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Impact of psychological and social assistance on professional reintegration

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Abstract

Do socio-psychological assistance have an impact on professional reintegration ? I consider the effect of 'Parcours Emploi Santé' program, set by the French Unemployment Agency, on treated job-seekers. Although the magnitude of the study does allow to assess for a positive impact on return to employment/formation, suggesting only what could be a lock-in effect for the first months, I was able to find a positive impact on the likelihood of requesting a disability status. A following heterogeneity analysis highlight the difficulty to reach certain types of populations (50 years old or older and long-term unemployed peoples). This paper ends with a concluding discussion talking about, among other things, the thorough work done by advisers in order to reconnect with isolated people and the difficulty to capture it.

1 Introduction

Health difficulties can significantly impact a person's ability to search for and secure employment. When health challenges are faced, whether physical or mental, it can create additional obstacles and complexities in their job search journey. The French Employment Agency (FEA) states that health difficulties are one of the three major impediments to re-employment [1].

To address this issue, the FEA designed a specific service towards job seekers expressing health difficulties: *"Le parcours Emploi Santé"* (PES). Its purpose is to help them making the connection between their health status and its impact on their professional project. This service aims to help job seekers become aware of their professional potential despite their health condition. Through individual appointment and group workshops, it also helps them understand the importance of taking care of their health and/or initiating an appropriate care pathway, as well as identifying the necessary actions to facilitate their return to employment.

In this paper I study the effect of PES, implemented in February 2022, that targets unemployed people showing health difficulties and/or social isolation, focusing on both transitions into employment and changes in career trajectory, using panel data.

My empirical strategy exploits existing prescribing rate disparities between agencies, disparities due to three main reasons: differences in number of PES slots available, in knowledge detained by employment advisers or local accessibility difficulties [2]. I use detailed individual information from FEA registration data to set up a propensity score matching (PSM) design. I then estimate the effect of PES, within two distinct periods of 9 and 12 months, on return to employment, access to training and recognition of disability status' requests.

I find that, 6 months after the beginning of the program, PES leads to a significant increase of 2,1 percentage points (pp) increase in the likelihood of requesting a disability status. To this day, the lack of hindsight and information available for this study does not allow to assess a significant impact on the return to employment nor the access to formation. Observed trends suggest a lock-in effect occurring during the individual's involvement in PES, followed by an increase of the return to employment and the access to formation.

The obtained residuals strongly suggest heterogeneity in the impact of PES on job seekers. Their analysis led me to the conclusion that older people (50 years and more) in one hand and long-term unemployed job-seekers in the other hand both are populations further away from socio-professional reintegration than the reference one. This goes along with the well-known consequences of long-term unemployment (Machin and Manning 1999 [3];

Nichols et al. 2013 [4]) and health issues (Dooley et al. 1996 [5]) on unemployment. Note that this heterogeneity may also represents
The rest of the paper is outlined as follows. In the next section I briefly explain the design of PES and the data used for conducting my estimations. Section 3 present my estimation strategy. Section 4 outlines the empirical findings, section 5 deals with heterogeneity and section 6 ends with a concluding discussion.

2 '*Parcours Emploi Santé*' design and data

2.1 Parcours Emploi Santé

The PES service was initially designed for long-term (DELD) unemployed people but has been quickly expanded to every registered people at the FEA. PES aims to help job seekers become aware of their health on their return to work, to understand the importance of taking care of their health, and to determine the actions needed to facilitate their return to work. 63% of the PES beneficiaries are registered as DELD (more than 15 months registered in category A in a row, see 3 and 20). PES consists of three phases. Phase 1 is a global approach to the situation of the job seeker. It involves a multidisciplinary team conducting an assessment to identify the obstacles and orientations to be considered. Phase 2 is the implementation of the action plan, which aims to initiate a new confrontation of the beneficiary with the professional world, to initiate a revitalization of their career path, and to begin to identify the contours of a realistic and achievable professional project. This is achieved by relying on work environments and/or working conditions compatible with the health situation of the beneficiary, as well as transferable skills. Phase 3 is the end-of-course interview, which aims to review the job seeker's progress through their engagement in the action, their perception of themselves, their sense of efficacy, etc. The whole process takes between 4 to 6 months. Fig. 1 displays the follow-up of PES once it has been introduced to a job seeker. 80 % of the people who have been given the possibility to start PES registered, and 55% of the actually started the program. Fig. 2 shows the different exits of PES for the job seekers whom started the process. 54% of them exited with more than 4 months of attendance and an end-of-the-program report. It is important to notice that the PES program has been outsourced to different service providers. Because of the strict technical specifications set by the FEA, I will assume no major differences between the providers.

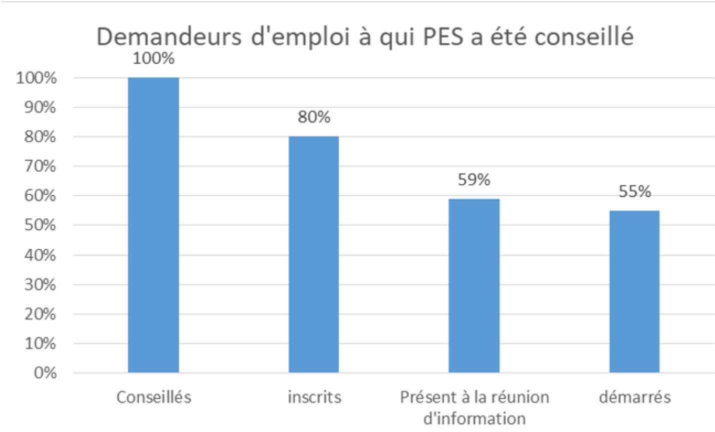

Figure 1: PES Conseil

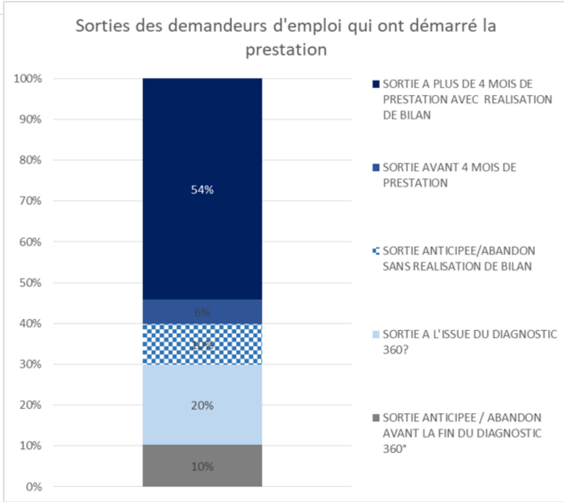

Figure 2: Sorties PES

2.2 Data

Data sources: The FEA keeps track of every job seeker joining or leaving PES, registration date, exit date, when did the adviser introduced PES for the first time, each reason leading to a decision. It allows me to identify the applicants and their paths. The unemployment register allows me to identify start and end dates of unemployment spells, and collect rich information on individual characteristics at the moment of registration: gender, education, skill level, location , age, etc. I also have information on the return to employment, the access to formation and the recognition of disability status' requests for each individual, every month. The period considered is February 2022 to May 2023.

Database construction:The objective is to carry out an intend-to-treat impact measurement, using a difference-in-differences strategy. Because it is based on prescribing rate disparities between agencies, my intend-to-treat population has been defined such as: PES beneficiaries coming from the 50% of the most prescribing agencies (including people who did not come in the first place / left before the final interview), whereas my control group is composed of non-beneficiaries coming from the 30% least prescribing agencies. I chose to only consider people with an health difficulty checked in the registers so that my control group is the closest possible from the treated one. The idea is to consider only people that, if they had been proposed to, would have joined the program. I therefore imposed this health difficulty condition on both groups. Furthermore, the category of registration had to be 'A' or 'B', I did not wanted to consider people doing a lot of reduced activity. See Fig. 3. My final data set is made of ten cohorts: from February 2022 to November 2022. The number of months was imposed by the context of the study. Fig. 19 shows the build up of PES through the period. The construction of the control groups results with cohorts in average 60 times bigger than my treatment groups. The geographical repartition of the chosen agencies does not seem to suffer of any heterogeneity (Fig. 21)

Month	Nb obs. treated	Nb obs. control	control/treated ratio
Feb	122	104550	856,9672131
Mar	1158	104570	90,30224525
Apr	1401	94097	67,16416845
May	1953	93828	48,04301075
Jun	1871	104592	55,90165687
Jul	1511	104721	69,30575778
Aug	1953	104372	53,44188428
Sep	2432	102553	42,16817434
Oct	2338	100730	43,08383234
Nov	1888	100174	53,05826271

Catégorie A	Demandeurs d'emploi tenus de faire des actes positifs de recherche d'emploi, sans emploi
Catégorie B	Demandeurs d'emploi tenus de faire des actes positifs de recherche d'emploi, ayant exercé une activité réduite courte (i.e. de 78 heures ou moins au cours du mois)
Catégorie C	Demandeurs d'emploi tenus de faire des actes positifs de recherche d'emploi, ayant exercé une activité réduite longue (i.e. de plus de 78 heures au cours du mois)

Figure 3: Catégories Pôle Emploi

Outcomes variables: As the analysis focus on two dimensions: transitions into employment and change in career trajectory, I consider three outcome variables. All binary, they give the information on whether the job seeker had completed the considered action during the month m. The transitions into employment are measured using the 'Return to employment' and 'Access to formation' variables (with the idea that access to formation is a first step towards reemployment). The 'Return to Employment' (resp. 'Access to formation') variable takes value 1 once it is known that the job seeker found a professional activity (resp. started a formation program). The change in career trajectory is measured using the recognition of disability status' requests (RQTH). The RQTH variable takes value 1 when the job seeker apply for recognition. Each of theses variables have been extracted from the unemployment register. Fig. 4, 5 and 6 shows the cumulative evolution of theses outcomes variables on treated and control groups, through time, where month 0 (resp. forma0, rqthm0 and accesm0) correspond to the beginning of PES. After four months (forma0), 2% of the treated group has had access to formation. It appears that the control group is more active than the treated one, following the idea that PES is only introduced to the most distant job seekers.

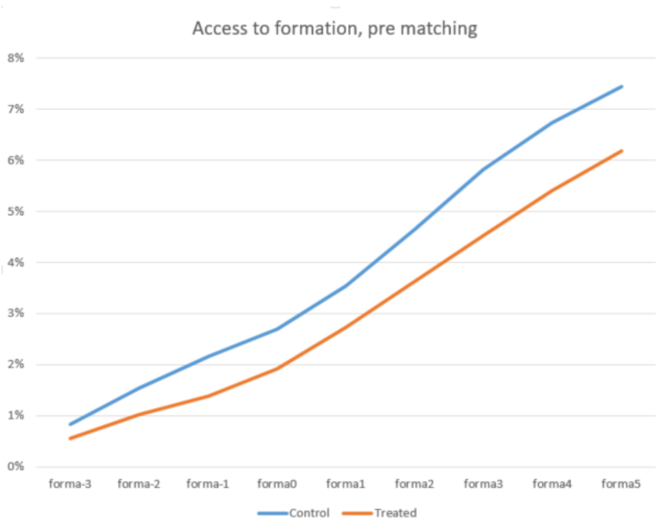

Figure 4: Acces to formation

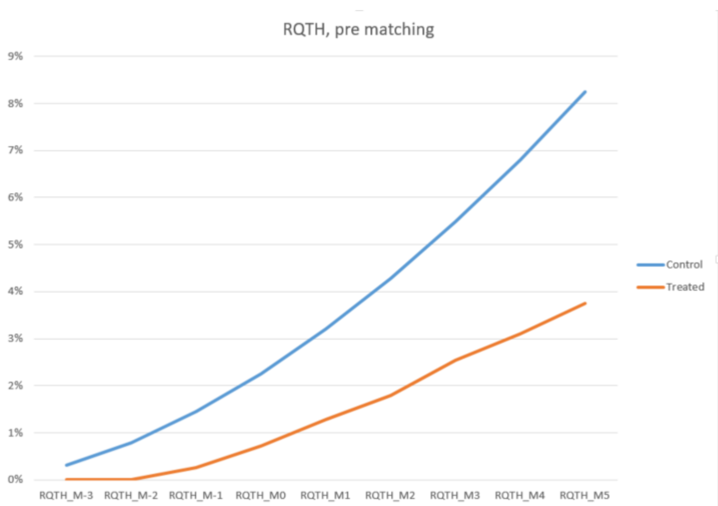

Figure 5: RQTH

Figure 6: Return to employment

Disparities between population: For privacy reasons, the FEA can not ask specific health questions to the registered people. The only information available, as mentioned before, is a binary variable called "Health difficulty" that takes value 1 if the respondent say so. It is only declarative information. In my case, job seekers' health is the main reason why they are offered to take part in PES. The FEA conducted a telephone survey of the PES populations: treated group and potential control group. Both of theses group are only composed by people that have declared health difficulties at their registration.

To the question asked 'In general, would you say that your health is : Very good, good, bad or very bad ?', 57% of the control group stated that the health was bad or very bad when 71% of the treated group said so [6]. This could be indicative of unobserved differences between the two populations.

3 Empirical strategy

3.1 Propensity score matching

When assessing the effect of a scheme on various indicators, simply comparing the evolution of these indicators for those benefiting from the scheme versus those who does not is not sufficient, as the very fact of benefiting from the scheme is often not random: in particular, the most dynamic people can be the most inclined to participate in PES. To correct for this selection bias, methods controlling for observable differences between beneficiaries and non-beneficiaries have been developed. In an attempt to identify a causal effect of PES on treated people ($T_i = 1$), I need to verify the following conditional independence hypothesis:

$$Y_i^0 \perp T_i | X_i \tag{1}$$

where Y_i^0 corresponds to the variable Y when individual i is not treated and X_i is a vector of observable characteristics relative to that individual. This means that, conditional on observable characteristics X, the evolution of people that did not benefit from PES provides a good counterfactual of the potential evolution of beneficiaries, had they not benefited. This is a strong assumption. It reflects the fact that, apart from observable X, there are no other characteristics that influence both future trends and the choice of treatments.

To control for observable characteristics, I use matching methods based on observable data, which allow me to construct a control group statistically close to the treated companies. This will enable me to assess the effect of PES on the treated people, by comparing the difference in the evolution of each variables of interest between the two groups after the treatment has been implemented. In view of the large number of different data and in order to use the maximum amount of information to create a control group, I opt for the propensity score matching methods (Rosenbaum and Rubin, 1983)[7]. The propensity score is defined as the probability of being treated conditional on observable characteristics:

$$p(X_i) = P(T_i = 1 | X_i) \tag{2}$$

Rosenbaum and Rubin (1983) show that if that if the outcome variable Y^0 is independent of treatment T conditional on observable X, then it is also independent of T conditional on the propensity score $p(X)$. The matching method then consists of pairing

treated peoples with untreated peoples with similar propensity score. I will use the control groups described in section 2.2 for the matching process. Figures 4, 5 and 6 shows that, before PES, the characteristics of the two groups do not follow the same trend, justifying the need for a matching method.
More precisely, the propensity score is estimated using a linear logit model:

$$\hat{p}(X) = \frac{1}{1 + e^{-\hat{\beta}X}} \tag{3}$$

Once the propensity score has been estimated for each individual, several methods exists for constituting a control group that is effectively comparable to the treated group (Quantin, 2018)[8]. For each treated individual, I select the untreated individual with the closest propensity score. I check the matching quality by looking at the differences in absolute values of the main variables' frequencies:

$$|\overline{F_c} - \overline{F_t}| \tag{4}$$

Fig. 7 shows the checks on the balancing of matching for the main categorical control variables. Are considered here:

Variable	Nb of levels	Source
Category of registration	2	FHA, SISP
Unemployment benefit	2	
RSA (Active Solidarity Income)	2	
Seniority of registration	4	
Level of qualification	4	
Level of formation	4	
Gender	2	
Age	5	

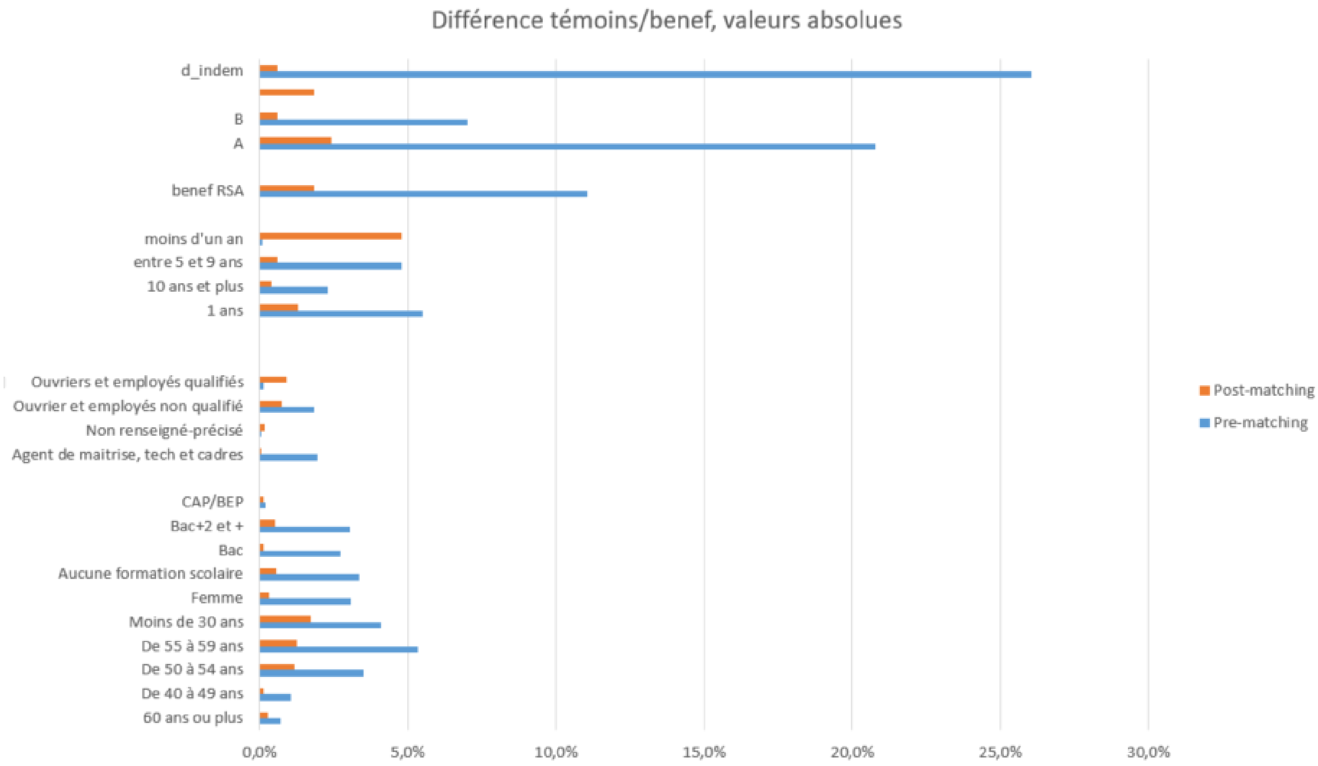

Figure 7: Differences of frequency, absolute values

Looking at the differences of the selected group frequencies resulting from the matching, all of them under 5% and the vast majority under 2%, I assume that the conditional independence hypothesis is verified.

3.2 The impact of PES

Once the control group has been constructed, differences in changes in the variables of interest between beneficiaries and non-beneficiaries are estimated using the difference-in-differences method: The specification used is as follows:

$$Y_{i,t} = \alpha + \beta_t T_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \tag{5}$$

where γ_i and λ_t are individual and time fixed effects, and $T_{i,t}$ the indicator for treatment that indicate when people went to PES. β_t represents the impact of PES on beneficiaries for the month t.

I chose to conduct linear instead of logistic regression, following the discussion on binary outcome variables analysis (Gomila, 2020 [9]; Beck, 2018 [10]) allowing direct interpretation of the coefficients as probabilities and offering safer results as my model includes fixed effects.

This specification allows me to estimate the impact of PES on treated people for each month since they started the program, controlling for individual specificity and seasonal variations, considering the three different outcomes variables chosen. A regression is performed for each of theses, for every month available. Since my groups are composed of people whom started the program between February 2022 (launch of PES) and November 2022 (beginning of the study), I have 8 months of hindsight (Nov 22 to June 23), in which 4 to 6 months of job seekers attending PES have to be considered.

4 Empirical results

Figures 9, 8 and 10 show the results of the impact of PES on the three considered outcomes variables: Access to formation, Return to employment and recognition of disability status' requests. Theses graphs display the estimated parameter β_t for each month considered and its confidence interval, starting 3 months before the beginning of PES for an individual i (month 4) and ending 7 months after (month 11).
PES have negative short-run employment and access to formation effects on treated people. This can be explained by the "lock-in" effect, meaning that job seekers involved in training program will see their probability of leaving unemployment and / or accessing to formation decrease because of their required presence and focus on the considered program. This phenomenon has been widely discussed and empirical evidence have been shown in the past decades (Fitzenberger et al, 2006 [11]; Wunsch, 2016 [12]). The depth of the analysis does not allow to assess a positive effect on the long-run nonetheless the observed trend on access to formation seems to be heading there. We can not see the same run on the employment effect (yet?). It makes sense as one can imagine that access to formation may be the gateway to return to employment, therefore we might have a slight lag between them.

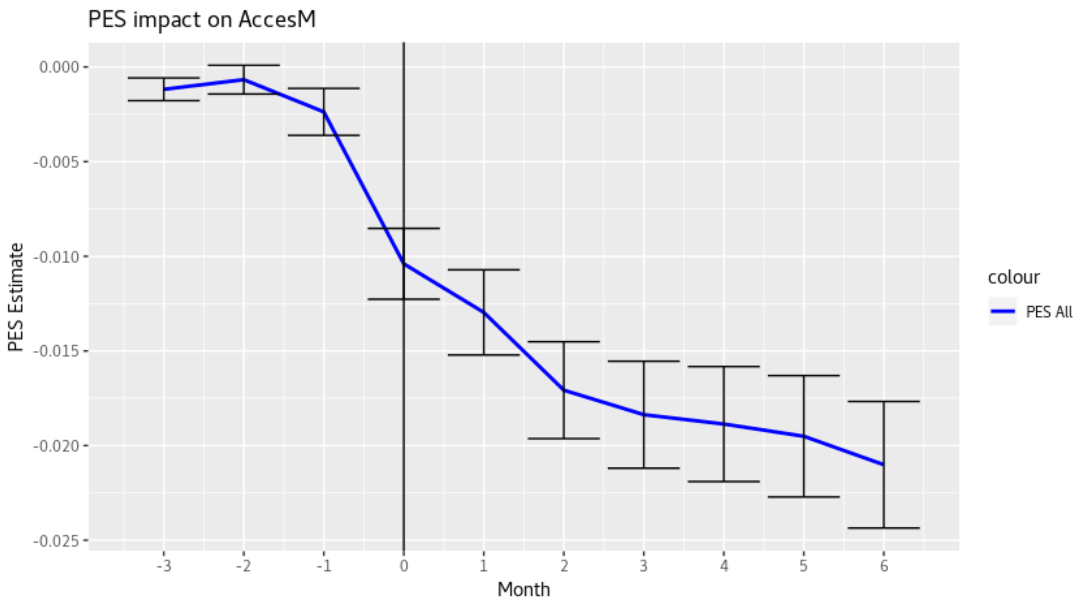

Figure 8: Return to employment

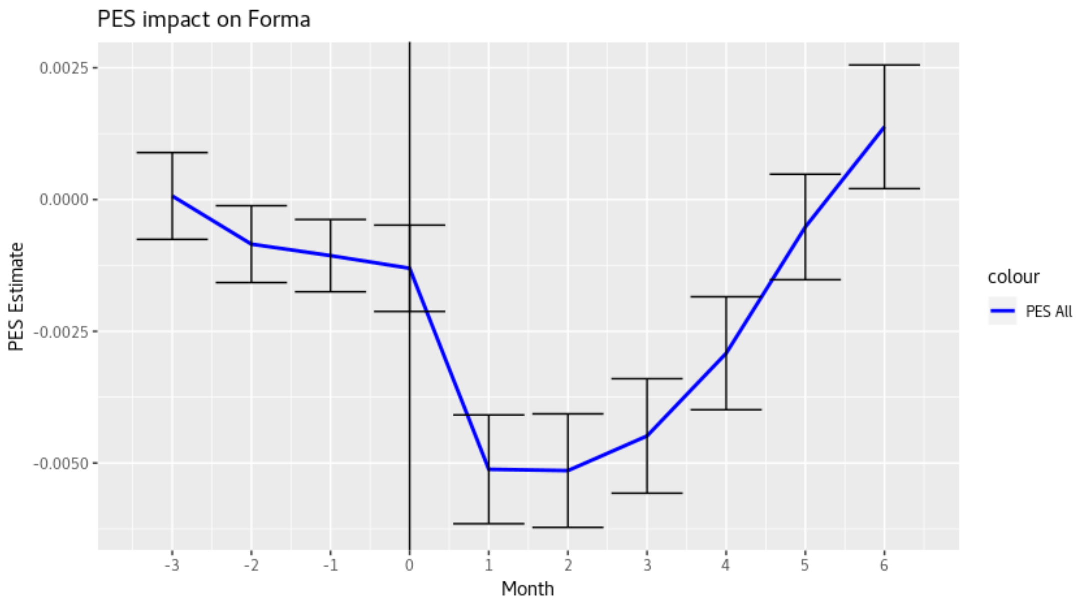

Figure 9: Acces to formation

On the other hand, PES have positive short-run effect on RQTH. It makes sense as the program itself was designed, in part to help its participants realize that they might need to apply for handicap recognition and if so, to help them filling the forms.

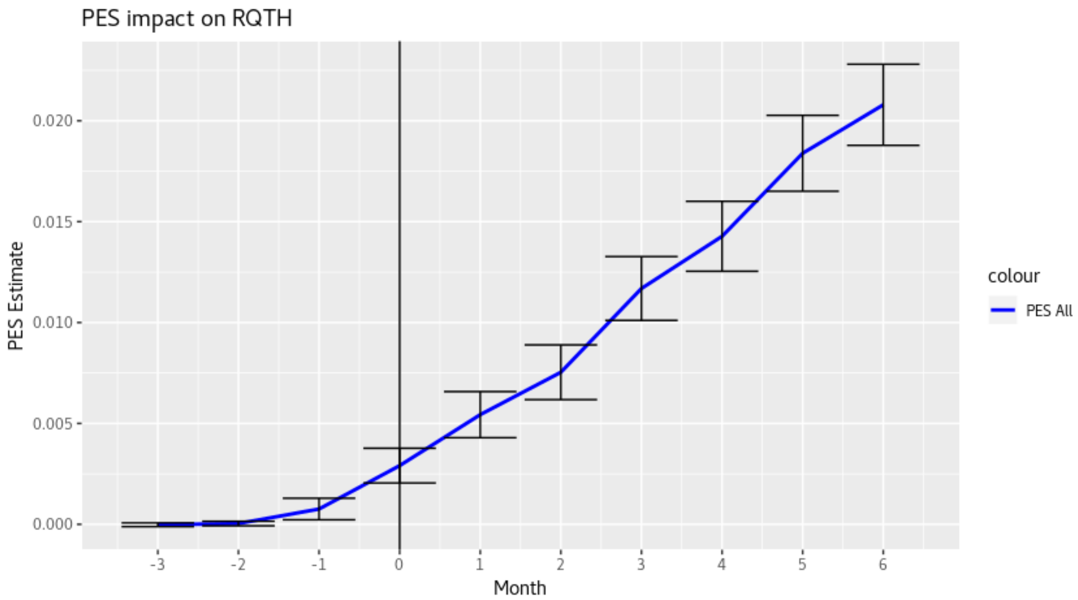

Figure 10: RQTH

At month 9 (6 months after the start of PES), the impact is ≈ - 2% on the return to employment, nil on the access to formation and ≈ + 2% on the RQTH. The following table gives the p-value for each estimate:

Also, details of the results show interesting model properties. Looking at the residual histograms plotted on figures 11 (Return to employment) and 13 (RQTH) can be somehow destabilizing. Answers come with the predicted values histograms, plotted on Fig. 12 (RE) and 14. We can see that for both of the considered outcome variables, the models almost always predict value 0 for return to employment or RQTH. The small fractions of residuals taking values around 1 are the people who actually found a job and/or filled RQTH forms.

Variable	1	2	3	4	5	6	7	8	9	10
AccesM	0,0487	0,3765	0,0558	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
RQTH	0.8126	0.7255	0.1539	0.0007	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Forma	0,9344	0,2458	0,1205	0,1112	< .0001	< .0001	< .0001	0,0065	0,6029	0,0495

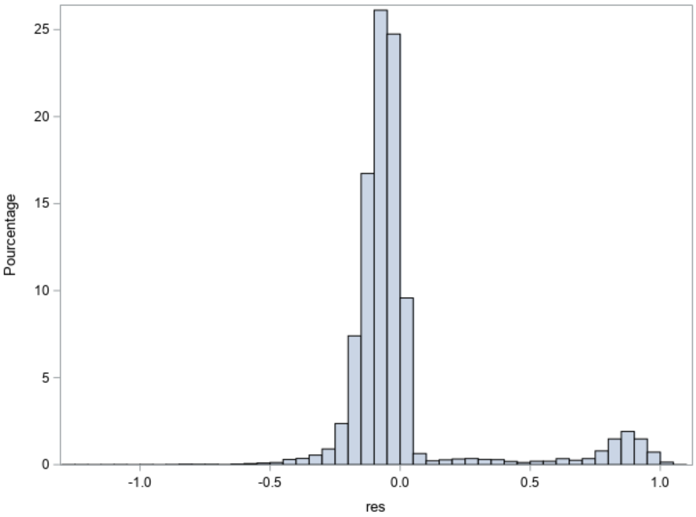

Figure 11: Histogram:Residuals Acces M8

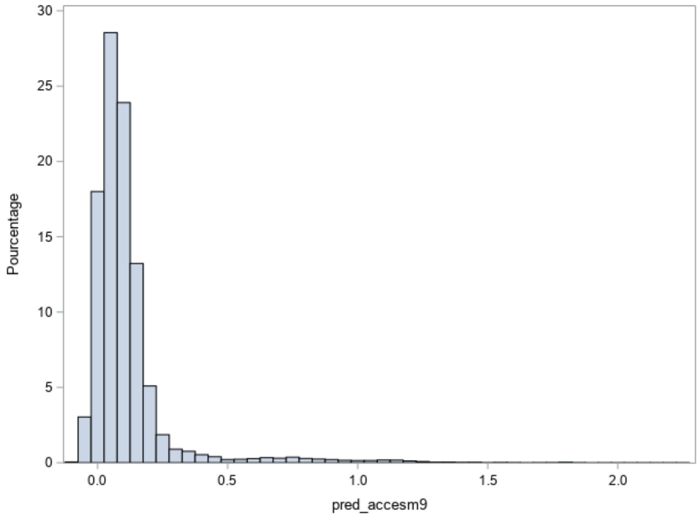

Figure 12: Histogram:Predicted Acces M8

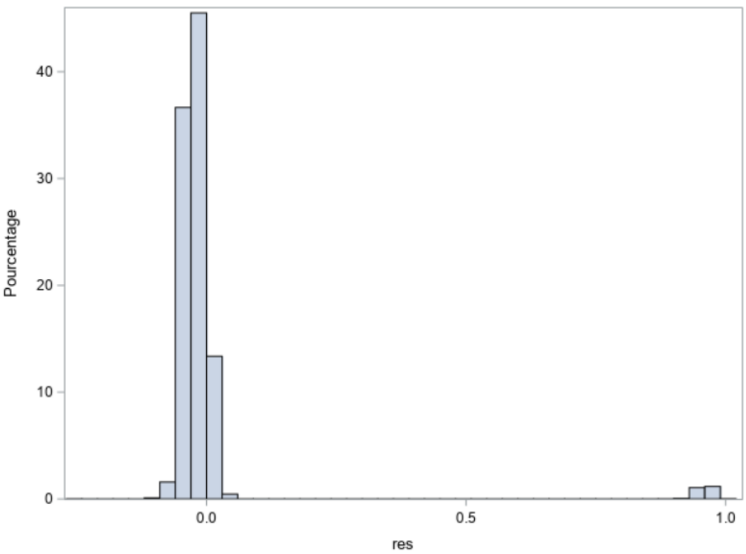

Figure 13: Histogram:Residuals RQTH M8

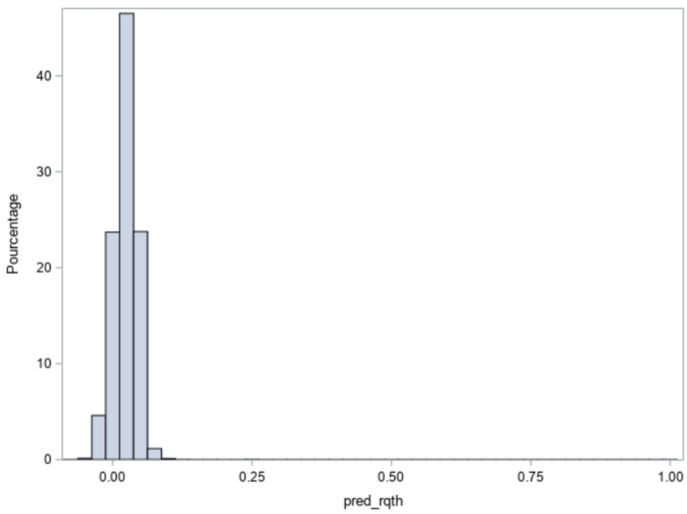

Figure 14: Histogram:Predicted RQTH M8

5 Heterogeneity analysis

Due to PES design, it is quite an heterogeneous population which was allowed to start the program. A logical continuation of the work done so far is to assess whether PES has a different impact on certain type of people, compared to its effects on the whole group, presented in the previous section. Looking at the characteristics of my final group, I was able to build on two specific populations: the 'long-term unemployed' group and the 'fifty-years or more' group.

'Long-term unemployed' group: A job seeker registered in the category A of the FEA for 15 months in a row or more is defined as a long-term unemployed person (DELD). As explained before, long-term unemployment is known to have negative impact on return to employment and social integration [3][4]. 64% of the treated group is made up of long-term unemployed peoples. They will be the first part of this complementary analysis.

'Fifty-years or more' group: Age can also be a barrier, widely discussed subject through the work of, among others, Warr, 1994 [13] and Duncan et al, 2003 [14]. 57% job seekers in my treated group are fifty years old or older. They will be the second part of my analysis.

Empirical strategy: Now that I have identified the two different parts of my heterogeneity analysis, I proceed as follow:

1. Set up of the rules (only DELD / only 50+) on the control and treated groups
2. Propensity score estimation
3. Matching (nearest neighbors)
4. Outcome variables retrieval (for this part I chose to focus on Return to Employment and RQTH)
5. Impact of PES estimation, using the same DiD strategy as detailed in section 3.2

5.1 'Long-term unemployed' group

Figures 15 and 16 shows the estimate of PES impact on the return to employment and the RQTH for the DELD group (red), compared to the reference group (blue). For the return to employment, we can see that the lock-in effect is slightly less marked for the DELD group, and we can also see a trend reversal through time, which did not appear for the reference group. As for the RQTH, the PES impact is a little less important for the DELD group but the trends seem to be the same.

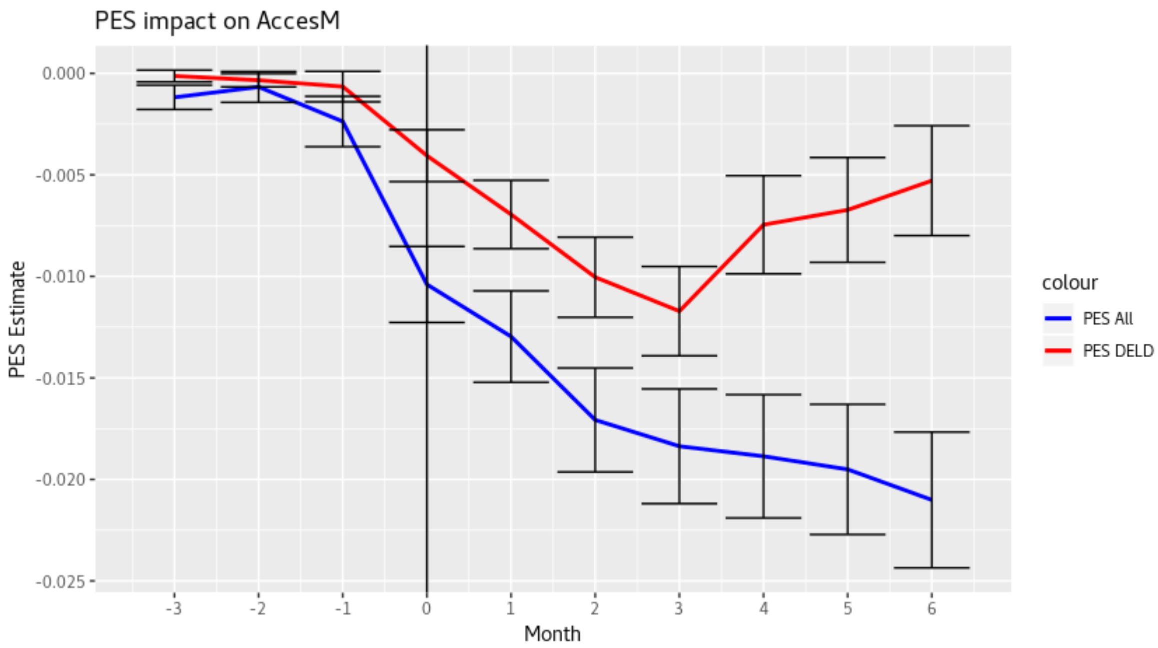

Figure 15: PES impact on RE, heterogeneity DELD group

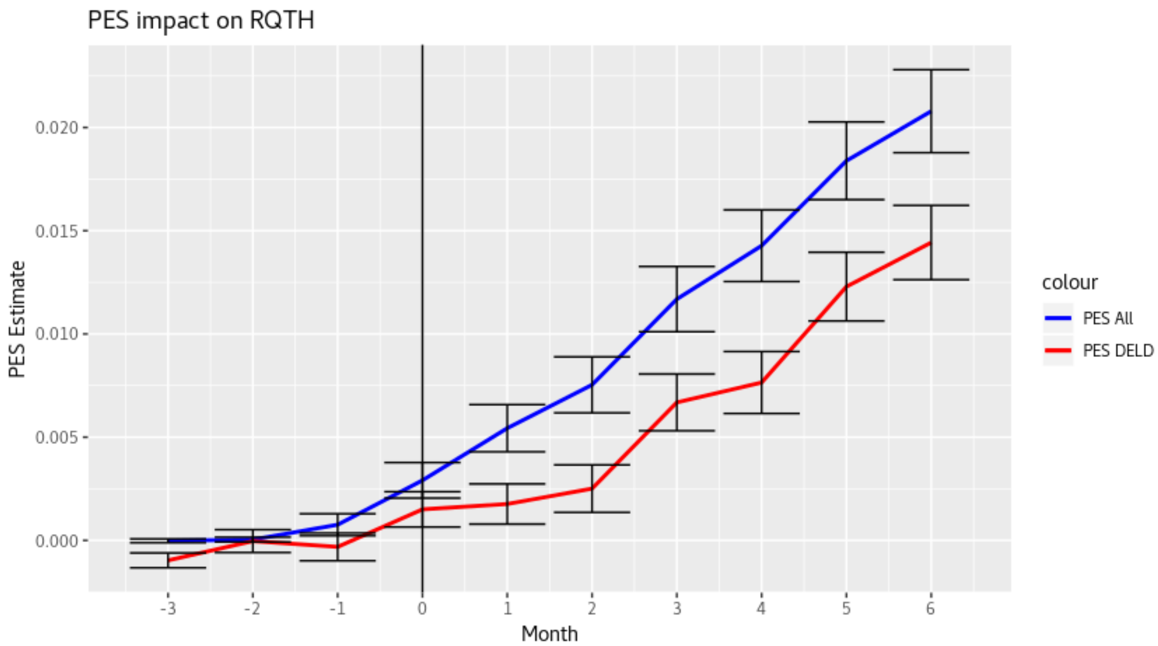

Figure 16: PES impact on RQTH, heterogeneity DELD group

The significance of the results is impacted, as we only have the months 1, 2 and 3 (resp. 3, 4, 5 and 6) significant at the threshold of 99 % for the RE(resp. RQTH).

5.2 'Fifty years or more' group

Figures 17 and 18 shows the estimate of PES impact on the return to employment and the RQTH for the 50+ group (red), compared to the reference group (blue). As for the DELD group, the PES impact is less important than for the reference group. The difference is even more marked, and for the last month the PES impact is no more negative, suggesting an end of the lock-in effect. The impact on RQTH appears to be the same than for the DELD group.

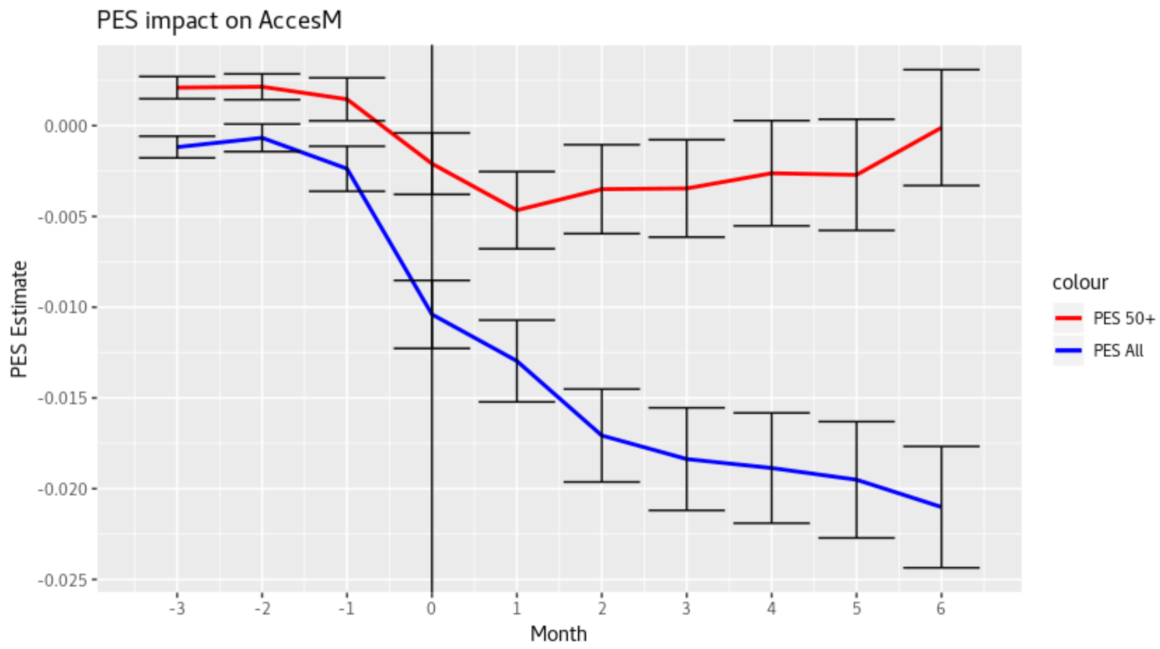

Figure 17: PES impact on RE, heterogeneity 50+ group

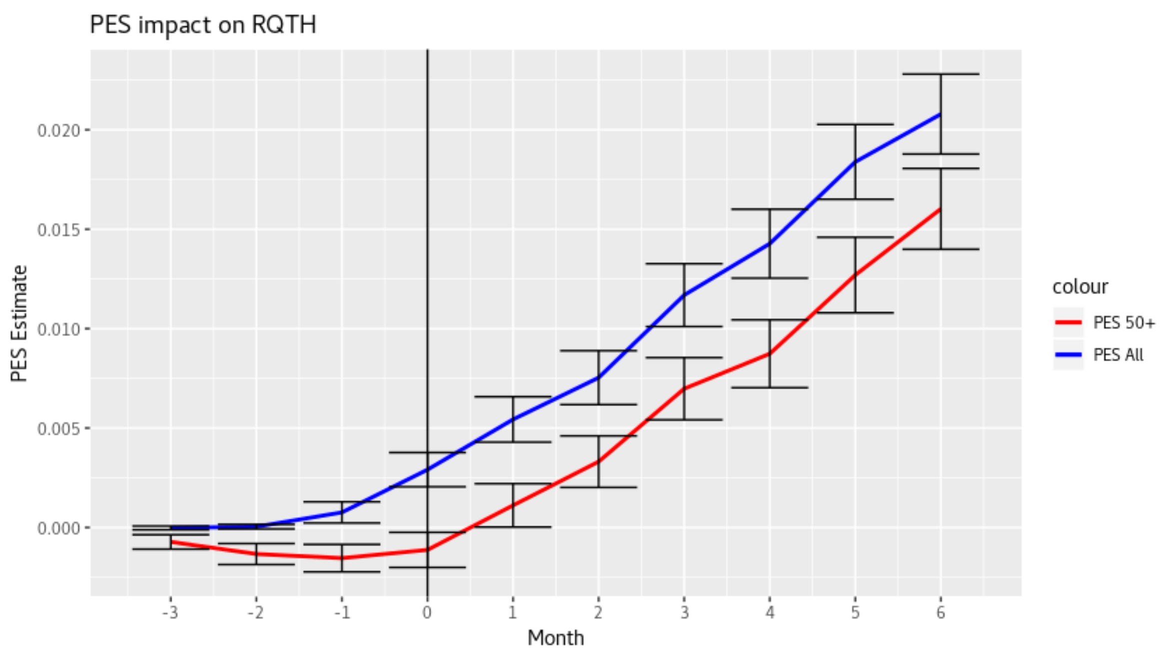

Figure 18: PES impact on RQTH, heterogeneity 50+ group

Theses results illustrate the differences in accessibility present across job-seekers populations. They go along with the literature detailed before, age and long-term unemployment have negative effect on return to employment. People with theses characteristics are harder to follow, discouragement comes sooner and health difficulties arise faster.

6 Conclusion

Even though the results detailed in this paper lack depth, they give us an order of magnitude of the PES impact 6 months after its beginning. With no positive effect (yet ?) on return to employment/formation, roughly 2% on RQTH and an heterogeneity analysis reflecting the difficulties associated with caring for older and/or long-term unemployed individuals, this large picture justifies the implementation of programs adapted to this situation. 'ATD quart monde', an organisation aiming to fight poverty produced a study estimating the cost of long-term unemployment in France at 32 billions euros per year (roughly 15 000 euros per DELD) for the state [15]. Although this number is to take with precaution, it gives material discussion on the means put in place in order to address the problem.

The PES impact study was initially asked by the FEA who needed items to decide whether, after one year of running PES, it had to continue or to stop. This study, produced by the Evaluations Department of the FEA, (this paper being its more expanded version) included a large qualitative part. Interviews with advisers, managers, providers and even beneficiaries, agencies visits, etc., theses were all elements aiming to depict the main impressions perceived by all PES actors. The restitution of this part of the study does not fit easily with a 'standard form impact-study paper'. I find it useful to end my work with the major components in the hope that they will allow an reasoned discussion. Most of the peoples we talked to expressed their positive reception of PES. They felt that it filled a gap of support towards the concerned peoples. However, some of them found that it was not suited for a part of their job-seekers, for several reasons such as specific health difficulty, mobility issues, language barriers, etc. The vast majority wanted PES to be renewed. They expressed the day-to-day difficulties in supporting isolated peoples and the issues in the program leading to a loss of contact with the beneficiaries.

This work highlights the long-term nature of the fight against socio-professional isolation. The Evaluations Department already acted its will to update the results next year for a deeper analysis. Last April, following the results of the study produced by the Department, among others, the FEA renewed PES.

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A Figures

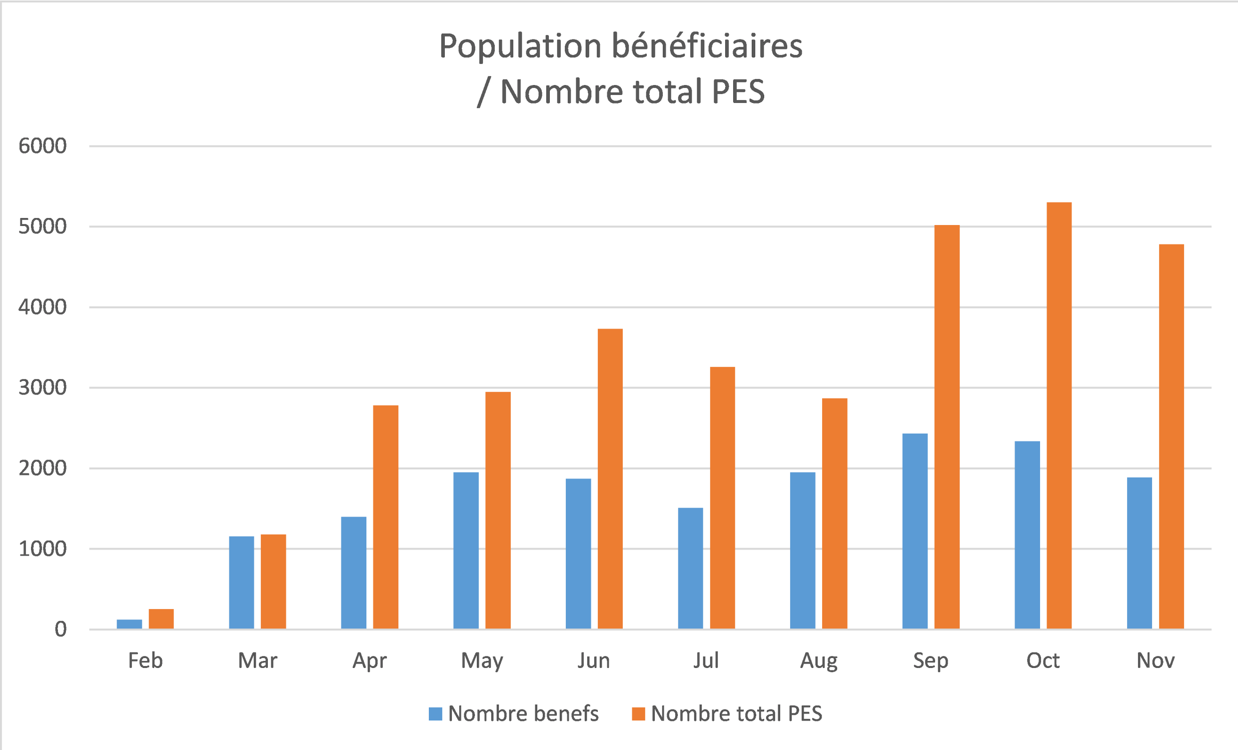

Figure 19: Montée en charge PES

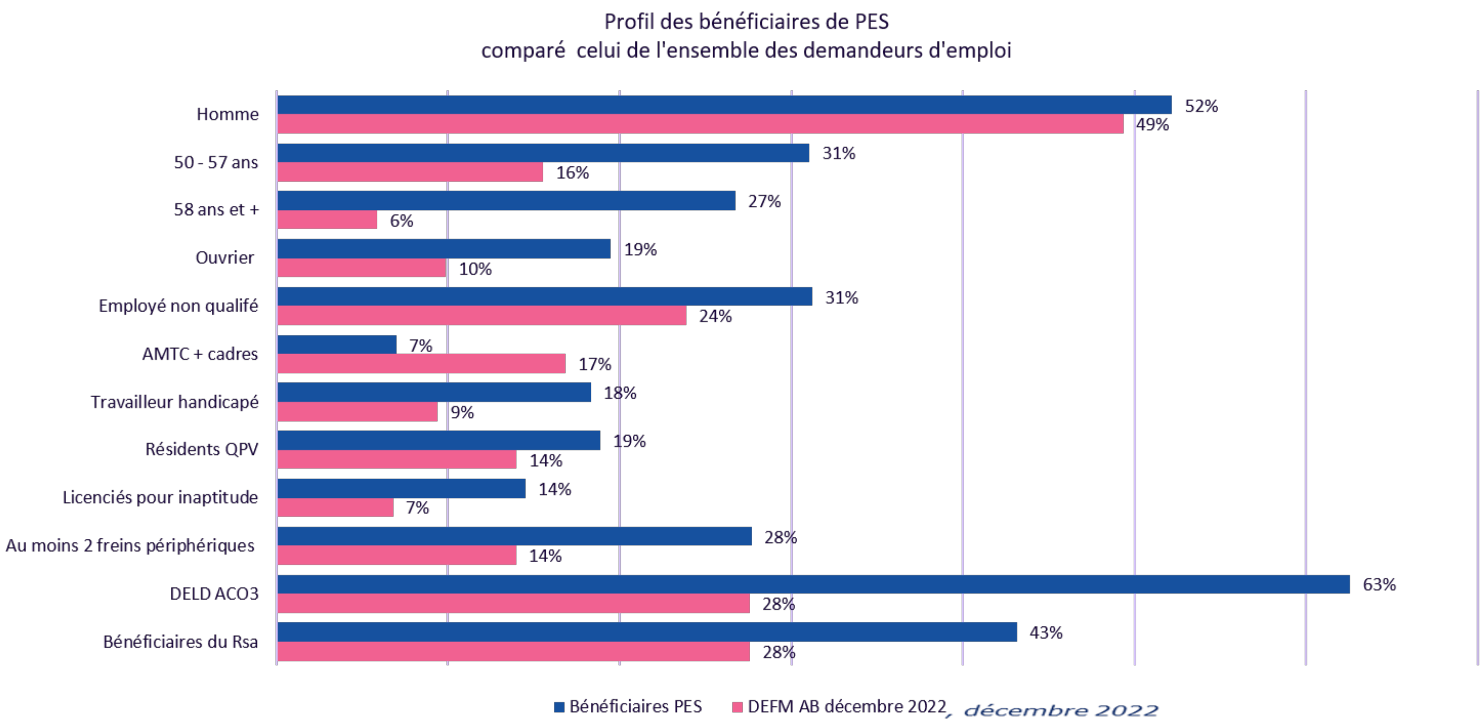

Figure 20: PES beneficiaries profile versus DEFM AB, December 2022

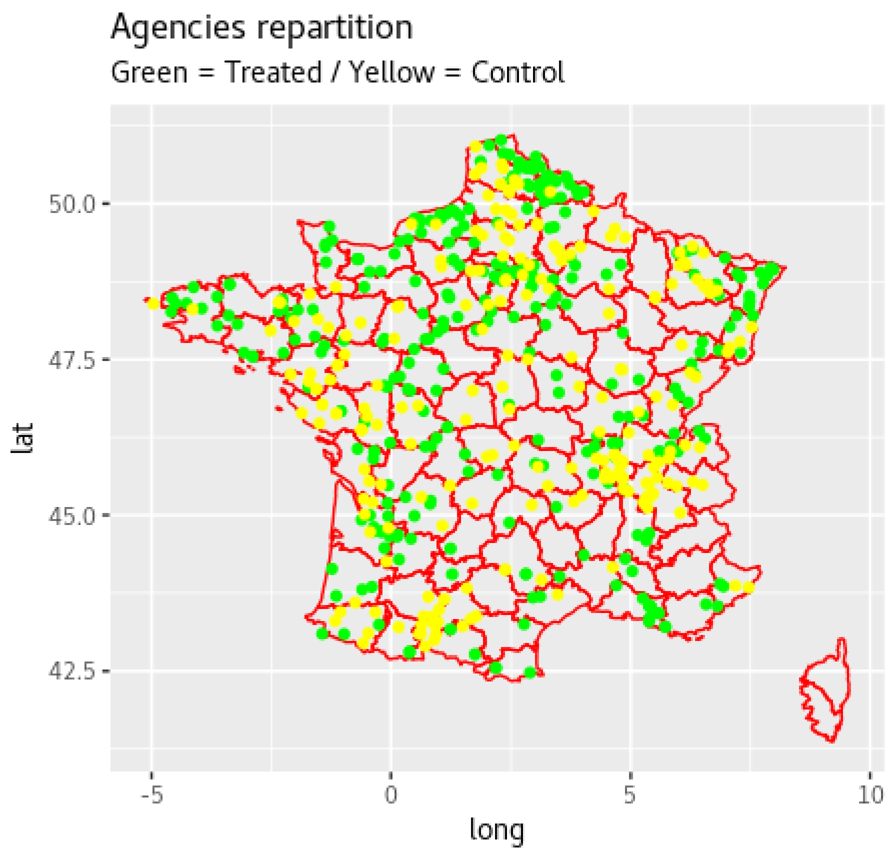

Figure 21: Agencies geographical repartition

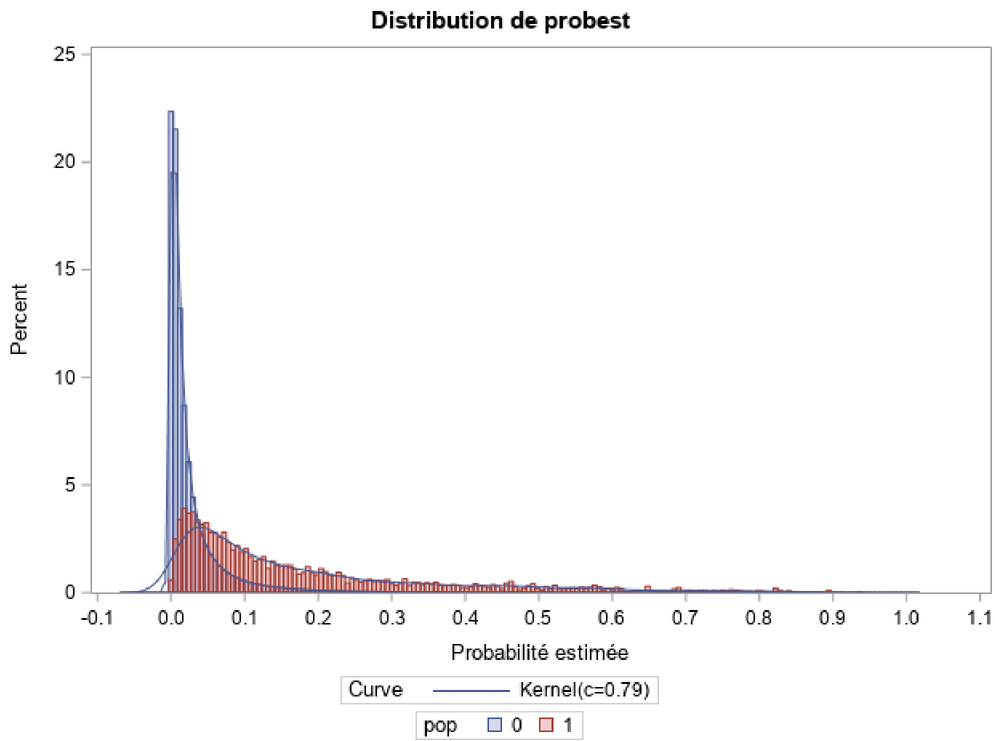

Figure 22: Propensity score distribution, pre matching

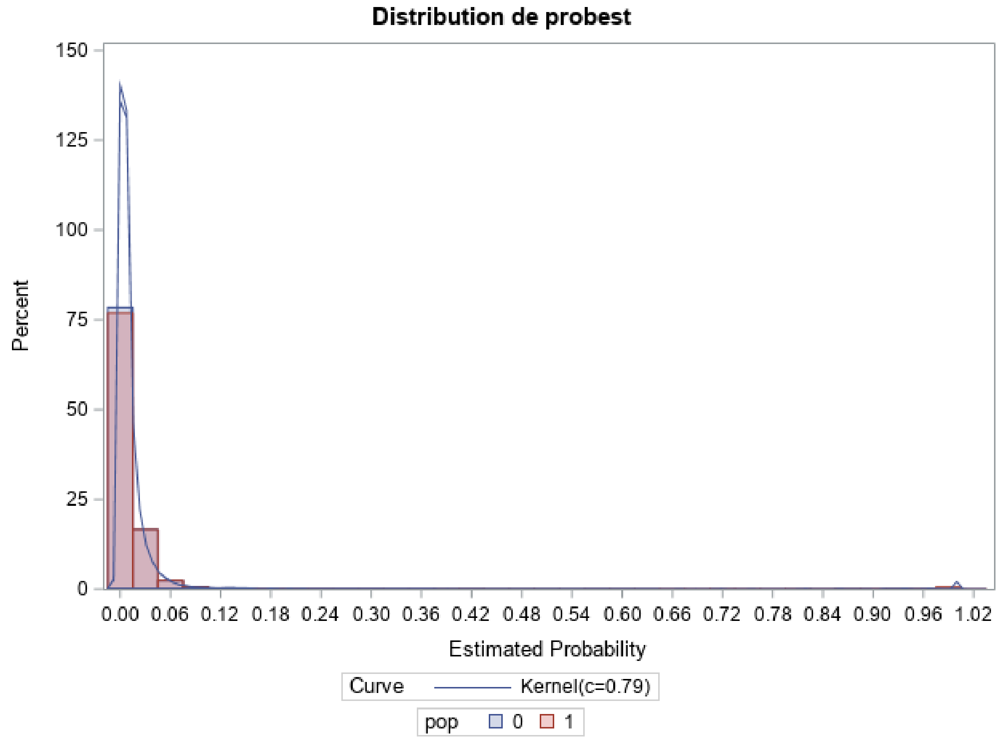

Figure 23: Propensity score distribution, post matching

Acronyms

DEFM Demande d'Emploi en Fin de Mois.

DELD Demandeur d'emploi de longue durée.

FEA French Employment Agency.

FHA Fichier historique des administrés.

RE Return to Employment.

SISP Système d'Information Statistiques et Pilotage.

UI Unemployment Insurance.