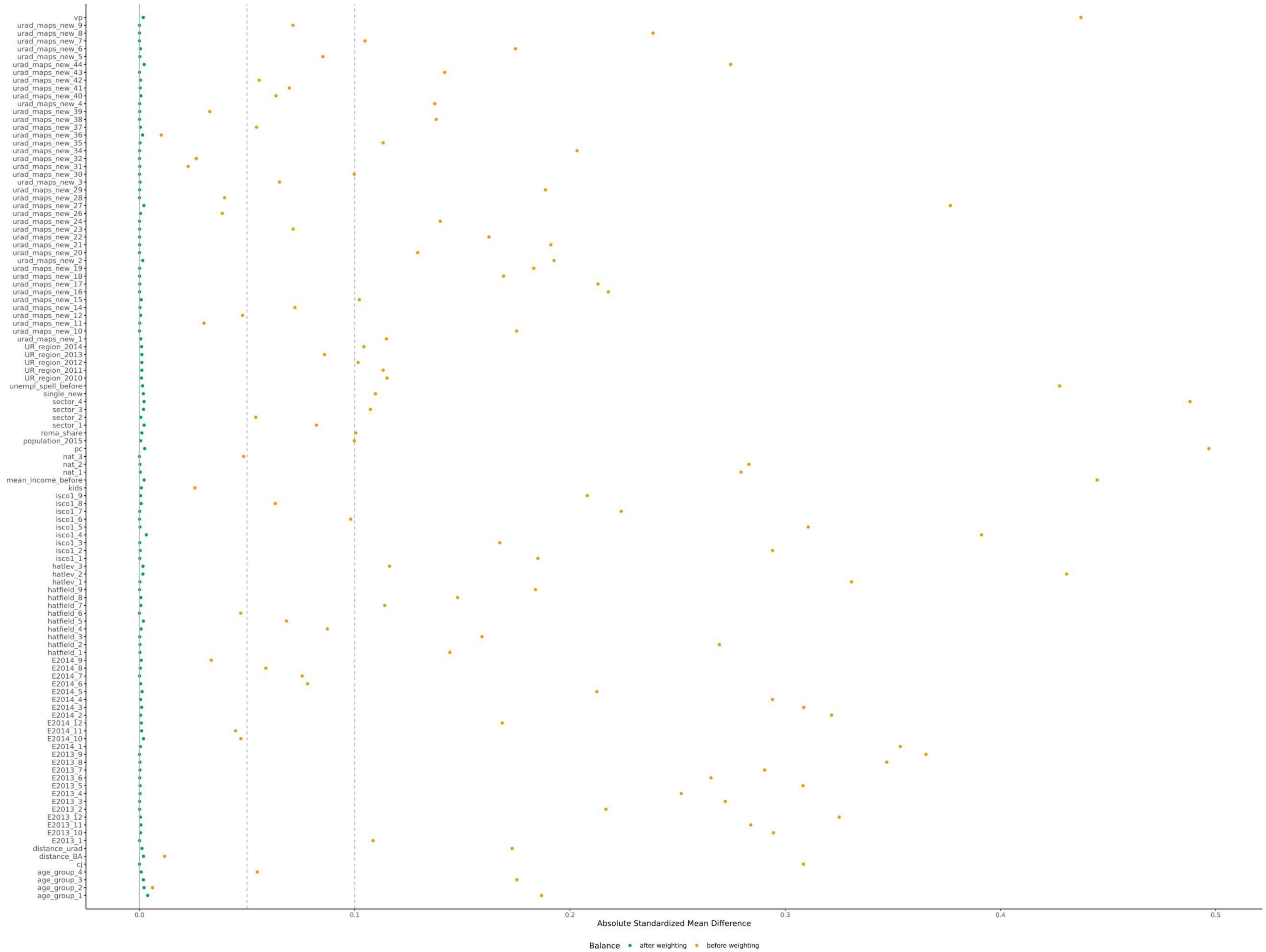


Figure A.9: Absolute standardized mean differences in unweighted and weighted samples for welders based on inverse probability weighting

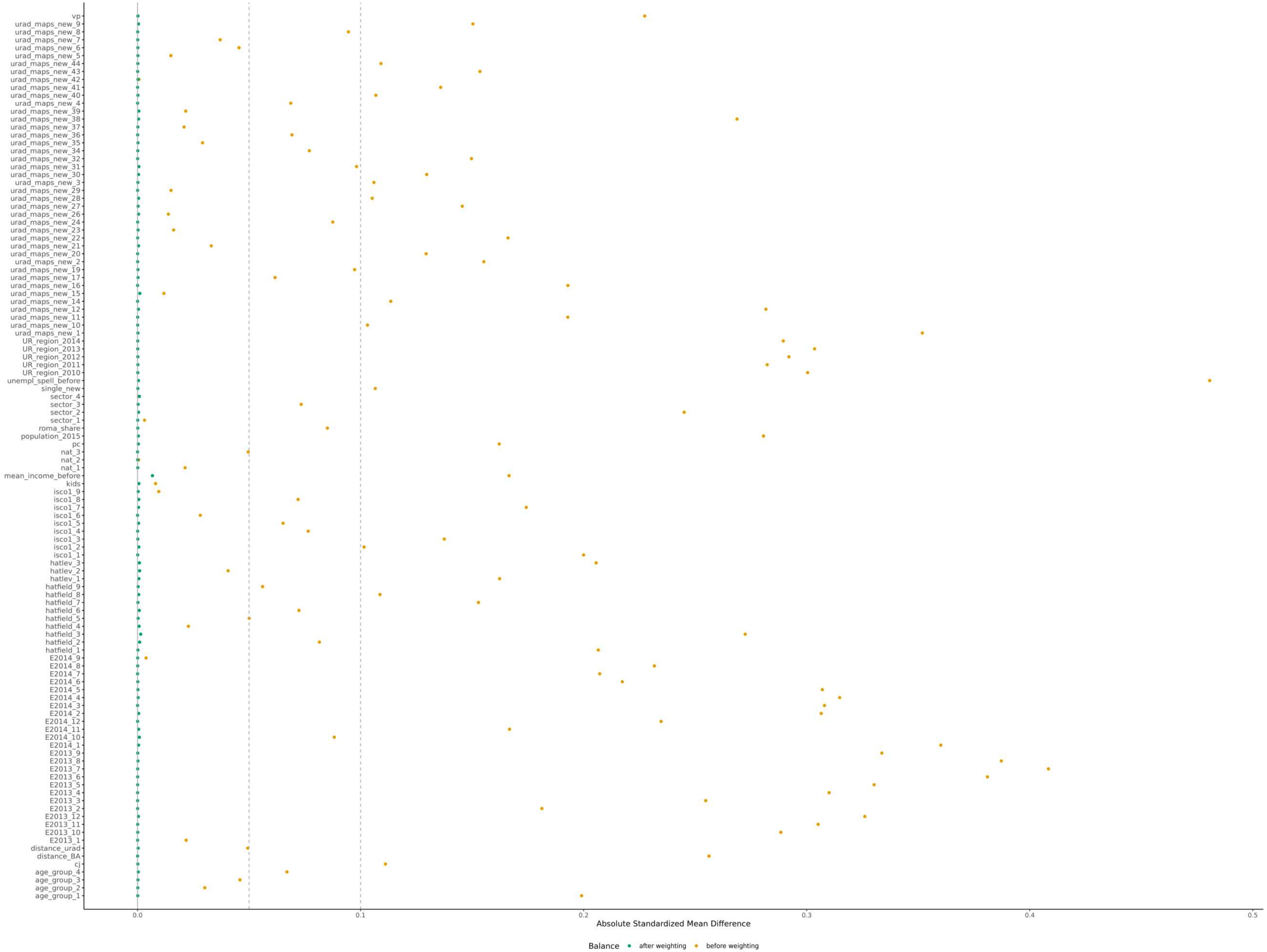


Figure A.10: Absolute standardized mean differences in unweighted and weighted samples for truck drivers based on inverse probability weighting

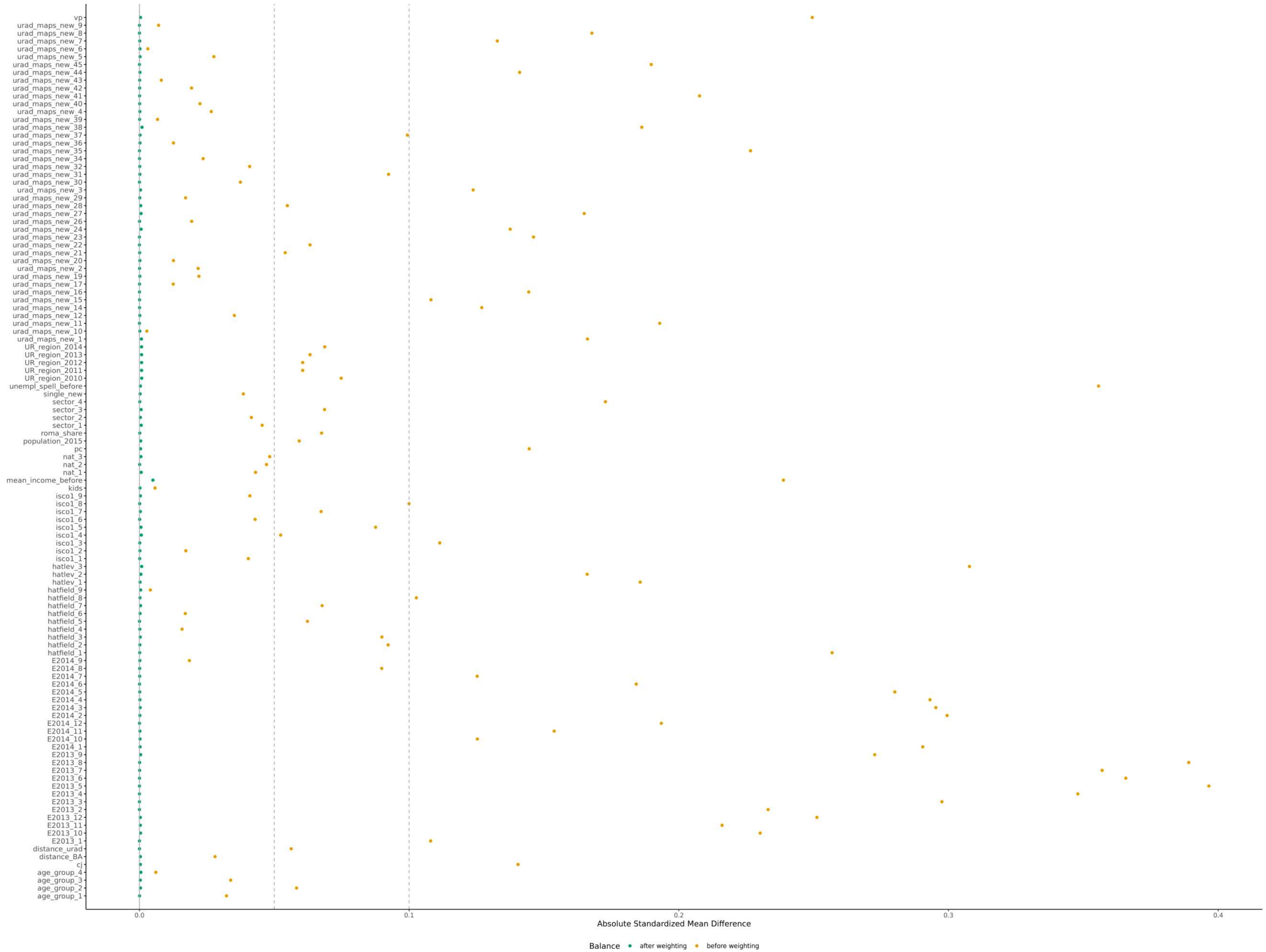


Figure A.11: Absolute standardized mean differences in unweighted and weighted samples for security guards based on inverse probability weighting

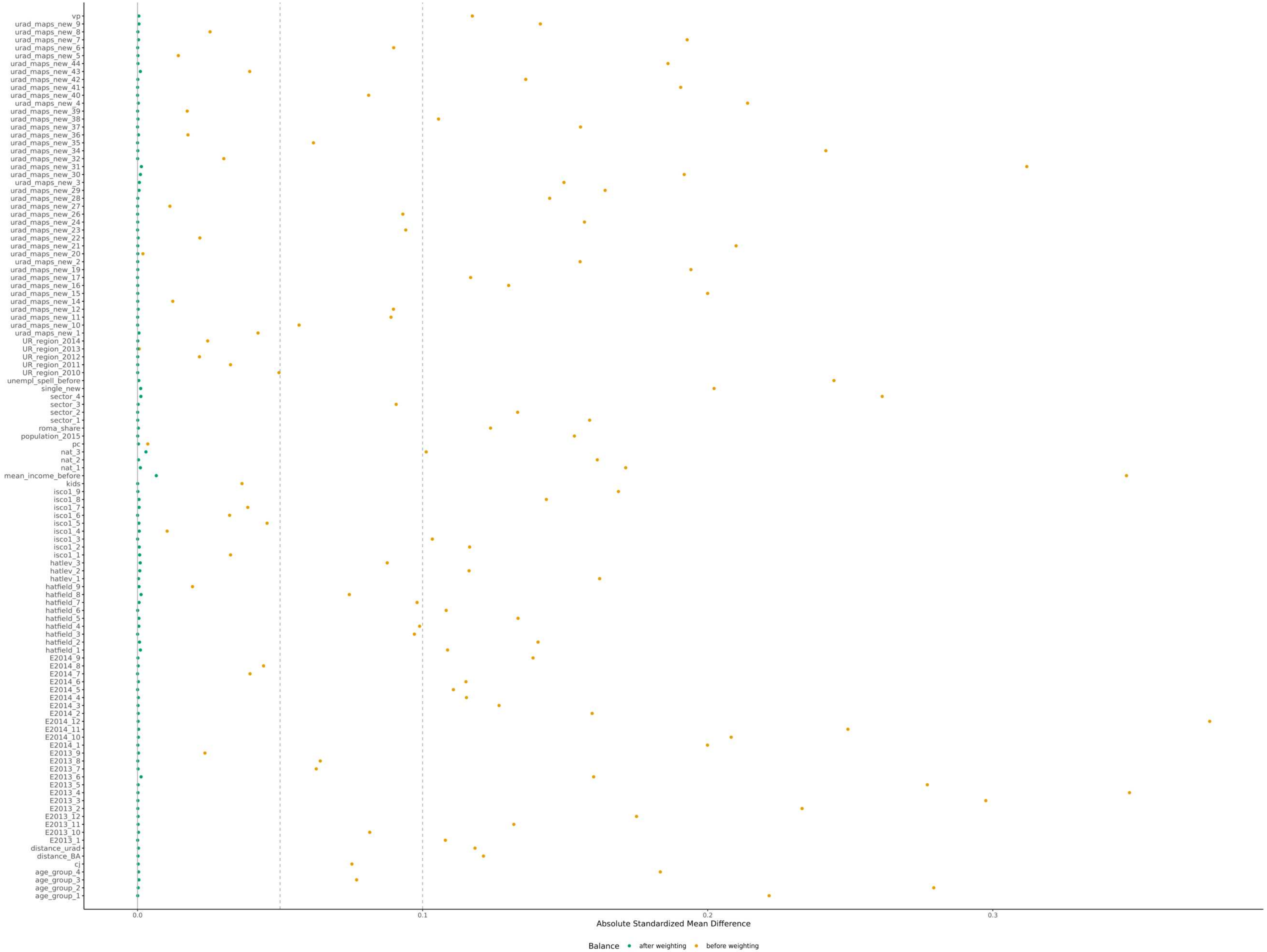


Table A.1: List of covariates

Variable	Abbreviation	Description
Marital status	single_new	
Kids in the household	kids	
Foreign language	cj	
Driving licence	vp	
PC skills	pc	
No education field	hatfield_1	National education classification
Natural sciences	hatfield_2	Educational field
Technical field I	hatfield_3	Educational field
Technical field II	hatfield_4	Educational field
Agricultural sciences	hatfield_5	Educational field
Health	hatfield_6	Educational field
Social sciences, business and law	hatfield_7	Educational field
Social sciences II	hatfield_8	Educational field
Art	hatfield_9	Educational field
TO Military and security	hatfield_10	Educational field
No education	hatlev	Educational field
Elementary education	hatlev_1	
Lower secondary education	hatlev_2	
Upper secondary education	hatlev_3	
Tertiary education	hatlev_4	
Regional unemployment rate for 2011	UR_region_2010	
Regional unemployment rate for 2012	UR_region_2011	
Regional unemployment rate for 2013	UR_region_2012	
Regional unemployment rate for 2014	UR_region_2013	
Regional unemployment rate for 2015	UR_region_2014	
Population at the place of residence	population_2015	In 2015
Unemployment spell	unempl_spell_before	Before the start of the 1st cohort
Travelling time to Bratislava	distance_BA	In minutes
Travelling time to the nearest PES	distance_urad	In minutes
Share of Roma in the city of residence	roma_share	
Age group	age_group_1	
Age group	age_group_2	
Age group	age_group_3	
Age group	age_group_4	
Age group	age_group_5	
Previous experience in Agriculture	sector_1	
Previous experience in Industry	sector_2	
Previous experience in Construction	sector_3	
Previous experience in Services	sector_4	
No previous employment	sector_5	
Experience in Managers	isco1_1	Major group based on ISCO-08
Experience in Professionals	isco1_2	Major group based on ISCO-08
Experience in Technicians and Associate Professionals	isco1_3	Major group based on ISCO-08
Experience in Clerical Support Workers	isco1_4	Major group based on ISCO-08
Experience in Service and Sales Workers	isco1_5	Major group based on ISCO-08
Experience in Skilled Agriculture, Forestry & Fishery	isco1_6	Major group based on ISCO-08
Experience in Craft and Related Trades Workers	isco1_7	Major group based on ISCO-08
Experience in Plant and Machine Operators, & Assemblers	isco1_8	Major group based on ISCO-08
Experience in Elementary Occupations	isco1_9	Major group based on ISCO-08
PES in Bratislava	urad_maps_new_1	
PES in Malacky	urad_maps_new_2	
PES in Pezinok	urad_maps_new_3	
PES in Dunajska Streda	urad_maps_new_4	
PES in Galanta	urad_maps_new_5	
PES in Piestany	urad_maps_new_6	
PES in Senica	urad_maps_new_7	
PES in Trnava	urad_maps_new_8	
PES in Partizanske	urad_maps_new_9	
PES in Nov Mesto n. Vahom	urad_maps_new_10	
PES in Povazska Bystrica	urad_maps_new_11	
PES in Prievidza	urad_maps_new_12	
PES in Trencin	urad_maps_new_13	
PES in Komarno	urad_maps_new_14	
PES in Levice	urad_maps_new_15	
PES in Nitra	urad_maps_new_16	
PES in Nove Zamky	urad_maps_new_17	
PES in Topolcany	urad_maps_new_18	
PES in Cadca	urad_maps_new_19	
PES in Dolny Kubin	urad_maps_new_20	
PES in Namestovo	urad_maps_new_21	
PES in Liptovsky Mikulas	urad_maps_new_22	
PES in Martin	urad_maps_new_23	
PES in Ruzomberok	urad_maps_new_24	
PES in Zilina	urad_maps_new_25	
PES in Banska Bystrica	urad_maps_new_26	
PES in Banska Stavnica	urad_maps_new_27	
PES in Brezno	urad_maps_new_28	
PES in Lucenec	urad_maps_new_29	
PES in Revúca	urad_maps_new_30	
PES in Rimavska Sobota	urad_maps_new_31	
PES in Velky Krtis	urad_maps_new_32	
PES in Zvolen	urad_maps_new_33	
PES in Bardejov	urad_maps_new_34	
PES in Humenne	urad_maps_new_35	
PES in Poprad	urad_maps_new_36	
PES in Presov	urad_maps_new_37	
PES in Stara Lubovna	urad_maps_new_38	
PES in Stropkov	urad_maps_new_39	
PES in Vranov n. Toplou	urad_maps_new_40	
PES in Kosice	urad_maps_new_41	
PES in Michalovce	urad_maps_new_42	
PES in Roznava	urad_maps_new_43	
PES in Spisska Nova Ves	urad_maps_new_44	
PES in Trebisov	urad_maps_new_45	
PES in Kezmarok	urad_maps_new_46	
Employment 1 month before the start of the 1st cohort	Empl_1	Employment status based on COLSAF register
Employment 2 months before the start of the 1st cohort	Empl_2	Employment status based on COLSAF register
Employment 3 months before the start of the 1st cohort	Empl_3	Employment status based on COLSAF register
Employment 4 months before the start of the 1st cohort	Empl_4	Employment status based on COLSAF register
Employment 5 months before the start of the 1st cohort	Empl_5	Employment status based on COLSAF register
Employment 6 months before the start of the 1st cohort	Empl_6	Employment status based on COLSAF register
Employment 7 months before the start of the 1st cohort	Empl_7	Employment status based on COLSAF register
Employment 8 months before the start of the 1st cohort	Empl_8	Employment status based on COLSAF register
Employment 9 months before the start of the 1st cohort	Empl_9	Employment status based on COLSAF register
Employment 10 months before the start of the 1st cohort	Empl_10	Employment status based on COLSAF register
Employment 11 months before the start of the 1st cohort	Empl_11	Employment status based on COLSAF register
Employment 12 months before the start of the 1st cohort	Empl_12	Employment status based on COLSAF register
Employment 13 months before the start of the 1st cohort	Empl_13	Employment status based on COLSAF register
Employment 14 months before the start of the 1st cohort	Empl_14	Employment status based on COLSAF register
Employment 15 months before the start of the 1st cohort	Empl_15	Employment status based on COLSAF register
Employment 16 months before the start of the 1st cohort	Empl_16	Employment status based on COLSAF register
Employment 17 months before the start of the 1st cohort	Empl_17	Employment status based on COLSAF register
Employment 18 months before the start of the 1st cohort	Empl_18	Employment status based on COLSAF register
Employment 19 months before the start of the 1st cohort	Empl_19	Employment status based on COLSAF register
Employment 20 months before the start of the 1st cohort	Empl_20	Employment status based on COLSAF register
Employment 21 months before the start of the 1st cohort	Empl_21	Employment status based on COLSAF register
Employment 22 months before the start of the 1st cohort	Empl_22	Employment status based on COLSAF register
Employment 23 months before the start of the 1st cohort	Empl_23	Employment status based on COLSAF register
Employment 24 months before the start of the 1st cohort	Empl_24	Employment status based on COLSAF register
Income 1 month before the start of the 1st cohort	Adj_IncAfterFirstCohort_1	Income reported in SIA

Table A.1: List of covariates

Variable	Abbreviation	Description
Income 2 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_2	Income reported in SIA
Income 3 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_3	Income reported in SIA
Income 4 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_4	Income reported in SIA
Income 5 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_5	Income reported in SIA
Income 6 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_6	Income reported in SIA
Income 7 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_7	Income reported in SIA
Income 8 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_8	Income reported in SIA
Income 9 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_9	Income reported in SIA
Income 10 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_10	Income reported in SIA
Income 11 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_11	Income reported in SIA
Income 12 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_12	Income reported in SIA
Income 13 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_13	Income reported in SIA
Income 14 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_14	Income reported in SIA
Income 15 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_15	Income reported in SIA
Income 16 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_16	Income reported in SIA
Income 17 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_17	Income reported in SIA
Income 18 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_18	Income reported in SIA
Income 19 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_19	Income reported in SIA
Income 20 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_20	Income reported in SIA
Income 21 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_21	Income reported in SIA
Income 22 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_22	Income reported in SIA
Income 23 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_23	Income reported in SIA
Income 24 months before the start of the 1st cohort	Adj_IncAfterFirstCohort_24	Income reported in SIA
Average income before the start of the 1st cohort	mean_income_before	Within 24 months

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