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TRAINING FOR JOBSEEKERS: A STRATEGIC RESPONSE TO LABOUR SHORTAGES

Héloïse Burlat

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GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

Training for Jobseekers: A Strategic Response to Labour Shortages?

Héloïse Burlat*
BETA (University of Strasbourg) & Ghent University †

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Abstract

Labour shortages persist in many countries, partly due to skill mismatches between job seekers and in-demand occupations. While prior research has examined the effect of training on reemployment, little is known about its role in addressing shortages. This paper identifies training programmes specifically targeted at shortage occupations and evaluates their impact on employment in these jobs across two different economic contexts: during the COVID-19 crisis and in the subsequent recovery period. Using Dynamic Inverse Probability Weighting, we find no significant medium-term effect in either context, except for men and minimum social income recipients during the COVID-19 crisis. Extending the horizon to 42 months for the 2019 cohort reveals a positive effect of targeted training, with an average of 40 additional days employed in shortage occupations. These findings suggest that training focused on shortage occupations may help mitigate labour shortages during downturns but appears less effective when labour demand is strong, informing the design of active labour market policies.

JEL codes: C21, J68, J08, J24
Keywords: Policy evaluation, Active labour market policy, Vocational training, Labour shortage, Dynamic Treatment Assignment

1 Introduction

Following the subprime mortgage crisis of 2007-2008, the subsequent global recovery generated strong labour demand against a backdrop of declining labour supply, thereby

*Email address: heloise.burlat@ugent.be. Address for correspondence: Héloïse Burlat, Ghent University, Department of Economics, Sint-Pietersplein 6, 9000 Gent, Belgium.

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intensifying labour market pressures. The end of the COVID-19 crisis in 2021 further amplified these tensions, as economic activity rebounded sharply once lockdown measures were lifted. This resurgence coincided with persistent mismatches between workers' skills and employers' requirements, in a context where occupations are evolving rapidly due to technological innovation, climate change, and demographic shifts,most notably population ageing, which is driving expansion in the silver economy. Europe, and France in particular, have been heavily affected: in 2023, France ranked tenth worldwide for talent scarcity (Manpower Talent Shortage Survey, 2024).

Shortage occupations are characterised by sustained recruitment difficulties arising from skill, working condition, and geographic mismatches. A shortage occupation refers to a job where vacancies outnumber available, interested, and qualified candidates. These occupations face an immediate lack of competent applicants due to factors such as skill gaps, high recruitment demand, poor working conditions, or spatial imbalances between employers and workers. Skill mismatches occur when jobseekers' qualifications do not align with employers' requirements, typically resulting in unfilled or hard-to-fill vacancies (McGuinness et al., 2018). Misallocation of workers further compounds both labour and skill shortages. High recruitment demand denotes occupations with exceptionally large numbers of openings, often exceeding the pool of suitably qualified applicants. Poor working conditions,such as physically demanding tasks, irregular or extended hours, and limited job security,also deter applications. Geographic mismatches arise when vacancies and qualified candidates are located in different regions, creating mobility constraints. Where shortages stem from skill mismatches, the required competencies are generally transferable within the same occupation but rarely across occupations, even within the same sector.

Although low-skilled individuals represent a substantial share of the unemployed, access to shortage occupations often requires specialised training, limiting the scope for direct reallocation without targeted upskilling. In France in 2021, many shortage occupations were classified as skilled jobs and required specific training.[1] At the same time, the national unemployment rate stood at 7.9%, rising to 16.7% among low-skilled workers (INSEE). Individuals with low levels of education therefore constitute a key pool of potential candidates for shortage occupations, provided they receive appropriate human capital investment.

Continuing Vocational Training (CVT) offers a potential mechanism to bridge this gap. However, its effectiveness remains uncertain due to heterogeneity in both individual characteristics and programme design. In this context, CVT appears to be a promising policy instrument to support jobseekers and steer them towards shortage occupations. This study focuses exclusively on qualifying training programmes, which prepare individuals for specific jobs. We further distinguish between training targeted at shortage occupations and training for other occupations. Admission criteria vary by occupation; for example, basic mathematical skills may be required in certain construction trades but not in other industrial fields. The decision to enrol in a programme linked to a shortage occupation, rather than one unrelated to shortages, depends primarily on individual preferences and the geographic availability of courses. CVT policy provides both

[1] According to DARES data (2021), 41% of occupations experiencing the most severe shortages were also those for which the indicator measuring the need for specialised training was highest.

occupation-specific training and broader human capital development tailored to shortage occupations. Its effectiveness in addressing labour market mismatches, however, remains to be established, particularly given the diversity in individuals' initial human capital and employment trajectories.

This paper evaluates whether continuing vocational training (CVT) increases employment duration in shortage occupations, using rich administrative data and a dynamic estimation framework. We compare two cohorts of jobseekers entering unemployment in the Grand Est region under contrasting economic conditions: a pandemic-induced downturn (2019) and a post-crisis recovery with low unemployment (2021-2022). The analysis tracks over 220,000 individuals, including nearly 10,000 participants in qualifying training programme, across horizons of 24 and 42 months. This design allows us to assess the effectiveness of CVT as a tool for alleviating labour shortages and to examine its cyclical sensitivity, as suggested by prior research on training during recessions (Lechner and Wunsch, 2009).

The dataset includes detailed socio-demographic characteristics, local labour market indicators, and employment histories, enabling robust control for selection on observables under the conditional independence assumption (Heckman et al., 1997; Lechner and Wunsch, 2013). We employ the Dynamic Inverse Probability Weighting (DIPW) estimator developed by Van den Berg and Vikström (2022) to identify the effect of training on treated individuals, specifically regarding employment duration in shortage occupations. This approach addresses biases arising from dynamic treatment assignment within unemployment spells (Fredriksson and Johansson, 2008). Robustness is assessed through placebo tests and sensitivity analyses.

Our findings indicate that, 24 months after entering unemployment, participation in training programmes targeting shortage occupations does not significantly affect employment duration in these jobs in either economic context. Positive heterogeneous effects emerge for men in both cohorts, and for minimum social income recipients in the 2019 cohort, which faced a more adverse labour market. Extending the observation horizon to 42 months for the 2019 cohort reveals a positive impact, adding on average 40 additional days employed in shortage occupations. Training appears more effective during downturns than when labour demand is strong.

This study contributes to the literature by evaluating training effects on employment duration in shortage occupations and by distinguishing between programmes targeting shortage occupations and those that do not. This differentiation enables a more granular assessment of policy effectiveness. Our main contribution is to extend and generalise the study of Frick et al. (2024) by including all unemployed individuals, irrespective of prior employment history, focusing on job duration rather than transitions, and accounting for programme heterogeneity. We also incorporate timing between unemployment onset, training entry, and job start, and analyse heterogeneity across education levels and economic contexts (Lechner and Wunsch, 2009). Our results show that fewer than half of qualifying programmes target shortage occupations, and aggregate effects mask substantial variation by gender and period. In this sense, CVT not only enhances individual employability but also plays a strategic role in addressing evolving labour market needs. These findings raise important questions about how current training provision addresses

skill shortages and how it might be optimised to better meet the needs of industries facing persistent recruitment difficulties.

Labour and skill shortages arise from multiple frictions, with labour misallocation playing a central role in amplifying market inefficiencies. A substantial body of theoretical and macroeconomic literature has examined labour shortages, their impact on equilibrium, and policy responses to mitigate them (Brunello and Wruuck, 2021; Şahin et al., 2014). Shortages may result from low wages, poor working conditions (Shah and Burke, 2010; Michaeli et al., 2024), or geographic mismatches (Marinescu and Rathelot, 2018). However, Şahin et al. (2014) and Marinescu and Rathelot (2018) show that misallocation of workers across industries exerts a greater influence on shortages. Misallocation also increases frictions in the matching function (Barnichon and Figura, 2013), as workers are allocated to sectors with lower demand, reducing their earning potential (Guvenen et al., 2020).

While training programmes have been widely studied for their effects on individual outcomes, few have assessed their role in alleviating labour or skill shortages. The literature on training programme evaluation for jobseekers is extensive, particularly regarding employment, wages, and job quality (Card et al., 2018). Yet, it is crucial to consider the broader impact of training on labour supply, especially in relation to shortages. School-to-work transitions have been examined in the context of apprenticeships (Eckardt, 2024), and a significant share of trainees ultimately work in occupations different from those for which they were trained. Few studies have evaluated active labour market policies (ALMPs) in terms of their effectiveness in placing individuals in specific occupations, with the exception of Frick et al. (2024), who found that training increased occupational mobility but did not promote transitions into shortage occupations.

Labour shortages are dynamic and cyclical, with evidence indicating that hiring standards and skill requirements shift with the economic cycle. These shortages tend to intensify during periods of economic growth, as employers raise educational requirements when unemployment is low and relax them when it is high (Modestino et al., 2016). For example, Cerić and Ivić (2020) document skills shortages in Croatia's construction sector due to declining qualifications. Short-term responses include increasing migration, but as immigrant workforces expand, as observed in the US (Albattah et al., 2015), the average education level of migrants tends to decline. Skilled individuals migrate first, followed by low-skilled workers. Firms also attempt to optimise their core workforce by increasing hours and offering higher pay (Healy et al., 2015), although McGuinness et al. (2018) highlight alternative strategies such as temporary employment and outsourcing.

Publicly funded training offers a more sustainable response to structural shortages, particularly where firms lack the capacity to provide adequate training. Unlike previously discussed measures, training represents a long-term solution. By enhancing human capital and facilitating labour reallocation across sectors, it can help alleviate persistent shortages. Firms may have incentives to provide non-specific training to employees, albeit within certain institutional settings (Wolter and Ryan, 2011). However, publicly funded training is likely to be effective only in addressing long-term skill gaps. This is especially relevant where firms cannot deliver training themselves due to the temporal disconnect between emerging skill needs and the implementation of public programmes (Shah and

Burke, 2010).

The remainder of the paper is structured as follows. Section 2 outlines the institutional context. Section 3 describes the data and sampling strategy. Section 4 details the methodological approach and parameters of interest. Section 5 presents the empirical findings, Section 6 reports robustness checks, and Section 7 concludes with a discussion of the main results.

2 Institutional context

The Grand Est Region plays a crucial role as a local actor in implementing this policy, using it as a strategic instrument to address structural unemployment. Each year, the Region finances training for 30,000 jobseekers on average. The design of the annual training programme and the selection of sectors are informed by biannual consultations with local firms and institutions, including labour market observatories and employment agencies. Between 2019 and 2023, dedicated regional funding amounted to €1.2 billion, sourced from both regional resources and contributions from the French government, making it one of the Region's largest budget allocations. At the national level, the French government aims to train one million jobseekers with limited or no qualifications and one million young individuals facing labour market exclusion.

Given this strategic orientation and the process for identifying workforce needs, the Region is expected to offer the majority of training programmes leading to occupations in high demand. This approach seeks to guide participants towards employment opportunities in these shortage occupations. However, according to the fourth report of the scientific committee evaluating the PIC (DARES, 2023), jobseekers who commenced a continuing vocational training programme in France in 2021 had only a 45% probability of enrolling in training for an occupation experiencing a labour shortage, and this figure fell to 16% when considering occupations with skill shortages specifically. This decline is largely attributed to the low attractiveness of these professions, which reduces the appeal of training in these fields. Furthermore, individuals with low educational attainment accounted for less than 40% of entrants into programmes targeting skill-shortage occupations, despite representing more than 50% of all entrants across all training types. This highlights the selectivity of these programmes and the demanding qualification requirements of the targeted occupations.

To identify occupations in high demand, DARES (Ministry of Labour) publishes an annual composite indicator of occupational tension. The shortage indicator developed is a composite measure ranking occupations by labour market tension. It is calculated for each occupation and for each territory where data coverage is sufficient. The indicator combines three weighted components for each occupation: (1) the ratio of online job postings to unemployed people seeking work in that occupation, where a high ratio signals strong demand and few candidates; (2) the outflow rate of jobseekers, showing how quickly people in that occupation leave unemployment lists, which reflects hiring dynamism; and (3) the share of recruitment projects employers expect to be difficult for this occupation, based on surveys. Together, these measures capture both quantitative pressure (vacancy-to-jobseeker ratio) and qualitative difficulty (employer expectations). Each component is standardised using historical averages and standard deviations from 2014-2018 to en-

sure comparability across occupations and regions. Complementary indicators provide further insight into the causes of tension: (1) hiring intensity, which relates recruitment volumes to employment levels; (2) working conditions, capturing physical strain, repetitive tasks, irregular hours, and fragmented schedules; (3) job sustainability, reflecting the prevalence of permanent, full-time, and non-seasonal positions; (4) labour supply, assessing the availability of jobseekers relative to employment; (5) training-job alignment, measuring the match between required qualifications and workers' training backgrounds; and (6) geographic mismatch, quantifying spatial imbalances between job offers and jobseekers using a dissimilarity index. These indicators draw on multiple sources, including administrative records, scraped online job offers classified via machine learning, employer surveys, working conditions surveys, continuous employment surveys, and census data, and are calculated at the level of occupations and regions, excluding non-salaried and public sector roles due to data limitations. Both the general shortage indicator and the complementary indicators are converted into discrete scores ranging from 1 (low tension) to 5 (high tension).

Of the 172 occupations considered by the indicator, 108 are classified at the highest tension level (5) in the Grand Est Region. Within this group, the Construction and Mechanics sectors are most represented, accounting for 13% of high-tension occupations (DARES). Industry and construction remain male-dominated sectors, with men accounting for over 71.5% of employment in industry and 88.9% in construction in France in 2020 (INSEE). This gender imbalance reflects historical patterns of occupational segregation, the physical nature of many tasks, and gendered educational pathways leading to technical and vocational qualifications. These patterns are likely to influence both entry into training programmes focused on shortage occupations and subsequent employment in these occupations after training, given that many shortage jobs are concentrated in male-dominated sectors.

The three occupations with the highest tension indicators in 2021 are Civil Engineers, Construction Site Managers and Construction Supervisors, Mechanical and Metalworking Technicians, and Electrical and Electronics Draftsmen. These occupations require skilled workers, with educational requirements ranging from a secondary school diploma for technicians to a master's degree for engineers. They are particularly in demand because of the strong link between training specialisation and employment—highlighted earlier as the fifth complementary indicator, training-job alignment, combined with a limited supply of available labour. Further details about indicators for all occupations with the highest global tension indicator are provided in Appendix A.

The strength of this training-occupation link reflects how concentrated training specialisations are within an occupation, in other words, how essential specific training is to access that job. If this indicator is set to 5, it means specific training is essential to access the occupation, whereas a score of 1 indicates that a general qualification, or even no formal training, may be sufficient. This classification is based on three combined indicators: the Herfindahl index of specialisation concentration (calculated for young entrants), the specificity of specialisations within each occupation relative to the overall workforce, and the proportion of young employees without formal qualifications in the occupation. In our study, an occupation with a general shortage score of 5 and a training-occupation link score of 5 is classified as a "shortage occupation requiring specific training" or a "shortage

occupation with a strong training-to-job link," since skill shortages are the main driver of the tension in this case.

However, as this indicator is released with a one-year lag, it cannot be used to inform the design of the current year's training programme. Consequently, the Region relies on alternative sources, such as data on recruitment projects employers expect to be difficult for a specific occupation from *France Travail* and feedback from local employers.

3 Data and sampling

3.1 The Dataset

This study draws on a rich dataset constructed from multiple administrative sources. The core component is the FORCE system, developed by DARES (French Ministry of Labour), which assigns a unique identifier to individuals across two major databases: the Historical Job Search Files from the French employment agency (FH) and the Job Contracts Base (MMO). We merge this system with the Regional Council's training programme database (Athena), which provides detailed information on the type of training, the targeted occupation, and precise entry and exit dates. The analysis uses the most recent matching wave available at the time of the study, namely wave 14, and relies on the latest DARES indicators of labour market tension available up to 2022 in the Grand-Est region. For 2023 and 2024, we assume that the same occupations remain under pressure as in 2022, a reasonable assumption given that most shortage occupations persist over time.

The combined dataset enables the tracking of unemployment and employment histories over a span of ten and five years, respectively. It captures individual trajectories comprising periods of unemployment, employment, and training at the national level, supplemented by granular data on participants in programmes funded by the Regional Council. This integration offers comprehensive individual characteristics, particularly employment and unemployment histories, which serve both as control variables for programme selection and as outcome measures (e.g., employment status, training continuation, earnings). The linkage with Athena allows differentiation between types of training actions, facilitating the assessment of programme heterogeneity given the large sample size.

However, certain limitations should be noted. The MMO database does not include self-employed individuals or cross-border workers and only began incorporating public sector employees in 2022. Consequently, reintegration rates for treated and control individuals may be slightly underestimated. Cross-border workers are identified based on residence within labour market areas located within 100 kilometres of Basel (Switzerland), Luxembourg, Freiburg im Breisgau (Germany), Karlsruhe (Germany), or Saarbrücken (Germany). To classify occupations associated with employment contracts and training programmes, we adopt the FAP 2009 classification, focusing on the aggregation of 226 occupational families.

3.2 The Sample

Our primary sample comprises individuals residing in the Grand Est region who were registered as jobseekers, immediately available for employment, and without a part-time job with the French employment agency between 1 June 2021 and 31 March 2022. This period was selected to allow a 24-month follow-up, sufficient to capture medium-run effects, and because it falls outside the COVID-19 lockdowns. To avoid including individuals close to retirement or those just leaving education, we restrict the sample to those aged 20-55. We further exclude individuals who started a training programme within one year prior to the unemployment spell or who entered training from another institution before leaving unemployment. These restrictions ensure that the estimated effects pertain exclusively to the training programmes under consideration. Individual characteristics are fixed at the start of the unemployment spell and remain unchanged throughout the observation window. Treated individuals are defined as those who commenced a qualifying training programme financed by the Regional Council within the first 24 months of their unemployment spell and completed at least one day of training.

To assess whether training effects vary with the economic context, we replicate the analysis on a second cohort of individuals who entered unemployment between 1 January and 31 December 2019. This cohort comprises 122,653 individuals, including 5,729 trainees, and spans a 42-month observation window encompassing the COVID-19 crisis. The same eligibility criteria and sample restrictions, age range, exclusion of prior training, and fixed individual characteristics,are applied to ensure comparability across periods.

Table 1: Descriptive statistics of the overall sample

Characteristic	Cohort 2019		Cohort 2021	
	Never-treated	Treated group	Never-treated	Treated group
Sample	**116,924**	**5,729**	**97,402**	**3,935**
Participation in shortage occupation training (%)	NA	55.1%	NA	36.9%
Average duration of qualifying training (days)	NA	156.98 (99.62)	NA	156.30 (94.64)
Average duration of training focused on shortage occupations (days)	NA	182.14 (95.33)	NA	184.69 (91.86)
Age	31.67 (10.18)	33.02 (10.09)***	31.84 (10.17)	32.38 (10.14)***
Female (%)	48.0%	43.8%***	48.1%	40.7%***
Average number of children	0.76 (1.19)	0.74 (1.13)	0.78 (1.22)	0.68 (1.14)***
Lives in disadvantaged urban area (%)	13.7%	14.1%	14.0%	13.6%
French citizen (%)	85.4%	88.9%***	83.9%	89.0%***
Registered as disabled (%)	5.0%	5.8%**	5.0%	6.6%***
Receives minimum income benefit (RSA) (%)	24.4%	20.4%***	25.8%	20.5%***
Receives unemployment insurance benefit (%)	20.4%	41.8%***	20.7%	38.1%***
Unemployment insurance benefit duration (days)	41.80 (133.58)	71.14 (133.97)***	36.96 (112.97)	60.83 (111.40)***
Participated in training in past 5 years (%)	11.1%	27.7%***	15.8%	44.9%***
Local unemployment rate (%)	8.30 (1.46)	8.36 (1.48)**	7.69 (1.43)	7.77 (1.39)***
Local employment growth rate (%)	0.14 (0.33)	0.16 (0.34)***	0.51 (0.37)	0.52 (0.37)**
Lives within 100 km of national border (%)	64.0%	56.0%***	63.4%	57.9%***
Level of education				
Below upper secondary education (%)	48.5%	45.2%***	47.7%	40.0%***
Upper secondary diploma (%)	24.8%	29.6%***	25.3%	30.9%***
Advanced Technician Diploma (BTS) (%)	11.4%	14.9%***	11.1%	15.6%***
Bachelor's degree (%)	7.9%	6.6%***	8.2%	8.3%
Master's degree or higher (%)	7.4%	3.7%***	7.7%	5.1%***
Occupation category				
Manual worker (%)	18.9%	22.6%***	17.4%	19.1%**
Technician (%)	5.2%	5.5%	5.1%	7.2%***
Unskilled employee (%)	22.5%	26.5%***	25.7%	29.0%***
Skilled employee (%)	30.3%	36.6%***	31.6%	35.6%***
Executive (%)	10.2%	5.2%***	8.7%	5.6%***
Unknown (%)	13.0%	3.6%***	11.6%	3.6%***
Employment history				
Employment days (past 24 months)	97.95 (179.63)	119.43 (185.54)***	165.51 (244.93)	176.24 (237.12)**
Employment days (past 6 months)	34.79 (61.74)	35.52 (59.64)	43.62 (67.72)	42.33 (65.62)
Employment days in shortage occupations (past 24 months)	40.49 (119.25)	41.44 (117.89)	54.04 (152.48)	54.06 (146.62)
Employment days in shortage occupations (past 6 months)	14.77 (43.29)	12.73 (38.80)***	14.24 (43.33)	13.31 (41.41)
Total income (€) - past 24 months	3,780.15 (8,571.06)	4,446.84 (7,677.74)***	4,452.57 (9,299.32)	4,785.71 (8,330.49)**
Total income (€) - past 6 months	595.21 (1,853.86)	645.64 (1,696.06)**	600.66 (1,872.69)	658.51 (1,773.86)*
Outcome variables post-unemployment start				
Shortage occupation employment days - month 6	1.94 (7.18)	1.03 (5.20)***	1.97 (7.19)	0.86 (4.67)***
Shortage occupation employment days - month 12	1.83 (7.01)	2.00 (7.17)*	2.24 (7.70)	2.63 (8.17)**
Shortage occupation employment days - month 24	2.25 (7.75)	3.29 (9.16)***	1.61 (6.54)	2.83 (8.47)***
Shortage occupation employment days - cumulative over 24 months	45.35 (128.43)	46.75 (113.03)	46.69 (124.08)	51.96 (116.08)***
Shortage occupation employment days - cumulative over 48 months	102.33 (238.85)	129.52 (243.46)***	NA	NA

Note: Values are presented as mean (standard error) for continuous variables and percentages for categorical variables. Significance levels are based on Welch Two Sample t-tests comparing the treated and never-treated groups within each cohort. Stars indicate significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 1 shows descriptive statistics of the never-treated group and the treated group with Welch Two Sample t-tests that determine whether the two groups are statistically significantly different on each variable in each cohort. It shows that the two groups are different, except for their employment history in shortage occupations and recent job contract. The trimming procedure described in Section 4 with sensitivity tests in Section 6, which excludes individuals with extreme values of propensity scores, and the addition of all the control variables available to us seem necessary to reduce the bias and ensure the validity of the results.

4 Econometric method

Evaluating the effect of a job-seeker training programme on the return to employment or the occupation of a job in short supply is difficult because the duration of the period of unemployment is random, as is the start date of the treatment, and the possibility of

entering training at period t is conditional on the fact of still being unemployed at period t. Indeed, to be eligible to a training programme, individuals have to be unemployed. Moreover, we cannot know the starting date of the training for never-treated individuals and, therefore, the duration between the beginnning of their unemploment spell and the beginning of their training programme. Within such a dynamic assignement to training framework, individuals who did not enter training may have undergone positive selection in the sense that they were offered a job before they had the opportunity to enter training. Moreover, individuals with a small probability of starting a training in subsequent periods may remain nontreated for a long time.

To adress this issue, Sianesi (2004) proposes to compare treated to not-yet treated only but this underestimates the effect of the training by disturbing the control by those who are treated later. By using the not-yet treated as the control group, this method requires a large sample size and an important number of treated individual for each cohort. Fredriksson and Johansson (2008) have also tried to solve this problem by making the difference of the survival function of the treated and the not-yet treated group as the average treatment effect for the treated (ATET). However, survival functions are the product of unemployment exit hazard rates over each previous period, which can mask the effect of training if these hazard rates are heterogeneous between each period, making it difficult to interpret the results and isolate the ATET. This approach does not allow the use of longer-term outcome variables, such as income, duration of employment or characteristics of the employment contract. An alternative approach by Lechner et al. (2011) is to compute a simulated starting date of a training programme for control individuals and use it as covariate in the propensity score. However, we need to be able to justify that we have all the covariates that allow us to predict the training entry date, which is a strong assumption.

Regarding those considerations, we use the Dynamic Inverse Probability Weighting (DIPW) estimator proposed by Van den Berg and Vikström (2022). This estimator generalizes the approach of Fredriksson and Johansson (2008) by allowing for time-variant covariates and long-term effects. We will first discuss the identification strategy and then the estimation.

4.1 Identification

We introduce the notation of this model, where the duration until the start of training and the duration spent in the unemployment spell are denoted by T_s and T_u, respectively. T_s is only observed for treated individuals, provided $T_s \leq T_u$. Indeed, it is possible to start training and find employment within the same month ($T_s = T_u$), as training programmes can last less than a month. When individuals are assigned a training start date t_s, this determines their potential duration in unemployment $T_u(t_s)$ and their potential outcome $Y(t_s)$, here the number of days in employment. If the individual remains untreated, these are denoted as $T_u(\infty)$ and $Y(\infty)$. X is the vector of individual characteristics, fixed at the beginning of the unemployment spell. This model assumes the Conditional Independence Assumption (CIA), which posits that, conditional on the observable individual characteristics, the decision to start training is independent of the potential outcomes. This assumption is dynamic, as we observe different treatment timings t_s and different

durations of unemployment spell T_u. The CIA is discussed further below.

This model allows us to estimate the Average Treatment Effect on the Treated (ATET) under four assumptions:

- No anticipation:

$$\begin{aligned} P(T_u(t') = t) = P(T_u(t'') = t), \quad \forall t < \min(t', t'') \\ \text{and } Y(t') = Y(t''), \quad \forall T_u(t') = T_u(t'') < \min(t', t'') \end{aligned} \tag{1}$$

where t' and t'' represent two possible treatment timings. The first equation concerns the current probability at time t of leaving unemployment due to a treatment starting at times t' or t''. The second equation states that the effect of the training timing, whether at t' or t'', does not affect potential outcomes as long as the individual has not yet received treatment. However, the potential outcomes $Y(t_s)$ realised at a future assignment date to training t_s can be influenced by behaviour prior to t_s, even if the future treatment timing t_s does not affect an individual's probability of leaving unemployment before t_s.

- Conditional Independence Assumption (CIA):

$$P_t \perp Y(\infty) \mid X, T_s \geq t, T_u(\infty) \geq t \tag{2}$$

where P_t is a binary indicator equal to 1 if the start of the training T_s is the current period t. Here, we apply a dynamic version of the unconfoundedness assumption from Rosenbaum and Rubin (1983). The CIA in this model is crucial. It assumes that treatment T_s is independent of the potential outcome $Y(\infty)$ conditional on covariates X, thus allowing causal identification via propensity scores.

However, in dynamic settings, additional factors, such as remaining unemployed during the considered period t and the probabilities of starting training (i.e., propensity scores) after t, must be taken into account, making standard methods unsuitable. The validity of the CIA depends on whether all factors influencing treatment assignment are observed, with potential biases arising from unmeasured characteristics like motivation or personality traits. The database is rich in individual characteristics, particularly employment and unemployment history, which supports the CIA hypothesis by minimising selection bias. Key covariates identified in previous studies (Heckman et al., 1997; Lechner and Wunsch, 2013) are controlled for, including individual characteristics, labour market history, industry, and regional factors. A placebo test further supports the plausibility of the CIA hypothesis in Section 6.

- Common Support (CS):

$$\forall t \text{ and } X, \Pr(P_t = 1 \mid T_s \geq t, T_u \geq t, X) < 1. \tag{3}$$

IPW estimation is highly sensitive to extreme propensity scores, as certain observations may receive excessively large weights (Huber et al., 2013). We apply the three-step trimming method from Huber et al. (2013) to mitigate this issue, using weights derived from multiple propensity scores as described by Van den Berg and Vikström (2022). Using the $q\%$ rule, we calculate the maximum weight $\overline{w}(s, k)$ that should not be exceeded for all individuals in the control group for all periods between t and s. This removes individuals with extreme values and ensures the common support assumption. Here, we set q to 1%.

Sensitivity tests to different values of q are conducted in Section 6.

- Stable Unit Treatment Value Assumption (SUTVA): This assumption implies that the treatment assigned to one individual does not affect the outcome of another individual, ensuring the absence of spillover effects.

Under these assumptions, we can identify the Average Treatment Effect on the Treated (ATET) as follows:

$$ATET(t_s) = \mathbb{E}[Y|T_s = t_s, T_u \geq t_s] - \mathbb{E}_{X|T_s=t_s,T_u\geq t_s}\left[\sum_{k=t_s}^{T_u^{\max}} h(k,X)\left[\prod_{m=t_s}^{k-1}(1-h(m,X))\right]\mathbb{E}[Y|T_s > k, T_u = k, X]\right] \tag{4}$$

where $h(t,X) = \Pr(T_u = t|T_s > t, T_u \geq t, X)$ and $T_u^{\max}$ is the maximum possible duration in the initial state, with the convention that $\prod_{m=t_s}^{t_s-1} \cdots = 1$.

The control group includes individuals who will enter training at a later time, exit the initial state by finding a job before starting training, or would never have participated in training during our observation period. It serves as a basis for identifying the counterfactual outcome for treated individuals after a given duration.

To ensure that control individuals are comparable to trainees, identification assigns different weights to each control individual and each period depending on their probability of leaving the unemployment spell if not yet treated, conditional on their individual characteristics X. This adjustment is necessary because some control individuals may exit unemployment earlier due to better job opportunities, leading to an underestimation of the effect of training. In this identification, greater weight is assigned to control individuals who are similar to the training entrants at t_s in terms of their characteristics X, but who take longer to leave the unemployment spell.

We can aggregate the ATET for each cohort to obtain the overall ATET for the treated as:

$$ATET = \mathbb{E}_{T_s}\left[\mathbb{E}\left(Y(t_s) - Y(\infty) \mid T_s = t_s, T_u(t_s) \geq t_s\right)\right] \tag{5}$$

where the outer expectation is taken over the distribution of T_s given that $T_u \geq T_s$.

We only consider cohorts with sufficient treated individuals to ensure statistical power. As a result, we measure ATET only for individuals who entered training within the first 6 months of their unemployment spell.

4.2 Estimation

Following the identification of the ATET, an unbiased estimator of the ATET(t_s) is:

$$\widehat{ATET(t_s)} = \frac{1}{\pi(t_s)N_{t_s}} \sum_{i\in T_s, i=t_s, T_u, i\geq t_s} Y_i - \frac{1}{\sum_{i\in T_s, i>T_u, i\geq t_s} w^{t_s}(T_{u,i}, X_i)} \sum_{i\in T_s, i>T_u, i\geq t_s} w^{t_s}(T_{u,i}, X_i)Y_i. \tag{6}$$

where N_t represents the number of non-treated individuals still in the initial state at the beginning of t, and where $\pi(t) = \Pr(T_s = t \mid T_s \geq t, T_u \geq t)$. The weights $w_{t_s}(\cdot, \cdot)$ are defined as follows:

$$w_{t_s}(t_u, X) = \frac{p(t_s, X)}{1 - p(t_s, X)} \cdot \prod_{m=t_s+1}^{t_u} (1 - p(m, X)),$$
$$\text{with } p(t, X) = \Pr(T_s = t \mid T_s \geq t, T_u \geq t, X). \tag{7}$$

The weights $w_{t_s}(t_u, X)$ are substituted with estimated weights that rely on approximations of the treatment probabilities (propensity scores) $p(t, X)$. $p(t_s, X)$ is the probability of control individuals being treated at t_s. It is static during all periods t for the estimation of $ATET(t_s)$ for this cohort t_s. However, $p(m, X)$ represents the probability of being treated at later periods (from t_s until 24, the last observation period of our sample), conditional on not having entered training or found employment in the period before t.

As in the identification strategy in Section 4.1, this estimator will give more weight to control individuals whose propensity score is close to that of the trainees, so they resemble each other in terms of X. It will also give more weight to those who experience a longer period of unemployment, to avoid underestimating the effect due to the positive selection of control individuals.

We compute standard errors by bootstrapping with 500 replications. Simulations from Van den Berg and Vikström (2022) show that this estimator is unbiased if the four assumptions are respected. To avoid excessive computation time, we randomly select only 20% of the control individuals. This subsample is representative of the overall control group.

5 Results

This study differentiates between two categories of vocational training programmes: (i) all qualifying programmes in general, and (ii) programmes specifically designed to address labour market shortages. The analysis focuses on three employment outcomes: employment in shortage occupations, employment in non-shortage occupations, and employment in shortage occupations characterised by a strong training-to-employment match. The strong training-to-employment match or shortage occupation with specific training refers to shortage occupations for which performing the job requires highly specific vocational training directly related to that occupation. In other words, these are jobs where general skills are insufficient, and a dedicated, occupation-specific training programme is essential to qualify for and successfully carry out the role.

Employment outcomes are measured both as the number of days employed per month and on a cumulative basis. The first month for which effects are estimated corresponds to the month in which training begins. Since individuals are considered treated in our study only if they enter training within the first six months of their unemployment spell, the maximum observation period after training entry is 18 months (24 months of total observation minus the six-month entry window).

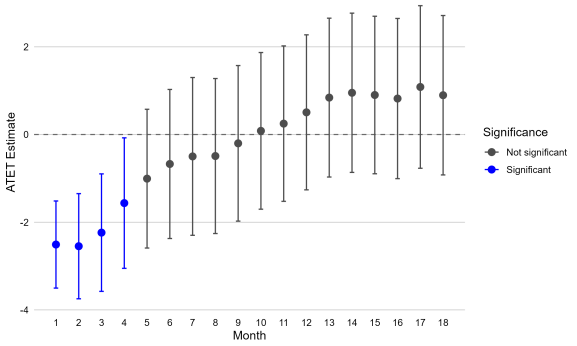
In addition, we compare these aggregated effects within a similar analytical framework for two distinct cohorts: individuals who entered unemployment in 2019, during the COVID-19 crisis, and individuals who entered between 2021 and 2022, in a context of

economic recovery. This comparison is crucial for assessing whether the effectiveness of vocational training programmes varies across different macroeconomic conditions, thereby providing insights into the role of business cycle dynamics in shaping programme impacts. The underlying hypothesis is that training may be more effective in periods of economic recovery than during times of crisis, due to improved job opportunities and stronger demand for labour, as suggested by previous evidence (Lechner and Wunsch, 2009).

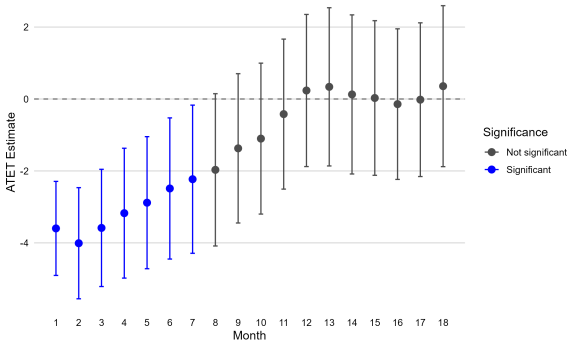
5.1 All qualifying training

Figure 1: ATET of qualifying training on shortage occupation employment for cohorts 2019 and 2021

Cohort 2019

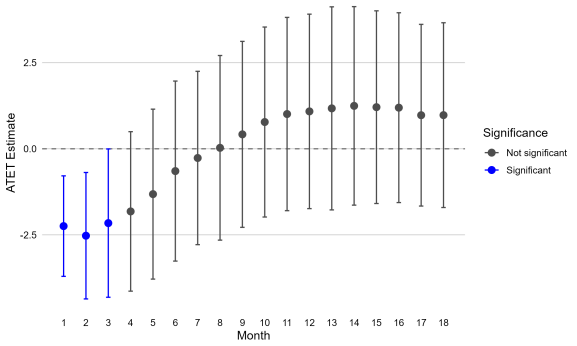


(a) Shortage occupation

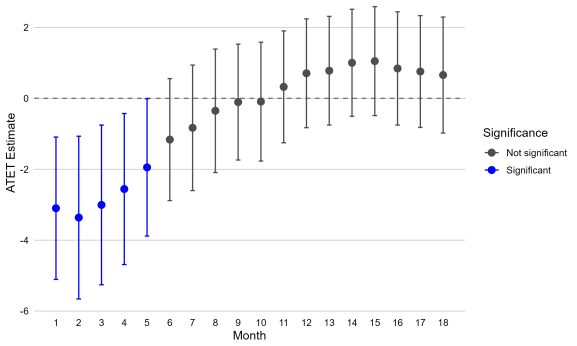


(b) Not shortage occupation

Cohort 2021



(c) Shortage occupation



(d) Not shortage occupation

Note: Outcomes are expressed in cumulative days of employment per month. Standard errors are computed by bootstrapping with 500 replications.

According to the results presented in Figure 1, entering qualifying training does not significantly increase the number of days employed in either shortage or non-shortage occupations 18 months after the start of training in both cohorts. Although more than 60% of occupations are classified as shortage occupations, this must be interpreted in light of the fact that only 36.9% of qualifying training programmes in the 2021 cohort and 55.1% in the 2019 cohort specifically targeted shortage occupations. Nevertheless,

a shorter lock-in effect is observed for employment in shortage occupations compared to employment in non-shortage occupations in both cohorts. Table 2 reports results for the cumulative number of days employed during the 18 months following the start of the unemployment spell, both for employment in shortage occupation and non-shortage occupations. Consistent with the monthly estimates, these cumulative effects are not statistically significant for either cohort.

5.2 Training focused on shortage occupations

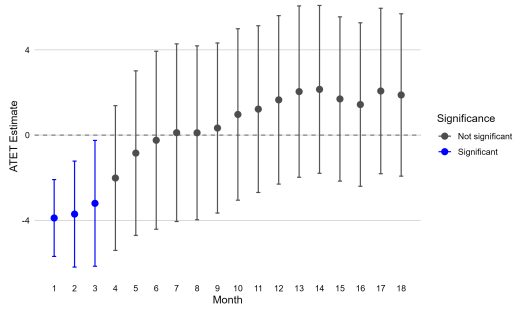
When restricting the analysis to training programmes specifically targeting shortage occupations in both cohorts, monthly medium-term effects are not statistically significant for employment in shortage occupations, non-shortage occupations, or shortage occupations with the strongest training-to-job match in Figure 2. However, a lock-in effect is observed between months 1 and 3 for employment in shortage occupations in both cohorts. Results for cumulative employment days are presented in Table 2. The ATET of training focused on shortage occupations is negative and significant for the cumulative number of days employed in shortage occupations with a strong training-to-job link, but only for the 2021 cohort. This suggests that the prolonged duration of the lock-in effect plays a significant role under favourable economic conditions. The ATET of training programmes targeting shortage occupations on the cumulative number of days employed in non-shortage occupations is also significant and negative, which aligns with expectations, as these programmes are not designed to lead to employment in such occupations.

Table 2: ATET of training on cumulative days of employment

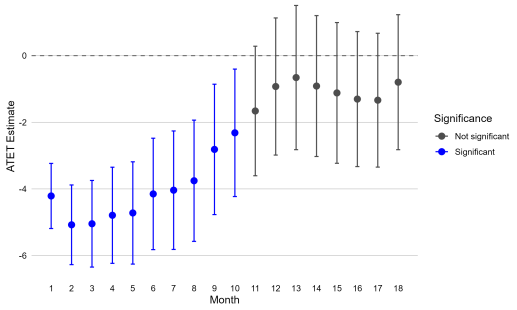
Outcome	**Cohort 2019**	**Cohort 2021**
All qualifying training		
Shortage occupation	3.80 (11.54)	-0.87 (16.97)
Not shortage occupation	-6.87 (18.05)	-15.04 (18.11)
Qualifying training focused on shortage occupations		
Shortage occupation	2.74 (10.63)	3.09 (9.21)
Not shortage occupation	-7.14 (18.41)	-35.86 (14.65)**
Shortage occupation with specific training	-17.37 (11.46)	-14.77 (5.21)***

Figure 2: ATET of training focused on shortage occupations on shortage occupation employment for cohorts 2019 and 2021

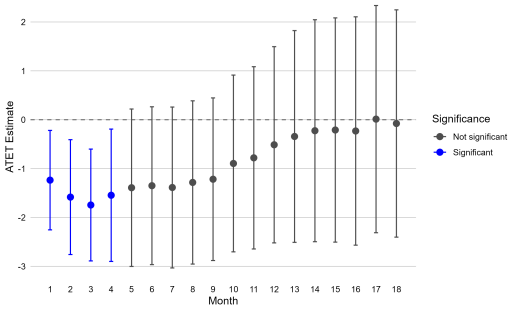
Cohort 2019



(a) Shortage occupation

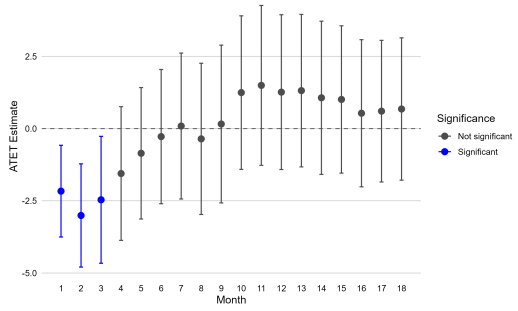


(b) Not shortage occupation

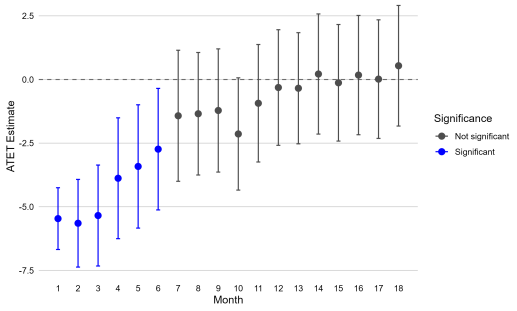


(c) Shortage occupation with specific training

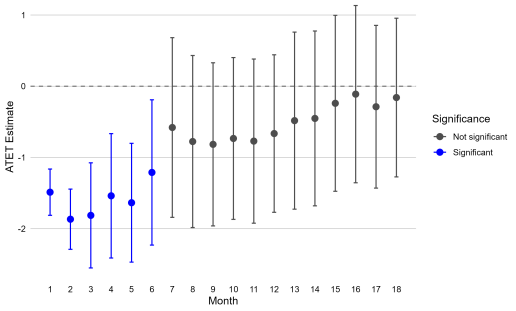
Cohort 2021



(d) Shortage occupation



(e) Not shortage occupation



(f) Shortage occupation with specific training

Note: Outcomes are expressed in cumulative days of employment per month. Standard errors are computed by bootstrapping with 500 replications.

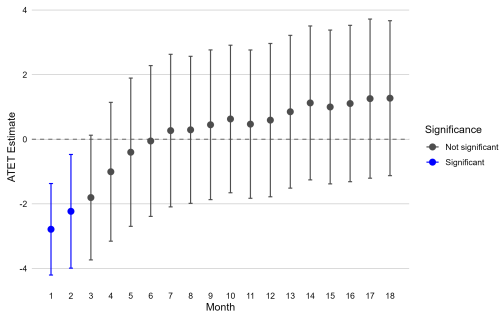
5.3 Heterogeneity analysis

To refine our findings, we conduct a heterogeneity analysis to explore whether the impact of training on employment in shortage occupations varies across specific population groups. For each heterogeneity dimension, we focus on the relevant subsample of individuals who display the characteristic under investigation. We then re-estimate the entire evaluation procedure within this subsample, including the propensity score. This approach ensures that the estimated treatment probabilities, the resulting weights and the common support condition are specific to the population under study, thereby yielding within-group causal effects that are not driven by the composition of the full sample. We anticipate that individuals with low levels of education will benefit most from training, as it compensates for their limited human capital and enhances their employability. Similarly, men are expected to experience stronger effects, given that shortage occupations are concentrated in male-dominated sectors such as industry and construction, as discussed in Section 2. Young individuals, below 25, are also likely to exhibit substantial gains, as they are at the beginning of their careers and therefore more flexible in redirecting their occupational trajectories. Finally, recipients of the minimum income (RSA) may see positive outcomes, although the magnitude of the effect could be constrained by structural barriers such as health issues or limited mobility, which training alone may not overcome.

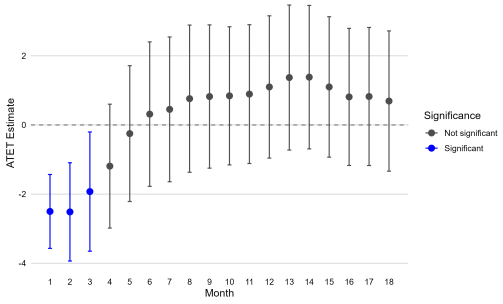
Figure 3 does not indicate statistically significant heterogeneity between the overall effect and that observed among individuals with low educational attainment across both economic contexts. However, we find a significant positive effect for men participating in training programmes targeting shortage occupations on the number of days employed in such occupations, starting from the 13th month for the 2019 cohort and from the 12th month for the 2021 cohort. 18 months after the start of the training programme, men who enrolled in training targeting shortage occupations are, on average, employed 1.37 additional days per month in a shortage occupation for cohort 2019 and 1.60 days for cohort 2021 compared to men who did not begin training within the first six months of their unemployment spell. This result is consistent with our expectation that men would experience stronger effects, given the concentration of shortage occupations in male-dominated sectors such as industry and construction. Furthermore, our findings reveal that younger individuals exhibit a positive medium-term effect exclusively in the 2019 cohort, beginning in the eighth month, with an increase of 2.66 additional days at month eighteen. Similarly, RSA recipients experience a significant improvement only in the 2019 cohort, starting after month eleven, with 2.30 additional days employed in shortage occupations at month eighteen. Training appears to have a positive medium-term effect for young people and RSA recipients, both groups that generally face greater difficulties in accessing employment, only in an adverse economic context. It is likely that, under such conditions, training acts as a favourable signal to employers compared to similar individuals, given the large pool of candidates. At the same time, the high unemployment rate may make individuals more willing to accept positions that are less aligned with their preferences or with more challenging working conditions.

Figure 3: ATET of training focused on shortage occupations on shortage occupation employment for cohorts 2019 and 2021

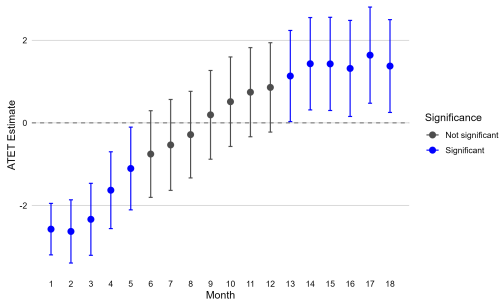
Cohort 2019



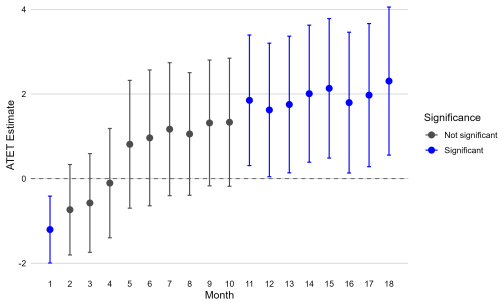
(a) Low educated



(b) Youth

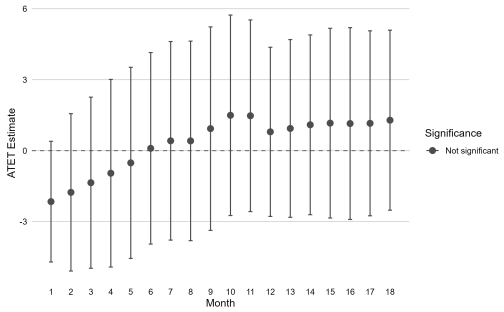


(c) Men

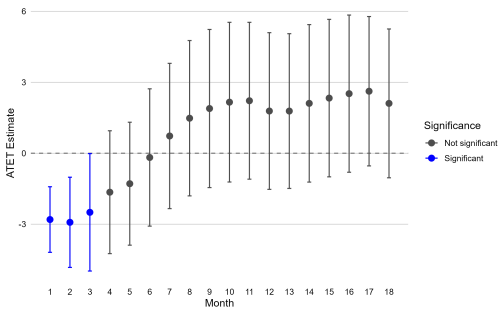


(d) RSA

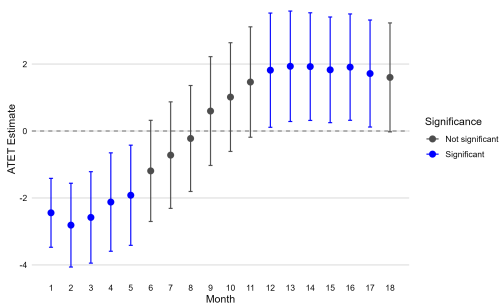
Cohort 2021



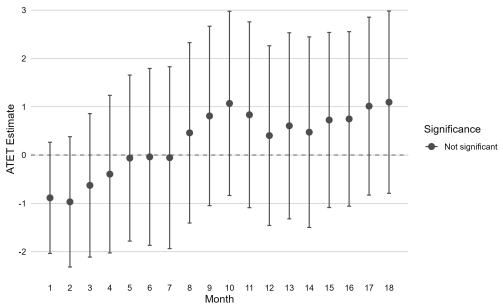
(e) Low educated



(f) Youth



(g) Men



(h) RSA

Note: Outcomes are expressed in cumulative days of employment per month. Standard errors are computed by bootstrapping with 500 replications.

5.4 Long-term Analysis

In the previous section, we examined the effect of training on employment in shortage occupations for jobseekers in cohorts 2019 and 2021 over an 18-month horizon. In this section, we extend the analysis to a longer time frame, up to 42 months after programme commencement. Due to data availability constraints, this long-term assessment can only be conducted for the 2019 cohort. The extended analysis allows us to explore whether the positive effects identified in the medium term persist, diminish, or intensify over time, providing insights into the durability of training benefits in a context marked by the COVID-19 crisis, which caused a sharp recession in France, and its aftermath.

Table 3 does not reveal significant effects on cumulative days of employment for all qualifying training programmes. However, we observe positive and statistically significant results for training specifically targeting shortage occupations: participants accumulate approximately 40 additional days of employment in shortage occupations and 69 fewer days in non-shortage occupations over a 42-month horizon following programme entry. This suggests that such training exerts a long-term influence on employment in high-demand occupations, offsetting the short-term lock-in effect and indicating that individuals do not subsequently reorient towards non-shortage occupations. Nevertheless, we find no evidence of long-term effects for shortage occupations with a strong link training-occupation.

Table 3: ATET of training on the cumulative days of employment - 2019 cohort

Outcome	**ATET (SE)**
All qualifying training	
Shortage occupation	10.83 (24.78)
Not shortage occupation	-22.48 (26.10)
Qualifying training focused on shortage occupations	
Shortage occupation	40.66 (8.43)***
Not shortage occupation	-69.48 (24.48)***
Shortage occupation with specific training	-19.84 (29.95)

6 Robustness

In this section, we present robustness checks, including placebo and sensitivity analyses. To assess the validity of the Conditional Independence Assumption (CIA) outlined in Section 4, we implement a placebo test. This test simulates the onset of unemployment three years prior to the actual date while preserving the actual duration between the start of the employment spell and the beginning of the training period. The results of these placebo tests are presented in Table B.1 in Appendix B. Tests yield no significant effects at 5%, supporting the validity of our main findings. It provides evidence that the identification strategy does not spuriously detect treatment effects in periods where no intervention was implemented.

We further perform sensitivity analyses by varying the value of q in the trimming procedure to ensure common support in Table B.2 in Appendix B. We do not observe

any substantial variation in the estimated treatment effect across different values of q in the trimming procedure. However, the coefficient is significant when no trimming is applied. This finding aligns with Huber et al. (2013), as the IPW estimator is highly sensitive to extreme weights associated with individuals who have extreme propensity scores. Trimming is therefore essential to mitigate bias. For instance, with $q = 0\%$, the coefficient is statistically significant, compared to the not significant coefficient with $q = 1\%$ in Table 2. Importantly, the estimated coefficient remains stable across trimming values, as all estimates are not significant as the result obtained at $q = 1\%$, supporting the robustness of our findings. As an additional robustness check, we compute treatment probabilities using a random forest model instead of the logit model used in the main specification in Table B.1 in Appendix B. The results remain essentially unchanged, indicating that our findings are not sensitive to the choice of propensity score specification.

7 Conclusion

We examine the impact of continuing vocational training programmes on employment in high-demand occupations using the Dynamic Inverse Probability Weighting method proposed by Van den Berg and Vikström (2022). Overall, our analysis reveals no significant effect of training on employment in shortage occupations in either favourable or unfavourable economic contexts over the medium term. The effect for low-educated individuals remains insignificant across both contexts, suggesting that this type of training may not sufficiently enhance their human capital to access high-demand occupations. The only positive and significant effects are observed among men, who benefit in both contexts, and among RSA recipients during the COVID-19 crisis. This pattern is consistent with the sectoral composition of shortage occupations, which are predominantly concentrated in construction and industrial sectors, traditionally male-dominated. These findings suggest that training programmes targeting shortage occupations are most effective in the medium term either for groups strongly aligned with shortage sectors or for vulnerable populations during periods of adverse labour market conditions. However, we find no evidence of any effect, regardless of economic context, for employment in shortage occupations that require highly specific vocational training directly related to the occupation. This suggests that training programmes do not significantly improve access to these highly specialised roles, possibly because the skills required are too narrowly defined and difficult to acquire within the scope of standard training interventions. This interpretation is consistent with Lechner and Wunsch (2009), who show that the higher the unemployment rate, the greater the effect of training on the return to employment. Our results are also consistent with those of Frick et al. (2024), who also report no significant medium-term effect of training on employment in shortage occupations. However, when we extend our analysis to a 42-month horizon for individuals who entered unemployment in 2019, we find a positive and statistically significant effect of training focused on shortage occupations on cumulative days of employment in these occupations. This result suggests that the benefits of such training may materialise gradually, overcoming short-term lock-in effects and leading to sustained improvements in employment outcomes over the long term.

According to our findings, training programmes do not offer a response to labour shortages. This absence of impact may be attributed to the fact that fewer than 60% of training

courses are specifically targeted at shortage occupations. Furthermore, when such occupations suffer from recruitment difficulties due to low attractiveness or a mismatch in human capital between jobseekers and employer requirements, these same factors may also deter individuals from enrolling in relevant training or accepting employment in such occupations after completing the programme. In addition, the structure of current training programmes does not permit the acquisition of high levels of human capital, such as engineering qualifications, which nonetheless represented the most in-demand occupation in the Grand Est region in 2021, but typically require longer training durations than those currently offered.

To enhance these outcomes, public policymakers should prioritise training programmes that target occupations facing labour shortages and limit access to individuals who have already had some exposure to the relevant profession. Indeed, some individuals may choose not to enter the occupation for which they were trained upon discovering, during or after training, that its working conditions are particularly demanding. During periods of low unemployment, individuals are more inclined to select jobs that impose fewer constraints compared to those in high-demand sectors. On the employers' side, recruitment becomes more challenging, leading them to favour candidates who apply promptly over those who are engaged in training programmes. Moreover, a structural effort to attract women into high-demand sectors such as industry and construction, traditionally male-dominated, could help alleviate labour shortages.

Additionally, the indicator of shortage occupations is published with a one-year delay. Providing policymakers with more timely and relevant data could help increase the alignment between training provision and labour market needs. Moreover, the main source of funding for jobseeker training in France (PIC) primarily targets individuals with low qualifications, and most of the training programmes it supports are designed to last less than one year to avoid prolonging unemployment spells. Given that many shortage occupations are highly skilled, current training provision often fails to provide sufficient human capital for the low-skilled, while also falling short of enabling the already skilled to retrain or transition into new careers.

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Appendix A: Shortage occupation indicator

Table A.1: Occupation and Labour Market Indicators

Occupation	Global Tension	Hiring Intensity	Training-Job Link	Lack Workforce	Job Instability	Working Conditions	Geographic Mismatch
Building and public works engineers, site managers, and works managers (executives)	5	5	4	4	1	1	4
Mechanical and metalworking technicians	5	1	4	5	3	2	5
Electrical and electronic drafters	5	5	5	4	1	1	5
Electrical and electronic technicians	5	1	5	5	1	2	4
Site managers, works managers (non-executives)	5	5	5	4	1	4	3
Setters	5	2	5	5	2	4	5
Nurses	5	2	5	5	3	3	1
Computer study, research, and development engineers and executives, IT project managers	5	5	5	4	1	1	2
Master craftsmen and equivalents in mechanical manufacturing	5	1	3	5	1	3	5
Roofers	5	5	4	4	3	4	4
Surveyors	5	5	5	5	1	2	5
Pipe fitters	5	5	5	3	3	4	5
Real estate agents, property managers	5	5	3	1	2	2	1
Building and public works drafters	5	5	5	2	1	1	3
Building and public works technicians and study officers	5	2	4	5	1	3	2
Butchers	5	2	5	4	2	5	4
Skilled workers in public works, concrete, and extraction	5	5	1	4	4	5	5
Stone and associated materials professionals	5	2	4	5	2	3	5
Plumbers, heating engineers	5	5	5	3	3	3	4
Wooden carpenters	5	5	5	4	3	3	5
Skilled workers in mechanical maintenance	5	3	5	5	3	4	5
Mechanical and metalworking drafters	5	5	5	3	2	1	4
Expert technicians	5	1	1	5	1	2	4
Headwaiters	5	2	5	4	1	5	3
Head chefs	5	5	5	3	1	5	1
Butchers, caterers	5	2	5	5	2	5	5
Skilled agents in heat treatment and surface treatment	5	5	3	3	4	5	5
Metal carpenters	5	5	1	3	3	5	5
Maintenance and environmental technicians and supervisors	5	5	4	4	2	2	2
Unskilled workers in metallurgy, glass, ceramics, and construction materials	5	3	1	5	4	4	5
Building and public works machinery operators	5	5	3	3	4	3	4
Vehicle mechanics and electronic technicians	5	5	5	2	2	4	2
Transport operations agents	5	2	3	5	1	4	5
Accounting and financial services technicians	5	3	5	5	1	1	2
Skilled workers in electricity and electronics	5	5	5	4	4	4	2
Carpenters and fittings and insulation workers	5	5	4	1	3	4	2

Occupation	Global Tension	Hiring Intensity	Training-Job Link	Lack Workforce	Job Instability	Working Conditions	Geographic Mismatch
Skilled workers working by metal removal	5	5	4	3	4	5	3
Road-based public transport drivers	5	2	1	4	3	4	4
Other paramedical professionals	5	5	5	5	2	1	2
Masons	5	5	4	3	3	4	4
Technicians and supervisors in flexible materials, wood, and graphic industries	5	1	4	5	1	2	4
Hotel management	5	2	4	4	2	3	5
Automobile body repairers	5	4	5	3	1	3	5
Skilled workers in building painting and finishing	5	4	4	1	4	4	4
Manufacturing and production engineers and executives	5	4	3	4	1	1	2
Unskilled workers in printing, press, and publishing	5	5	3	3	4	4	5
Insurance technicians	5	2	4	5	1	1	5
Technical supervisors in maintenance and environment	5	5	4	4	1	1	2
Truck drivers	5	4	4	4	3	4	4
Building electricians	5	5	5	2	3	4	3
Administrative, accounting, and financial executives (excluding lawyers)	5	5	1	4	1	1	1
Process industry supervisors and equivalents	5	1	4	5	1	2	5
Home helpers and housekeepers	5	3	1	4	3	4	3
Electrodomestic maintenance technicians	5	5	4	1	1	5	5
Skilled workers in electrical and electronic maintenance	5	4	5	3	2	2	3
Transport administrative agents	5	1	1	5	1	3	5
Unskilled workers in building construction	5	5	1	2	3	3	4
Technical-commercial engineers and executives	5	5	1	5	1	1	2
Medical device specialists	5	3	5	4	1	3	4
Medical technicians and preparers	5	1	5	5	2	4	2
Boilermakers, sheet metal workers, tracers, locksmiths, metalworkers, blacksmiths	5	3	5	4	3	5	3
Insurance executives	5	1	3	5	2	1	5
Accounting clerks	5	3	5	4	2	1	1
Cooks	5	5	5	3	2	5	1
Hotel employees	5	5	1	2	5	3	2
Nursing assistants	5	2	5	5	3	4	1
Logistics managers (non-executives)	5	5	1	3	2	2	1
Light vehicle drivers	5	2	1	3	2	3	5
Unskilled workers in building finishing	5	5	1	2	3	3	4
Production, operation, installation, and maintenance technicians, IT support and user services	5	4	5	2	2	1	4
Hotel and restaurant executives	5	4	1	1	1	2	3
Maintenance supervisors	5	2	3	5	2	2	5
Bakers, pastry chefs	5	4	5	3	1	5	2
Commercial attachés	5	3	3	5	1	2	2
Welders	5	5	4	2	4	5	4
Telecommunications engineers and executives	5	5	5	3	2	2	4

Occupation	Global Tension	Hiring Intensity	Training-Job Link	Lack Workforce	Job Instability	Working Conditions	Geographic Mismatch
Unskilled workers working by metal removal or shaping	5	5	1	3	4	5	4
Skilled workers in printing and binding in the graphic industries	5	1	3	4	3	4	3
Apprentices and unskilled workers in food (excluding agri-food industries)	5	5	3	3	1	4	4
Unskilled workers in metalwork, locksmithing, assembly	5	5	1	3	3	4	4
Trainers	5	4	1	3	2	1	1
Loggers, salaried foresters, and forestry agents	5	2	5	4	2	4	5
Hairdressers, beauticians	5	3	5	1	2	3	1
Representatives for individuals	5	5	3	2	1	2	4
Telesales representatives	5	5	1	1	3	3	1
Skilled workers in woodworking and furniture making	5	1	5	5	4	5	5
Production methods engineers, quality control	5	5	1	4	1	1	1
Specialized educators	5	2	5	4	2	1	1
Wholesale sellers of equipment and supplies	5	1	3	5	2	1	5
Salaried sailors	5	5	5	2	3	5	5
Skilled workers in textile and leather artisanal work	5	1	4	2	2	1	5
Architects	5	4	5	2	1	1	1
Assemblers, fitters, and other skilled workers in mechanics	5	2	4	3	3	4	5

Appendix B: Robustness Checks

Table B.1: Placebo results by sample year

Test	2019 Sample		2021 Sample	
	ATET (SE)	p-value	ATET (SE)	p-value
Placebo tests				
Placebo - Shortage occupation	-0.44 (2.60)	0.86	-13.28 (8.22)	0.10
Placebo - Not shortage occupation	1.30 (8.73)	0.88	-5.41 (10.75)	0.61
Placebo - Shortage occupation - shortage training	-0.50 (0.91)	0.58	-9.95 (5.67)	0.07
Placebo - Not shortage occupation - shortage training	1.96 (7.19)	0.78	-2.91 (9.01)	0.74

Note: Outcome measured in days. Bootstrapped standard errors (500 replications).

Table B.2: Sensitivity results of qualifying training focused on shortage occupation on cumulative days of employment in shortage occupation

Test	2019 Sample		2021 Sample	
	ATET (SE)	P-value	ATET (SE)	P-value
Sensitivity analysis (varying q)				
$q = 0\%$	-50.74 (18.67)	0.00	-56.32 (15.99)	0.00
$q = 5\%$	-8.11 (27.35)	0.76	6.20 (43.74)	0.88
$q = 10\%$	-7.57 (27.45)	0.78	6.53 (43.83)	0.88
Other propensity score specification				
Random Forest	-6.62 (20.56)	0.74	8.18 (25.86)	0.75

Note: Outcome measured in days. Bootstrapped standard errors (500 replications).